Journal of Management
Print ISSN: 0120-4645 / E-ISSN: 2256-5078 / Short name: cuad.adm.
Pages: e2413227 / Vol: 40 / Issue: 78 / Jan. - Apr. 2024
Faculty of Administration Sciences / Universidad del Valle / Cali - Colombia

Design and psychometric validation of a Customer Analytics Capabilities (CAC) scale: empirical evidence in Colombian organizations*

Diseño y validación psicométrica de una escala de Capacidades de Analítica del Cliente (CAC): evidencia empírica en organizaciones colombianas

[1] ***María Alejandra Maya Restrepo***
Head of analytics, Incolmotos-Yamaha, Medellín, Colombia. e-mail: alejandra.maya@udea.edu.co

[2] ***Jorge Iván Pérez Rave***
Director, IDINNOV research group, Medellín, Colombia. e-mail: investigacion@idinnov.com

Article of Scientific and Technological Research
Submitted: 12/09/2023
Reviewed: 30/10/2023
Accepted: 10/03/2024
Published: 18/03/2024
Thematic lines: Administration and Organizations
JEL classification: DM10
https://doi.org/10.25100/cdea.v40i78.13227

Abstract

Although the measurement of Customer Analytics Capabilities (CAC) has aroused interest among scholars and entrepreneurs, there is a lack of an instrument that synthesizes the main organizational routines involved in such a construct, based on empirical manifestations provided by scientific literature. The study contributes to closing this gap through the design and psychometric validation of a CAC measurement model. The sample includes survey data from 101 Colombian companies. The source of information corresponds to professionals in marketing or analytics areas. A psychometric analytical framework is used, which incorporates exploratory and confirmatory factor analysis. Two plausible measurement models are obtained: The three-dimensional model consists of 10 items grouped into the factors: customer acquisition analytics capability; customer maintenance analytics capability; and customer economic evaluation analytics capability. This satisfies fit, content validity, convergent and discriminant validity, reliability, and equity criteria. The unidimensional model contains 14 items, it also fulfills psychometric quality requirements, and it is useful when a parsimonious approach to the general attribute of CAC is desired. The developed scales make CAC measurable through a set of routines that reconfigure traditional operational capabilities in marketing. In addition, they facilitate the execution of reliable organizational diagnoses, the definition of work agendas for analytics departments and promote future work on the relationship between CAC and business performance.

Keywords: Customer analytics capabilities; Analytics; Organizational capabilities.

* This manuscript was one of the outcomes of the research carried out as master thesis to obtain the master in administration degree.

[1] Industrial engineer, Master in Administration, Universidad de Antioquia, Colombia.

[2] Industrial engineer, Universidad de Antioquia, Colombia, Doctor in Systems Engineering, Universidad Nacional de Colombia, Doctor in Business Management, Universitat de València, Spain.

Resumen

Aunque la medición de las Capacidades de Analítica del Cliente (CAC) ha venido despertando interés entre académicos y empresarios, se carece de un instrumento que sintetice las principales rutinas organizativas implicadas en tal constructo, sobre la base de manifestaciones empíricas aportadas por la literatura científica. El estudio aporta al cierre de esta brecha, mediante el diseño y validación psicométrica de un modelo de medida de las CAC. La muestra comprende datos de encuestas de 101 empresas colombianas; la fuente de información corresponde a profesionales de áreas de mercadeo o analítica. Se utiliza un marco de analítica psicométrica, que incorpora análisis factorial exploratorio y confirmatorio. Se obtienen dos modelos de medida plausibles: uno unidimensional y otro tridimensional. El tridimensional consta de 10 ítems agrupados en los factores: capacidad para la analítica de captura de clientes, capacidad para la analítica del sostenimiento de clientes, y capacidad para la analítica de la evaluación económica de clientes. Éste satisface criterios de ajuste, validez de contenido, validez convergente y discriminante, fiabilidad y equidad. El modelo unidimensional contiene 14 ítems, también presenta calidad psicométrica y es útil cuando se desea una aproximación parsimoniosa al atributo general de las CAC. Las escalas desarrolladas hacen medibles las CAC a partir de un conjunto de rutinas que reconfiguran capacidades operacionales tradicionales en mercadeo. Además, facilitan la ejecución de diagnósticos organizativos confiables, la definición de agendas de trabajo para departamentos de analítica y propician futuros trabajos de relacionamiento entre las CAC y el desempeño empresarial.

Palabras Clave: Capacidades de analítica del cliente; Analítica; Capacidades organizativas.

1. Introduction

Customer Analytics Capabilities (CAC) is a concept recently integrated into business management vocabulary, which emerges from the combination of organizational capabilities and customer analytics. The first component has been extensively studied under approaches that define it as a set of organizational routines that are imperfectly imitable and hardly substitutable, among other characteristics (e.g., dynamic capabilities approach; Teece *et al.,* 1997). However, the second component is more ambiguous, as no consensus has yet been reached on its definition. This is evidenced by the different conceptions underlying the attempts to define customer analytics: as an action or method (e.g., dealing with recognizing customer behavior and predicting their buying patterns; Nethravathi *et al.,* 2020); as a process (e.g., acquisition, storage, processing, and analysis of vast volumes, variety, and velocity of customer-related data; Hallikainen *et al.,* 2020); and as a strategic resource (e.g., final insertion of the analytics concept into marketing and strategy disciplines; Louro *et al.,* 2019).

Despite these considerations, some authors have made efforts to operationalize CAC. Hossain *et al.* (2020a) propose a measurement scale obtained from the review of 59 empirical studies that address analytics in the retail context. Consequently, the scale does not capture the multiple facets in which interactions between organizations and customers can occur, but only those typical in the retail context. Furthermore, CAC is approached as a formative construct, implying that it exists as the result of executing marketing routines. This approach contradicts the interpretation of CAC as a process, through which organizational routines capable of reconfiguring customer-related operational routines are executed. Likewise, the empirical manifestations considered (e.g., detecting trends, creating creative strategies for new offers, investing resources to make current offers) do not describe the role of data analytics in their execution.

Louro *et al.* (2019) propose a CAC measurement scale with three dimensions: customer information quality; team expertise; and customer knowledge absorption. The “team expertise” dimension includes three skills that people who process customer data must have: technical skill; technological skill; and business skill. This view makes it difficult to understand and represent CAC as organizational routines that create value for the organization. So much so that the scale does not specify those practices that an organization should adopt to guide the development of concrete work plans for analytics departments in customer contexts.

Hallikainen *et al.* (2020) model CAC as a unidimensional construct with seven empirical manifestations. Although a unidimensional scale is useful because of its parsimony, it does not delve into the dimensions underlying the phenomenon and, therefore, does not make explicit the main

https://doi.org/10.25100/cdea.v40i78.13227

macro-themes that make up the CAC. The seven items on this scale capture the use of big data to segment customers and markets, to evaluate customer retention and lifetime value, to personalize offers and channels, and to identify the best customers. Therefore, it leaves out other possible interactions of the organization with the customer, such as the deployment of loyalty strategies, the launch of new products, and the execution of strategies aimed at deepening the relationship with the customer.

Given the opportunity to provide a new scale that synthesizes and describes the main organizational routines involved in CAC based on empirical manifestations extracted from scientific literature, this work aims to answer the following research question:

How can CAC be measured, considering an organizational routines approach emerging from scientific evidence on the subject and ensuring psychometric quality?

Answering the above question makes it easier for scholars to carry out comprehensive, reliable, and valid measurements of CAC, in such a way that they can relate the construct to business performance, as well as carry out effective organizational diagnoses on the subject and generate agendas and plans for the improvement of analytics departments.

This study is organized in five sections. The first section introduces the problem to be addressed. The second part presents a theoretical framework that conceptualizes analytics, customer analytics, and customer analytics capabilities. In the third section, the analysis methods used are described and the results are presented in the fourth. The fifth section presents the discussion, followed by conclusions and future challenges. Finally, in section seven the limitations of our study are provided.

2. Theoretical framework

2.1. Conceptualization of analytics, customer analytics and CAC

The concept referred to as CAC still needs to be addressed in organizational management. To clarify such a concept, it is necessary to resort to foundational concepts, such as customer analytics, and frame them within the organization's capabilities. The taxonomy presented in Figure 1 illustrates the relationship between different denominations that can be found in the literature to refer to customer analytics, as well as the differentiation between customer analytics and CAC.

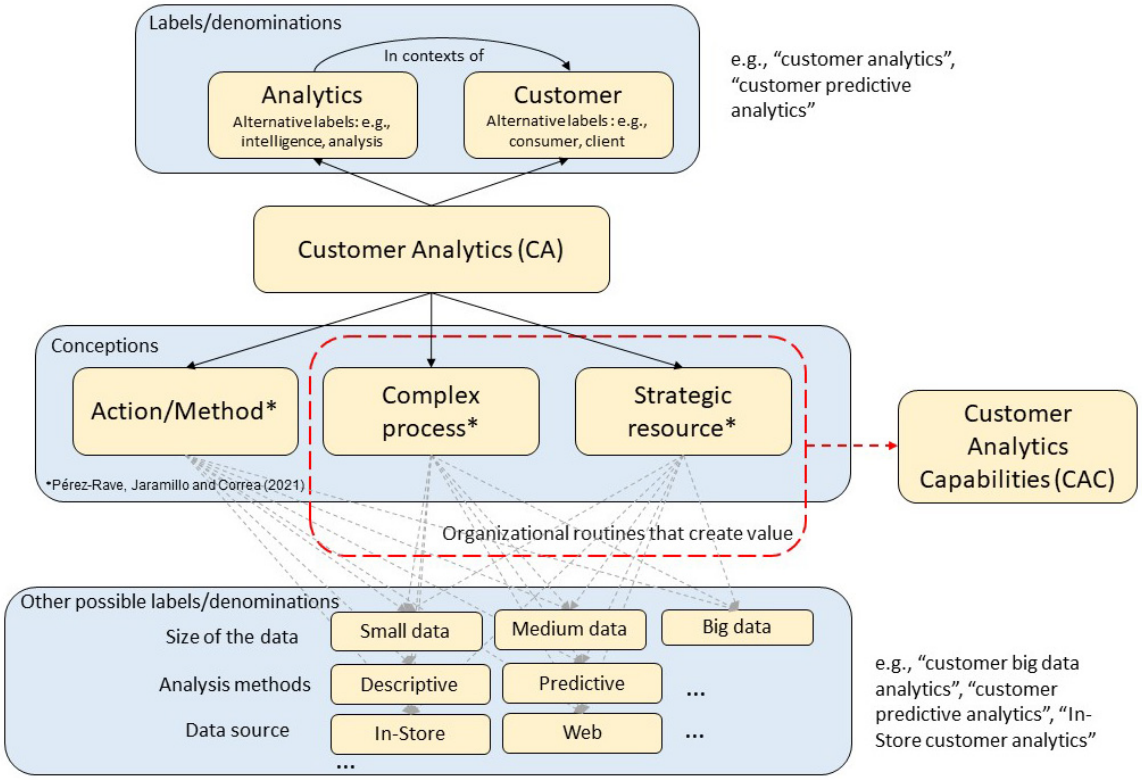
Figure 1 shows that the study of customer analytics lies at the intersection between analytics and the customer. Analytics can be understood as the application of processes and techniques that transform raw data into relevant information for decision-making (Wilder and Ozgur, 2015). Analytics is a primary concern for decision-makers in the current business environment. Due to organizational complexity, decision-makers cannot rely on their limited knowledge and are turning to analytics to improve the results of their decisions (Rezaei *et al.,* 2022). Analytics has been highlighted by several authors as a capability that helps organizations have better competitive performance. Thus, Gunasekaran *et al.* (2017) find that analytics positively affects organizational performance, O'Neill and Brabazon (2019) found a significant relationship between higher levels of analytics skill and the ability to generate organizational value and competitive advantage, and Dubey *et al.* (2018) also found that analytics is effective in gaining competitive advantage.

Customer analytics is one of the subdimensions of marketing analytics, which is, at the same time, a subdimension of analytics (Hossain *et al.,* 2020b) and has recently been gaining importance due to the rise of innovative technologies and because of the pressure that exists today, more than ever, to satisfy customers by leveraging structured and unstructured data (Sun *et al.,* 2014).

As seen in Figure 1, although some authors refer to customer analytics with the literal term, it is possible to find in the literature that the terms "analytics" and "customer" have different labels or names referring to the same essence: analytics in customer contexts. Thus, for example, it is possible to find references to "customer intelligence" (Dam *et al.,* 2021), "client analytics" (Ediger

https://doi.org/10.25100/cdea.v40i78.13227

Figure 1. Representation of the conceptual difference between customer analytics and CAC



Source: Authors' own elaboration.

et al., 2014), "consumer analytics" (Erevelles *et al.,* 2016), among others, referring to analytics within the specific domain of the customer.

Given the lack of conceptual maturity that still exists regarding customer analytics, different conceptions underlying the attempts to define analytics in customer contexts can be identified. Thus, there is a conception that refers to it as an action or a method. For example, Nethravathi *et al.* (2020) define it as the discipline that deals with recognizing customer behavior and predicting their purchasing patterns to improve business and environmental sustainability. In this sense, Fernández (2019) suggests that organizations can thus develop personalized products and services and even anticipate their needs, which enhances the user experience. Another conception refers to analytics in customer contexts as a process. For example, Hallikainen *et al.* (2020) define it as the acquisition, storage, processing, and analysis of an immense volume, variety, and velocity of customer-related data, with the aim of creating meaningful information for decision-making in the company and discovering insights in a timely manner. A third conception of analytics in the customer context refers to it as a strategic resource. Louro *et al.* (2019) point out that customer analytics is the final insertion of the concept of analytics into the disciplines of marketing and strategy.

Under these considerations, CAC can be understood as a set of organizational routines that create value for the organization, within the framework of processes and methods for exploring and exploiting customer data and their interactions with the organization.

2.2. CAC as a source of competitive advantage using the dynamic capabilities approach

Teece *et al.* (1997) define dynamic capabilities as the ability to integrate, build, and reconfigure internal and external competencies to rapidly cope with

https://doi.org/10.25100/cdea.v40i78.13227

environmental changes. Pavlou and Sawy (2011) propose that they are an essential driver of an organization's competitive advantage, through the renewal of operational capabilities. Consistent with that conceptualization, Louro *et al.* (2019) define CACs as a dynamic capability present in organizations that continuously respond to trends in their markets and remain attentive to potential customer opportunities.

A market-oriented organization places importance on understanding both the expressed and unexpressed needs of its customers, as well as on building unique capabilities to satisfy their desires (Slater and Narver, 1999). CAC, by acting on the operational routines of marketing and related areas (Hossain *et al.,* 2020a) to reconfigure them, contributes to achieving competitive advantages to the extent that it enables the organization to address all customer- management fronts in a rare, valuable, imperfectly imitable, and difficult-to-substitute manner, in accordance with the theory of resources and capabilities.

2.3. Psychometric properties for the development of measurement scales

According to the Real Academia Española (s.f.), a construct is a theoretical framework used to comprehend a particular issue. CAC is conceptualized as a construct, serving as an underlying factor in a series of observed manifestations.

The traditional paradigm for the development of construct measurement scales includes: generation of items; definition of the evaluation scale; evaluation of content validity; selection of a sample; execution of exploratory factor analysis; evaluation of internal consistency; execution of confirmatory factor analysis; and the evaluation of convergent and discriminant validity (Swanson and Holton, 2005). Following these steps leads to the development of measurement scales that meet the following psychometric properties:

- ***Content validity:*** the degree to which a measure covers the content domain of what it is trying to measure (Yaghmale, 2003; Pérez-Rave, 2021a)
- ***Construct validity:*** the degree to which the measurement of a given construct evaluates what it is supposed to measure. Thus, it is expected that the measures among themselves reflect convergence towards the underlying construct, but also that they help to discriminate with respect to the measures of other constructs. It includes convergent and discriminant validity (Pérez-Rave, 2021a; Ployhart and Schneider, 2012; Sacket *et al.,* 2012).
- ***Reliability:*** has to do with the measurement error in the measurement process. In general, reliability is the tendency towards consistency of scores, which gives an idea of the precision of the instrument and its ability to generate stable scores (Martínez, Hernández and Hernández, 2006; Pérez-Rave, 2021a).
- ***Equity:*** this is the ability of the instrument to evaluate individual differences impartially, independent of personal characteristics such as gender, age, position held, etc. (AERA *et al.,* 1999; Pérez-Rave, 2021a).

3. Method

This section describes the formulation of the items, the participants and the analytical framework used.

3.1. Formulation of the items

The generation of the items was based on the identification of the manifestations or uses of analytics in customer contexts, as found in the 42 studies subjected to the previously conducted systematic literature review (Maya-Restrepo, 2023). From these manifestations, an adjustment process was conducted considering the inclusion, where appropriate, of different phases of the analytical process in which such manifestation could occur (e.g., collecting, analyzing, evaluating). That is, for example, if the use of analytics in a customer context was found as "identifying the best customers for the company," it was transformed into "analyzing transactional data to identify the best customers for the company."

Twenty-eight items were developed to

https://doi.org/10.25100/cdea.v40i78.13227

Table 1. Items associated with the studies from which they originated

Item	Reference study	item	Reference study
CAC1	Sohrabi *et al.* (2019)	CAC15	Nethravathi *et al.* (2020)
CAC2	Sohrabi *et al.* (2019)	CAC16	Hallikainen *et al.* (2020)
CAC3	Holland *et al.* (2019)	CAC17	Hossain *et al.* (2020a)
CAC4	Holland *et al.* (2019)	CAC18	Ramana *et al.* (2019)
CAC5	Boldosova (2019)	CAC19	Mariani & Wamba (2020)
CAC6	Petrescu *et al.* (2020)	CAC20	Kolsarici *et al.* (2020)
CAC7	Vecchio *et al.* (2020)	CAC21	Cao & Tian (2020)
CAC8	Yerpude & Singhal (2019)	CAC22	Cao & Tian (2020)
CAC9	Rajan (2019)	CAC23	Cao & Tian (2020)
CAC10	Hallikainen *et al.* (2020	CAC24	Liao & Hsu (2020)
CAC11	Cao & Tian (2020)	CAC25	He *et al.* (2019)
CAC12	Rajendran (2020)	CAC26	Mariani & Wamba (2020)
CAC13	Le *et al.* (2020)	CAC27	Mariani & Wamba (2020)
CAC14	Le *et al.* (2020)	CAC28	Rakhman *et al.* (2019)

Source: Authors' own elaboration.

represent CAC. An example of these is "How often does the organization where you work analyze data on the performance of competitors on customer-related issues?" The response format was a 5-point Likert scale: 1= Not carried out or carried out more frequently than once a year; 2 = At least once a year; 3 = At least once every six months; 4 = At least once every three months; 5 = At least once a month. In Table 1, the items associated with the reference studies from which they were extracted are observed. The items of the final scale after psychometric validation are presented in Appendices 1 and 2.

3.2. Content validity analysis

Following the above, the analysis of the content validity of the proposed items was conducted. The method used to carry it out was the expert panel, in which a group of experts in the area of interest (in this case, organizational administration) assessed the attributes of the items. Egaña *et al.* (2014) conducted a literature review of 40 studies to capture the methods used to carry out the analysis of content validity in the design of measurement scales. According to them, the expert panel is the most used method for evaluating this type of validity. The same authors cite references indicating that the appropriate number of experts can range from 7 to 30 and suggest that the most important aspect when using this method is to select experts with the appropriate profile. The present study involved 10 experts in organizational management, who evaluated the attribute of clarity of the items. Although the attribute of relevance is also often evaluated as part of content validity, it was not considered on this occasion, as the items were obtained from empirical evidence provided by the 42 studies previously reviewed.

For the evaluation of the attribute of clarity, a matrix-type format was developed, which included the formulated items (rows) and five possible ratings for the clarity of the items: very clear (5); clear (4); moderately clear (3); unclear (2); and very unclear (1). As mentioned, it was administered to 10 experts in the field of organizational management. Table 2, shows the descriptive statistics of the scores. Items rated 4 or 5 were immediately accepted and those rated 3 or less were subject to modifications to improve clarity.

https://doi.org/10.25100/cdea.v40i78.13227

Table 2. Descriptive statistics of the attribute of clarity

n	Mean	Min	Max	St. Dev.	Item	Mean	Min	Max	St. Dev.
CAC1	4.5	3	5	0.71	CAC15	4.9	4	5	0.32
CAC2	4.4	3	5	0.70	CAC16	5	5	5	0
CAC3	4.5	3	5	0.71	CAC17	4.6	3	5	0.70
CAC4	4.4	3	5	0.70	CAC18	4.7	4	5	0.48
CAC5	4.2	3	5	0.92	CAC19	4.8	4	5	0.42
CAC6	4.5	3	5	0.71	CAC20	4.7	4	5	0.48
CAC7	4.7	4	5	0.48	CAC21	4.8	4	5	0.42
CAC8	4.5	4	5	0.53	CAC22	4.8	4	5	0.42
CAC9	4.5	3	5	0.71	CAC23	4.7	4	5	0.48
CAC10	4.6	4	5	0.52	CAC24	4.5	3	5	0.71
CAC11	4.5	4	5	0.53	CAC25	4.6	3	5	0.70
CAC12	4.9	4	5	0.32	CAC26	4.7	4	5	0.48
CAC13	4.7	4	5	0.48	CAC27	4.6	2	5	0.97
CAC14	4.7	4	5	0.48	CAC28	4.7	4	5	0.48

Source: Authors' own elaboration.

Table 3. General information about the experts

Expert	Gender	Activity	Academic degree	Undergraduate program	Years of experience
E1	M	Teaching/Research	Ph.D.	Administrative eng.	16
E2	M	Teaching/Research	Ph.D.	Economics	11
E3	F	Teaching/Research	Ph.D.	Administrative eng.	15
E4	F	Teaching/Research	Ph.D.	Accounting	14
E5	F	Teaching/Research	Ph.D.	Business management	18
E6	M	Teaching/Research	M.Sc.	Industrial eng.	15
E7	M	Strategic, tactical and operational tasks in a company	M.Sc.	Software eng.	10
E8	F	Teaching/Research	Ph.D.	Business management	15
E9	M	Teaching/Research	Ph.D.	International business	12
E10	M	Teaching/Research	M.Sc.	Business management	14

Source: Authors' own elaboration.

According to Table 2, 11 out of the 28 items underwent some form of modification after evaluation by the experts, as they received a rating equal to or less than 3.

Table 3 shows the basic information of the experts who served as validators of the proposed instrument: gender; activity with which their current professional work is most related; highest academic degree; training undergraduate degree; and years of work experience. Table 3 corroborates the suitability of the experts to carry out the evaluation, due to their academic degree, field of training related to organizational administration, and years of professional experience.

https://doi.org/10.25100/cdea.v40i78.13227

Table 4. Items before and after the content validation process described above

Items before content validity analysis	Item ID	Items after analysis of content validity (final version)
Collect data on the variables that affect the company's income	CAC1	Monitor the variables that most affect the company's economic performance
Collect data on competitors' behavior in customer-related dimensions	CAC3	Collect data on competitors' behavior on customer-related issues
Determine the best commercial strategy to implement based on the analysis of customer-related data (e.g., needs, preferences, sociodemographic variables, recommendation intentions).	CAC5	Define commercial strategies to implement based on the analysis of customer-related data (e.g., needs, preferences, sociodemographic variables, recommendation intentions)

Source: Authors' own elaboration.

Table 4 shows a sample of the items before and after content validation with the experts. The changes made corresponded to the suggestions and evaluation of the experts to improve the clarity of the item. As seen in Table 4, clarity adjustments primarily involved substituting those words that held some degree of ambiguity and précising the action that was intended to be talked about (e.g., determine, monitor, etc.).

3.3. Sample description

Between September and October 2022, the questionnaire was administered to professionals working in areas related to customer data analysis (e.g., marketing, customer-centric data analytics, consumer insight, market surveillance). Most of the professionals were contacted through LinkedIn, the largest professional social network in the world with more than 200 million members (Sumbaly *et al.,* 2013), and others through professional networks in Colombia. In total, approximately 520 requests were sent out, of which 101 completed questionnaires were obtained (response rate: 19%, boosted by the promise of receiving an executive report upon completion of the study). The respondents belong to 101 different companies and include individuals working in analytics (26.7%; analysts: 7.9%; supervisors or coordinators: 11.8%; director or manager: 6.9%), in marketing or related functions (72.2%; analysts: 10.8%; supervisors or coordinators: 27.7%; director or manager: 33.6%) and in general management (1%). Eighty-two percent of the organizations to which the respondents belong are engaged in commerce or service provision, while the remaining 18% are involved in industrial activities.

3.4. Analytical framework

The study is cross-sectional, employing a design for the development and validation of scales with psychometric rigor. The methodology used to refine and validate the scale follows the MinerConstructo framework (Pérez Rave, 2021b), which contains seven stages, four of which are useful in the present study: *observe* (a descriptive diagnosis of the variables is carried out using measures of central tendency, dispersion, and correlation); *explore* (the necessary conditions for conducting an exploratory factor analysis are assessed, potential underlying factors in the data are identified, an exploratory factor structure is provided, and the Cronbach's Alpha reliability measure is calculated); *confirm* (a confirmatory factor analysis is performed in which the functional relationships between constructs and their factor loadings are identified, as well as the analysis of convergent and discriminant validity between factors); and *communicate* (the results are expressed through scientific article format). The other stages of the framework are not applied in this work (apply, explain, and predict), as covering structural relationship analysis and practical application (e.g., diagnoses) is beyond the scope of the study. This framework combines analytical capabilities (e.g., machine learning methods, automated tasks, among

https://doi.org/10.25100/cdea.v40i78.13227

Table 5. Description of responses to items

Item	Min	Max	Mean	St.dev.	Median	Q1	Q3	Kurto	Assym	n.obs
cac1	1	5	4,782	0,642	5	5	5	14,397	-3,594	101
cac2	2	5	4,485	0,832	5	4	5	1,766	-1,604	101
cac3	1	5	4,05	1,081	4	4	5	0,93	-1,18	101
cac4	1	5	3,96	1,148	4	3	5	0,401	-1,062	101
cac5	1	5	4,495	0,844	5	4	5	4,468	-2,01	101
cac6	1	5	3,871	1,222	4	3	5	-0,308	-0,863	101
cac7	1	5	3,97	1,323	4	4	5	0,363	-1,256	101
cac8	1	5	3,911	1,327	4	3	5	-0,283	-1,007	101
cac9	1	5	3,97	1,33	5	3	5	-0,036	-1,108	101
cac10	1	5	4,317	1,183	5	4	5	1,922	-1,737	101
cac11	1	5	4,208	1,211	5	4	5	1,148	-1,502	101
cac12	1	5	3,752	1,577	5	3	5	-0,969	-0,819	101
cac13	1	5	2,901	1,473	3	1	4	-1,463	-0,017	101
cac14	1	5	3,416	1,437	4	2	5	-1,121	-0,503	101
cac15	1	5	3,663	1,478	4	3	5	-0,781	-0,832	101
cac16	1	5	3,564	1,519	4	2	5	-1,134	-0,621	101
cac17	1	5	3,99	1,237	4	3	5	-0,101	-1,017	101
cac18	1	5	3,98	1,28	4	4	5	0,226	-1,18	101
cac19	1	5	3,97	1,338	4	3	5	0,083	-1,163	101
cac20	1	5	4,337	1,186	5	4	5	1,992	-1,769	101
cac21	1	5	3,95	1,252	4	3	5	-0,073	-1,028	101
cac22	1	5	4,02	1,208	4	4	5	0,659	-1,25	101
cac23	1	5	4,208	1,16	5	4	5	1,559	-1,546	101
cac24	1	5	3,822	1,26	4	3	5	-0,422	-0,854	101
cac25	1	5	3,683	1,392	4	3	5	-0,639	-0,816	101
cac26	1	5	3,624	1,489	4	2	5	-0,966	-0,733	101
cac27	1	5	4,05	1,299	5	4	5	0,27	-1,229	101
cac28	1	5	3,752	1,424	4	3	5	-0,734	-0,819	101

Source: Authors’ own elaboration.

others) and psychometric analysis of latent variables, integrating resources from various R packages, and has been applied in other constructs, such as: dynamic capabilities of continuous improvement, (Pérez-Rave, Guerrero *et al.,* 2022); quality of health services (Pérez-Rave, Figueroa *et al.,* 2022) and dignified treatment for health workers (Pérez-Rave, González-Echavarría *et al.,* 2022).

4. Results

The results are presented according to the above-mentioned stages.

4.1. Observe

Table 5 displays the descriptive statistics of the responses provided by the survey participants to the 28 items of the CAC scale.

https://doi.org/10.25100/cdea.v40i78.13227

Table 6. Pearson correlations between items

	cac1	cac2	cac3	cac4	cac5	cac6	cac7	cac8	cac9	cac10	cac11	cac12	cac13	cac14	cac15	cac16	cac17	cac18	cac19	cac20	cac21	cac22	cac23	cac24	cac25	cac26	cac27	cac28
cac1		0,462	0,174	0,083	0,072	0,142	0,11	0,13	0,227	0,197	0,149	0,084	0,146	0,045	0,133	0,158	0,161	-0,03	0,179	0,018	0,074	0,096	0,035	0,088	0,09	0,039	0,025	0,072
cac2	0,462		0,307	0,24	0,167	0,328	0,04	0,248	0,176	0,076	0,097	0,024	0,276	0,064	0,118	0,208	0,267	0,112	0,175	0,157	0,273	0,12	-0,002	0,16	0,048	0,076	0,107	0,085
cac3	0,174	0,307		0,816	0,499	0,482	0,456	0,484	0,502	0,387	0,344	0,488	0,493	0,405	0,399	0,513	0,554	0,218	0,423	0,471	0,564	0,436	0,438	0,381	0,369	0,329	0,233	0,398
cac4	0,083	0,24	0,816		0,464	0,374	0,368	0,496	0,386	0,466	0,351	0,403	0,453	0,331	0,499	0,569	0,507	0,258	0,448	0,407	0,576	0,455	0,352	0,327	0,399	0,412	0,256	0,343
cac5	0,072	0,167	0,499	0,464		0,644	0,506	0,441	0,423	0,362	0,456	0,416	0,434	0,389	0,391	0,31	0,57	0,324	0,527	0,581	0,534	0,579	0,415	0,356	0,475	0,38	0,315	0,477
cac6	0,142	0,328	0,482	0,374	0,644		0,598	0,523	0,502	0,291	0,431	0,414	0,476	0,458	0,524	0,368	0,614	0,427	0,512	0,603	0,499	0,537	0,449	0,453	0,558	0,396	0,451	0,527
cac7	0,11	0,04	0,456	0,368	0,506	0,598		0,545	0,591	0,402	0,385	0,476	0,455	0,343	0,399	0,352	0,422	0,295	0,452	0,485	0,518	0,539	0,604	0,477	0,56	0,421	0,373	0,421
cac8	0,13	0,248	0,484	0,496	0,441	0,523	0,545		0,423	0,413	0,509	0,5	0,527	0,512	0,53	0,343	0,42	0,44	0,562	0,617	0,605	0,463	0,46	0,457	0,472	0,393	0,455	0,353
cac9	0,227	0,176	0,502	0,386	0,423	0,502	0,591	0,423		0,362	0,42	0,454	0,448	0,341	0,376	0,271	0,498	0,299	0,393	0,539	0,468	0,492	0,555	0,367	0,421	0,393	0,221	0,345
cac10	0,197	0,076	0,387	0,466	0,362	0,291	0,402	0,413	0,362		0,708	0,321	0,231	0,275	0,376	0,228	0,426	0,301	0,221	0,394	0,369	0,374	0,396	0,273	0,456	0,278	0,289	0,279
cac11	0,149	0,097	0,344	0,351	0,456	0,431	0,385	0,509	0,42	0,708		0,388	0,382	0,392	0,576	0,262	0,536	0,506	0,325	0,522	0,561	0,558	0,453	0,333	0,52	0,404	0,337	0,413
cac12	0,084	0,024	0,488	0,403	0,416	0,414	0,476	0,5	0,454	0,321	0,388		0,476	0,558	0,423	0,334	0,44	0,359	0,342	0,521	0,444	0,338	0,493	0,445	0,492	0,424	0,338	0,378
cac13	0,146	0,276	0,493	0,453	0,434	0,476	0,455	0,527	0,448	0,231	0,382	0,476		0,657	0,416	0,472	0,455	0,375	0,501	0,529	0,572	0,428	0,369	0,464	0,506	0,58	0,436	0,408
cac14	0,045	0,064	0,405	0,331	0,389	0,458	0,343	0,512	0,341	0,275	0,392	0,558	0,657		0,448	0,418	0,424	0,423	0,365	0,498	0,389	0,387	0,307	0,511	0,451	0,494	0,519	0,393
cac15	0,133	0,118	0,399	0,499	0,391	0,524	0,399	0,53	0,376	0,376	0,576	0,423	0,416	0,448		0,544	0,572	0,398	0,511	0,516	0,531	0,519	0,426	0,451	0,492	0,523	0,352	0,445
cac16	0,158	0,208	0,513	0,569	0,31	0,368	0,352	0,343	0,271	0,228	0,262	0,334	0,472	0,418	0,544		0,461	0,145	0,412	0,354	0,446	0,462	0,307	0,372	0,407	0,417	0,416	0,592
cac17	0,161	0,267	0,554	0,507	0,57	0,614	0,422	0,42	0,498	0,426	0,536	0,44	0,455	0,424	0,572	0,461		0,423	0,538	0,527	0,542	0,556	0,371	0,454	0,515	0,378	0,361	0,521
cac18	-0,03	0,112	0,218	0,258	0,324	0,427	0,295	0,44	0,299	0,301	0,506	0,359	0,375	0,423	0,398	0,145	0,423		0,268	0,433	0,38	0,446	0,259	0,5	0,541	0,337	0,415	0,271
cac19	0,179	0,175	0,423	0,448	0,527	0,512	0,452	0,562	0,393	0,221	0,325	0,342	0,501	0,365	0,511	0,412	0,538	0,268		0,669	0,578	0,526	0,384	0,448	0,419	0,441	0,381	0,39
cac20	0,018	0,157	0,471	0,407	0,581	0,603	0,485	0,617	0,539	0,394	0,522	0,521	0,529	0,498	0,516	0,354	0,527	0,433	0,669		0,692	0,582	0,545	0,502	0,52	0,475	0,366	0,5
cac21	0,074	0,273	0,564	0,576	0,534	0,499	0,518	0,605	0,468	0,369	0,561	0,444	0,572	0,389	0,531	0,446	0,542	0,38	0,578	0,692		0,662	0,496	0,52	0,53	0,548	0,383	0,548
cac22	0,096	0,12	0,436	0,455	0,579	0,537	0,539	0,463	0,492	0,374	0,558	0,338	0,428	0,387	0,519	0,462	0,556	0,446	0,526	0,582	0,662		0,611	0,482	0,533	0,566	0,541	0,561
cac23	0,035	-0,002	0,438	0,352	0,415	0,449	0,604	0,46	0,555	0,396	0,453	0,493	0,369	0,307	0,426	0,307	0,371	0,259	0,384	0,545	0,496	0,611		0,388	0,456	0,399	0,371	0,37
cac24	0,088	0,16	0,381	0,327	0,356	0,453	0,477	0,457	0,367	0,273	0,333	0,445	0,464	0,511	0,451	0,372	0,454	0,5	0,448	0,502	0,52	0,482	0,388		0,731	0,438	0,5	0,505
cac25	0,09	0,048	0,369	0,399	0,475	0,558	0,56	0,472	0,421	0,456	0,52	0,492	0,506	0,451	0,492	0,407	0,515	0,541	0,419	0,52	0,53	0,533	0,456	0,731		0,55	0,545	0,656
cac26	0,039	0,076	0,329	0,412	0,38	0,396	0,421	0,393	0,393	0,278	0,404	0,424	0,58	0,494	0,523	0,417	0,378	0,337	0,441	0,475	0,548	0,566	0,399	0,438	0,55		0,63	0,55
cac27	0,025	0,107	0,233	0,256	0,315	0,451	0,373	0,455	0,221	0,289	0,337	0,338	0,436	0,519	0,352	0,416	0,361	0,415	0,381	0,366	0,383	0,541	0,371	0,5	0,545	0,63		0,515
cac28	0,072	0,085	0,398	0,343	0,477	0,527	0,421	0,353	0,345	0,279	0,413	0,378	0,408	0,393	0,445	0,592	0,521	0,271	0,39	0,5	0,548	0,561	0,37	0,505	0,656	0,55	0,515	

Source: Authors' own elaboration.

https://doi.org/10.25100/cdea.v40i78.13227

As can be seen in Table 5, nearly all item scores range from 1 to 5, except for cac2, with mean values ranging between 2.901 (cac13) and 4.782 (cac1), and standard deviations ranging from 0.642 (cac1) to 1.577. (cac12). Ten of the 28 items had an average rating higher than 4, 17 of them between 3 and 4, and only one had an average rating lower than 3. The above shows that, although the survey managed to capture different positions among the respondents, there is a tendency to positively value customer analytics practices in organizations. Furthermore, all items have negative asymmetry values, which also indicates the tendency to adopt favorable positions regarding organizational practices related to customer analytics. In most cases (except for cac1 and cac5), kurtosis is between -2 and 2, suggesting that there are no extreme deviations from normality.

Table 6 contains the Pearson correlation coefficients for all pairs of items. The mean value of the correlation coefficients is 0.40, and the first and third quartiles are 0.34 and 0.504, respectively. The moderate correlation observed among most of the items suggests the presence of underlying patterns to be discovered in the following steps.

4.2. Explore

The result of the Bartlett test contrasts the hypothesis that the correlation matrix is the same (null hypothesis) or different (alternative hypothesis) from an identity matrix. The test yields a p value < 0.05 (0.000; chi.square = 1888.690, degrees of freedom = 378), so the null hypothesis is rejected. The Kaiser–Meyer–Olkin (KMO) test provides a measure of the proportion of global and individual variance that is possibly due to one or more latent factors. Values less than 0.5 are usually considered unacceptable, which is why cac1 is excluded. Table 7 details the KMO coefficients for each item.

As Table 7 shows, the overall suitability value is 0.872 with individual values ranging from 0.548 (cac2) to 0.943 (cac5). These results justify proceeding with exploratory factor analysis to uncover potential association patterns.

Table 7. KMO coefficients of the items

Global score: 0.872			
Item	**KMO**	**Item**	**KMO**
cac1	0.475	cac15	0.865
cac2	0.548	cac16	0.83
cac3	0.859	cac17	0.93
cac4	0.765	cac18	0.891
cac5	0.943	cac19	0.882
cac6	0.884	cac20	0.888
cac7	0.856	cac21	0.924
cac8	0.902	cac22	0.912
cac9	0.934	cac23	0.913
cac10	0.748	cac24	0.874
cac11	0.839	cac25	0.893
cac12	0.924	cac26	0.857
cac13	0.905	cac27	0.843
cac14	0.87	cac28	0.879

Source: Authors' own elaboration.

According to the Kaiser criterion (eigenvalues greater than 1) and Horn's parallel analysis (corrected eigenvalues greater than 1), 6 and 1 factor(s) should be considered, respectively. Table 8 presents the criteria used to select the number of factors.

As Table 8 shows, based on Horn's parallel analysis, a single-factor model is suggested (a single eigenvalue greater than 1). Likewise, under the Kaiser criterion it is suggested to have 6 factors (6 eigenvalues greater than 1).

Table 8. Criteria for factors selection

Corrected eigenvalues	Eigenvalues	Bias
11,217	12,349	1,132
0,834	1,782	0,948
0,64	1,452	0,812
0,559	1,255	0,696
0,542	1,138	0,596
0,578	1,081	0,503
0,576	0,995	0,418

Source: Authors' own elaboration.

https://doi.org/10.25100/cdea.v40i78.13227

Table 9. One-factor model		
Item	**Description**	**F1**
cac3	… of competitors in customer-related matters	0,661
cac4	… competitors in customer-related matters	0,638
cac5	…to implement based on customer-related data analysis	0,678
cac6	… service personalization strategies based on results obtained from customer data analysis	0,729
cac7	…relationship strategies, supported by the analysis of social network data	0,685
cac8	…most influence customer commitment to the brand, with the support of data analysis methods	0,715
cac9	… digital performance metrics on the website or social networks	0,628
cac10	… transaction data to identify the best customers for the company	0,526
cac11	… retention level from data analysis	0,658
cac12	… quality based on comments published on social networks	0,635
cac13	… psychological variables of consumers to complement customer segmentation criteria	0,691
cac14	… understand customer purchasing behavior	0,635
cac15	… purchasing behavior based on historical data analysis.	0,696
cac16	… company market share	0,583
cac17	… reconfigure the value offer based on results derived from customer data analysis	0,724
cac18	…customer retention supported by evidence derived from data analysis	0,539
cac19	… of new products/services before, during, and after they are launched on the market	0,666
cac20	… marketing campaigns on company performance, based on data analysis	0,775
cac21	… marketing mixes (pricing, promotion, placement, product) considering customer data analysis	0,783
cac22	… acquisition strategies supported by data analysis methods	0,759
cac23	…performance with support in data analysis methods	0,638
cac24	… at all touchpoints with the customer, with the help of data analysis methods	0,666
cac25	… of loyalty strategies, based on evidence derived from data analysis	0,752
cac26	…promotion of products/services based on customer geolocation data	0,666
cac27	… from the segmentation analysis of current or potential customers.	0,594
cac28	… cross-selling strategies (exploitation of complementary products) based on data on customer consumption patterns	0,669
Varianza explicada		45.1 %
Varianza explicada acum.		45.1 %
Source: Authors' own elaboration.		

The items from the single-factor model are presented in Table 9, in the supplemental material. The items and their respective factor loadings (correlation between the item scores and the respective factor) are presented there.

The one-factor model is composed of 26 items. Although the accumulated variance

https://doi.org/10.25100/cdea.v40i78.13227

Table 10. Five-factors model

ítem	Descripción	F1	F2	F3	F4	F5
cac3	… of competitors in customer-related matters				0,778	
cac4	… competitors in customer-related matters				0,827	
cac5	… to implement based on customer-related data analysis		0,583			
cac6	… service personalization strategies based on results obtained from customer data analysis		0,546			
cac17	… reconfigure the value offer based on results derived from customer data analysis		0,524			
cac19	… of new products/services before, during, and after they are launched on the market		0,621			
cac20	… marketing campaigns on company performance, based on data analysis		0,644			
cac21	… marketing mixes (pricing, promotion, placement, product) considering customer data analysis		0,51			
cac7	…relationship strategies, supported by the analysis of social network data			0,669		
cac9	… digital performance metrics on the website or social networks			0,582		
cac23	…performance with support in data analysis methods			0,59		
cac10	… transaction data to identify the best customers for the company					0,759
cac11	… retention level from data analysis					0,748
cac13	… psychological variables of consumers to complement customer segmentation criteria	0,461				
cac22	… acquisition strategies supported by data analysis methods	0,461				
cac24	… at all touchpoints with the customer, with the help of data analysis methods	0,612				
cac25	… of loyalty strategies, based on evidence derived from data analysis	0,695				
cac26	…promotion of products/services based on customer geolocation data	0,668				
cac27	… from the segmentation analysis of current or potential customers.	0,72				
cac28	… cross-selling strategies (exploitation of complementary products) based on data on customer consumption patterns	0,596				
Explained variance		17.9 %	15.4 %	10.5 %	10.2 %	9 %
Cumulative explained variance		17.9 %	33.3 %	43.8 %	54 %	63 %

Source: Authors' own elaboration.

explained by this single factor is less than 50%, it will continue to be considered to verify the relevance of item refinement actions and compliance with the confirmatory criteria of psychometric quality.

The six-factor model contains two items with a factor loading of less than 0.45 (cac1 and cac2), so they are excluded. By excluding them, the model becomes one of five factors. The items and their respective factor loadings are presented in Table 10.

https://doi.org/10.25100/cdea.v40i78.13227

Table 11. Initial confirmatory factor analysis

Initial models	Items	n.obs	p-value	chi-sq	df	chisq/df	RMSEA	SRMR	CFI	TLI
M1 (one factor)	26	101	0.00	713	299	2,386	0.118	0.074	0.751	0.73
M2 (five factors)	twenty	101	0.00	274,905	160	1,718	0.085	0.06	0.907	0.89

Source: Authors' own elaboration.

Table 12. Summary of refined models

	Models	M1 (one factor)	M2 (five factors)	M2A (three factors)
Indicators	Items	14	15	10
	chi-sq	130,602	125,118	51,486
	df	77	80	32
Fit indicators	chi-sq/df	1,696	1,564	1,609
	RMSEA	0.083	0.075	0.078
	SRMR	0.054	0.05	0.053
	CFI	0.932	0.949	0.964
	TLI	0.92	0.933	0.949
Conv./discr. validity and composite reliab.	Val. convergent	0.516	F1:0.577, F2:0.655, F3: 0.82, F4: 0.584, F5:0.729	F1: 0.655, F2: 0.578, F3: 0.734
	Val. discriminating	NA	No: between F1 and F4, Yes: F2, F3, F5	Yes: F1, F2 and F3
	Composite Reliab.	0.937	F1: 0.872, F2: 0.849, F3: 0.901, F4: 0.808, F5: 0.841	F1: 0.849, F2: 0.872, F3: 0.844

Source: Authors' own elaboration on the results from the refinement process.

The five-factor model comprises 20 items in total and accounts for 63% of the total variance of the data.

4.3. Confirm

The results of the initial confirmatory factor analysis are presented in Table 11. Two structures were examined: one factor (M1) and five factors (M2).

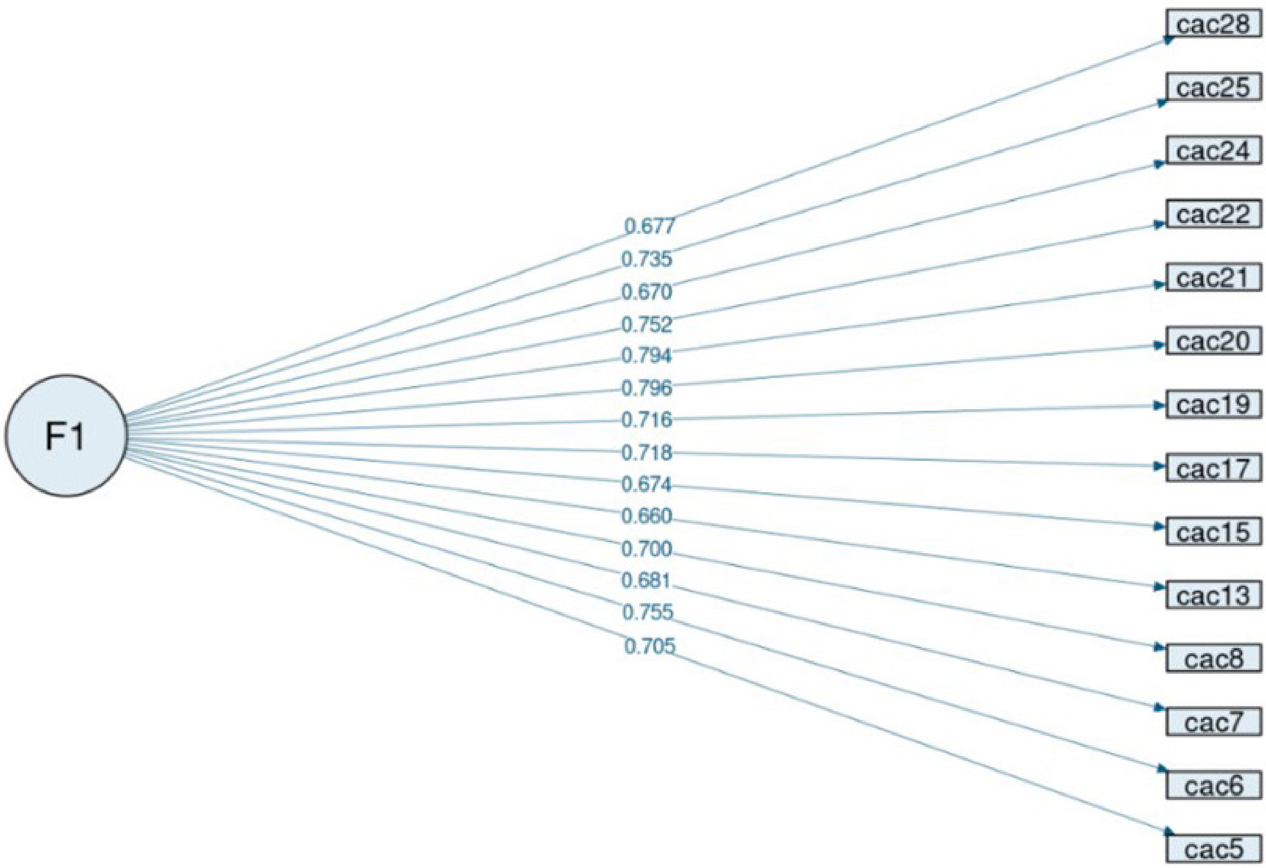
With regard to Table 11, although neither of the two models meet the plausibility conditions in this initial test, a refinement is carried out considering items with confirmatory factor loadings below 0.7, as well as the analysis of modification indices. The plausibility conditions to be met are: RMSEA < 0.06, SRMR < 0.08, CFI and TLI > 0.95, Chisq/df < 2, AVE > 0.5, Fiab.Comp >= 0.7.

Following this refinement, Model M1 (one factor) remains with 14 items that satisfy the goodness-of-fit indicators, convergent validity, and composite reliability, while Model M2 (five factors) remains with 15 items but the criterion for discriminant validity between two of the factors is not met, despite satisfactory goodness-of-fit indices. Given this, starting from model M2, a third model (M2A) is generated, which includes the fusion of the two factors that did not pass the discriminant validity test. After a new refinement process like the one described, the model ends up with 10 items and achieves discriminant validity and fit.

Table 12 shows the comparative summary of the fit metrics, discriminant validity, and composite reliability of the three resulting models.

https://doi.org/10.25100/cdea.v40i78.13227

Figure 2. Model M1 to represent CAC



Source: Generated by Minerconstructo.

According to Table 12, models M1 and M2A satisfy the minimum criteria for model fit, validity, and reliability. Figures 2-3 show the two plausible models (M1 and M2A) to represent CAC. It should be noted that the factors labeled in M1 and M2A, despite being named in the same way (F1, F2, F3), represent different constructs after undergoing the aforementioned refinement process. The complete items of both scales (M1 and M2A) can be seen in Appendix 1 and 2.

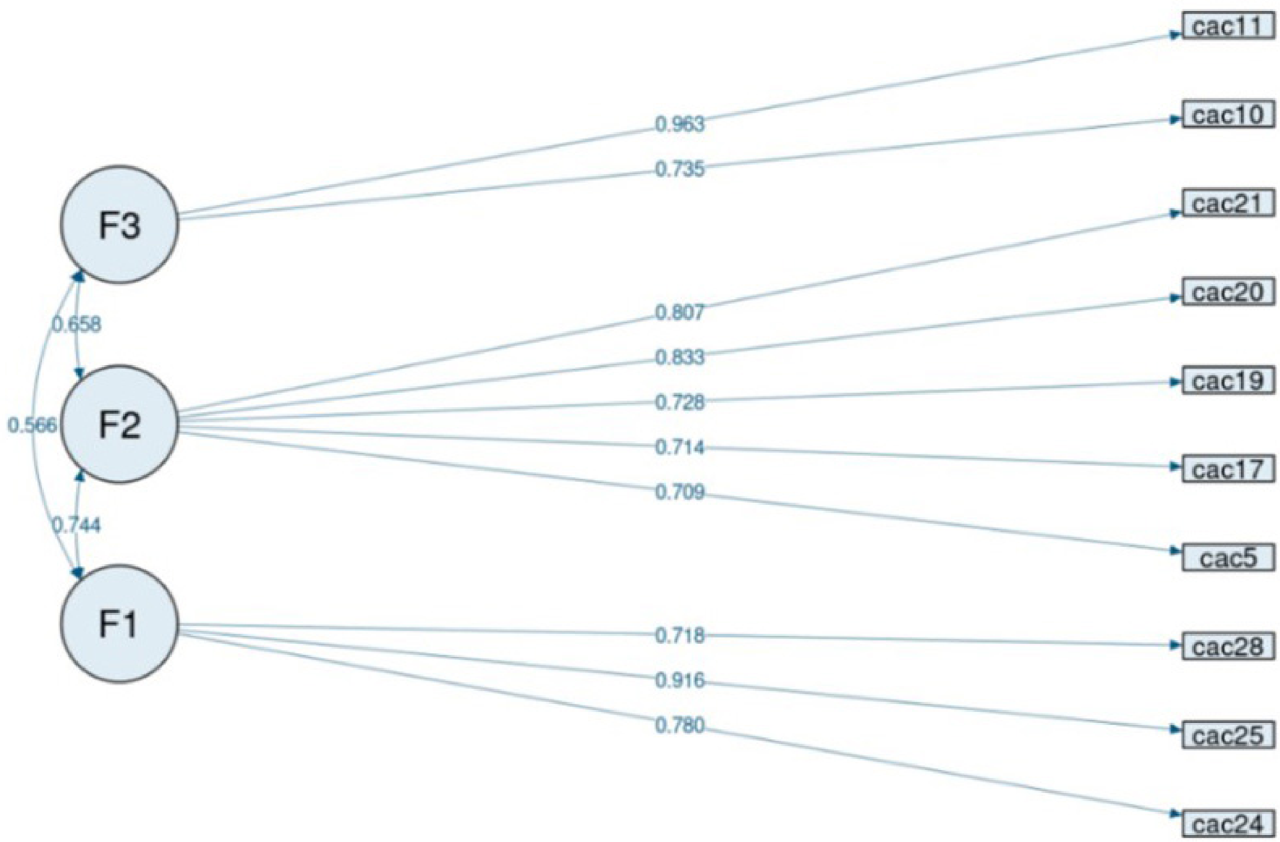
Figure 2 displays model M1, unidimensionally, composed of 14 items. It is observed that all items exhibit high loadings close to or greater than 0.7. This CAC scale has an average variance extracted (AVE = 0.516) greater than 0.5 and a composite reliability greater than 0.7 (0.937).

Figure 3 presents the M2A model, made up of three factors and 10 items. It is observed that all items exhibit high loadings (greater than 0.7). This CAC scale presents an average variance extracted (AVE = F1: 0.655; F2: 0.578; F3: 0.734) greater than 0.5 and a composite reliability (0.855) greater than 0.7. Furthermore, the overall Cronbach's alpha for the final factors (F1, F2, and F3) was 0.866, 0.835, and 0.829, respectively.

The M1 model is useful for measuring CAC globally and parsimoniously, which is valuable when one wants to measure the most representative latent trait behind the existence of these capabilities in organizations, without delving into specific subtopics that compose them. The M2A Model is useful when the organization wants to explore in more depth the dimensions that constitute them and into the specific ways to materialize them. The interpretation of the tridimensional model is further elaborated below.

https://doi.org/10.25100/cdea.v40i78.13227

Figure 3. M2A model to represent CAC



Source: Generated by Minerconstructo.

The M2A model suggests that CACs in organizations have three underlying dimensions (factors):

Factor 1 (F1): C*ustomer maintenance analytics capability*. This is manifested through the practices of evaluating the customer experience across all touchpoints through data analysis, assessing the performance of loyalty strategies derived from data analysis, and designing cross-selling strategies based on customer consumption patterns. These manifestations can be interpreted as a set of routines that occur after the sale, when the customer has already established a commercial relationship with the organization and it aims to evaluate their purchasing experience, retain them for future returns, and attempt to sell complementary products or services to those already acquired. This front aims to generate outcomes that the customer will eventually perceive directly.

Factor 2 (F2): *Customer acquisition analytics capability*. This is manifested through practices of evaluating different marketing mixes considering customer data, monitoring the impact of marketing campaigns based on data, evaluating the performance of new products or services in the market, reconfiguring the value offer based on customer data analysis results and defining commercial strategies derived from customer-related data analysis. These manifestations can be interpreted as a set of routines that the organization develops prior to the sale, when it is attempting to capture customers with new value offers, new commercial strategies, campaigns with appropriate mixes of pricing, promotions, placements, and products.

Factor 3 (F3): C*ustomer economic evaluation analytics capability.* This is manifested through the identification of the organization's best customers based

https://doi.org/10.25100/cdea.v40i78.13227

Table 13. Equity results of the three-dimensional scale incorporating organizational factors based on resampling with 2000 replications

left side	relationship	right side	estim	err.est	lowlim	uplimit	stand	result
area	→	F1	0,069	0,279	-0,457	0,662	0,03	No.Signif
position	→	F1	-0,13	0,141	-0,411	0,162	-0,095	No.Signif
Inf.analit.	→	F1	0,346	0,244	-0,116	0,853	0,17	No.Signif
area	→	F2	0,173	0,291	-0,349	0,771	0,077	No.Signif
position	→	F2	0,034	0,149	-0,241	0,34	0,025	No.Signif
Inf.analit.	→	F2	0,161	0,243	-0,318	0,625	0,08	No.Signif
area	→	F3	-0,176	0,242	-0,633	0,301	-0,078	No.Signif
position	→	F3	0,08	0,147	-0,201	0,37	0,059	No.Signif
Inf.analit.	→	F3	0,179	0,242	-0,259	0,673	0,089	No.Signif

Source: Authors' own elaboration.

Table 14. Equity results of the unidimensional scale incorporating organizational factors based on resampling with 2000 replications

left side	relationship	right side	estim	err.est	lowlim	uplim	stand	result
area	→	F1	0,084	0,268	-0,409	0,66	0,038	No.Signif
cat_cargo2	→	F1	0,036	0,133	-0,226	0,296	0,027	No.Signif
Inf.analit.bin	→	F1	0,236	0,235	-0,205	0,712	0,117	No.Signif

Source: Authors' own elaboration.

on commercial transactions and through the evaluation of customer retention levels through data analysis. These manifestations can be interpreted as the organizational routines conducted to measure the economic contribution of customers and their value to the organization. Unlike the first front, this one does not seek to generate results that can be perceived directly by customers, but rather by the organization, in order to adjust its strategy in pursuit of profitability.

Next, confirmatory factor analysis is conducted on the models, incorporating control variables to verify the equity of the scale. In this case, three control factors are considered: the position of the person answering the survey; the area to which the person answering the survey belongs (marketing or analytics); and infrastructure for analytics. The variable "position" has three response levels: marketing/analytics analyst; marketing/analytics head or coordinator; and marketing/analytics director or manager. The variable "area" has two levels of response: marketing; and analytics. The variable "infrastructure for analytics" is a binary variable that summarizes the rating given by the respondents on the level of maturity that the organization has for carrying out analytics activities at the level of human effort (manual, semi-automatic, and automatic), tools used (spreadsheet, licensed software and free software), processing capacity (individual computer, computer network and cloud), and analysis methods used (statistical description, association between pairs of variables, association between more than two variables or multivariate).

Tables 13 and 14 present the confidence intervals based on bootstrapping (resampling technique) with 2000 replications with the aforementioned control variables, to verify the equity of the scales.

The absence of significance among the control variables for any of the factors, in both scales, as depicted in Tables 13 and 14, implies that organizational factors are

https://doi.org/10.25100/cdea.v40i78.13227

not prioritized by the scales. In other words, the proposed measurement models for CAC enable robust scores of CAC to be generated regardless of (a) factors such as the area or position of the individuals responding to the instrument, and (b) the maturity levels of the analytical infrastructure available to the organization of the respondent.

5. Discussion

This work has allowed the identification and proposal of two measurement models of CAC. One is unidimensional, and the other is tridimensional. The aspects covered in the three-dimensional scale (M2A) have been individually acknowledged by other authors as matters of strategic significance. For example, for Carbone and Haeckel (1994) and Pine and Gilmore (1998), customer experience (central issue of item cac24, F1) is a strategic issue that achieves differentiation and sustained competitive advantage. Hanaysha *et al.* (2021) refer to the design of marketing tactics based on customer understanding (core issue of cac21, F2) as a key element to deliver customer value better than competitors. Madhaven *et al.* (1994) refer to customer retention (the focus of item 11, F3) as a way to exert indirect control over potential competitors by keeping them out of a particular market. This demonstrates that CAC, as proposed in the developed scale, has a scope that allows them to impact organizational strategy by reconfiguring marketing operational routines and related domains.

Other authors have proposed alternative measurement models of CAC. Hossain *et al.* (2020b) contribute four dimensions: customer analytics management capability (ability to plan customer analytics); customer analytics technological capability (ability to connect various customer-related data sources); customer analytics staff expertise capability (ability to use the necessary technical elements to process customer data); and the capability to model the 4Ps of marketing (ability to incorporate data into marketing mix allocation). The administrative factors of CAC considered in this scale do not find common ground with the factors contained in the scale developed in this study. However, similarities are observed between the factor related to the capability to model the 4Ps of marketing and the factor in the scale presented in this study related to the capability of analytics for customer acquisition.

In the context of retail, the same authors (Hossain *et al.*, 2020a) propose three formative dimensions of CAC, namely the ability to create, deliver, and manage value. Some of the manifestations of these dimensions that are most related to the scale presented in this study include: the capability to offer value; personalization capability; distribution capability (delivering value through different channels); and communication capability through different channels. These manifestations are related to the items contained in the factor related to the analytical capability for customer acquisition and tangentially with the factor related to the analytical capability for customer maintenance. The conception of CAC as a formative and non-reflective construct is an important difference with the present study.

Louro *et al.* (2019) propose that CAC consists of three dimensions: customer information quality; team expertise; and customer knowledge absorption. The latter relates to the ability to capture data in order to understand the market and is the one that is most closely related to the factor related to analyzing pre-sale or sale-concluding data related to the customer.

It can be seen that the developed scale shares a common issue with other scales – the analysis of data on pre-sale events (customer acquisition analytics capability); but it is broader in scope by encompassing manifestations related to data analysis after the sale (customer maintenance analytics capability) and the overall value contribution from customers (customer economic evaluation analytics capability). At the same time, it excludes issues that other authors include, such as customer data management, personnel structure, and technological infrastructure, which may not necessarily be compatible with the vision of CAC as an organizational routine. The study of these factors could be a part of future research, as well as the incorporation of other constructs that allow for understanding the mechanism

https://doi.org/10.25100/cdea.v40i78.13227

of generating competitive advantages from CAC.

The existence of a factor with only two items (customer economic evaluation analytics capability) in the scale proposed in the M2A model is justified by three aspects:

a) Although, from a methodological point of view, at least three items per factor are desirable, scientific literature has also proposed scales with reasonable quality that consist of at least one factor with 2 items. Such is the case of in Nicholas *et al.* (2015), Hinkin (1995) and Hays *et al.* (2017), which highlight the parsimony in the composition of their models.

b) The two items of the factor "customer economic evaluation analytics capability" represent two fundamental facets of it. One is the identification of the best customers for the company through data analysis, while the other is the evaluation of customer retention through data analysis. In relation to the first, works such as Hallikainen *et al.* (2020) point it out as a key empirical manifestation of the factor in question. The second one is described by Hallikainen (2020) and Cao and Tian (2020) as a routine that contributes to the essence of the factor found. Likewise, a basic definition of economic evaluation ("economic evaluation is responsible for comparing the costs and consequences of two or more interventions", Fox-Rushby and Cairns, 2013) interpreted in the context of customers makes it feasible to consider the two items in question as being relevant empirical manifestations of the construct of interest. In summary, the fact that the factor has two items is not only consistent with other valid and reliable works in the scientific literature, but also provides relevant elements on the theoretical content of the construct.

c) In addition to previous works with factors consisting of only 2 items with theoretical rationale, the reliability metric (Cronbach's alpha) in the current study (0.829) meets the minimum permissible threshold (>0.7). Similarly, convergent validity, as indicated by the AVE (0.655), also surpassed the minimum threshold for acceptance (>0.5). Despite these strengths of the factor under consideration, the present study acknowledges that future research could enrich the factor with other possible empirical manifestations. Therefore, this declaration is explicitly stated in the limitations section.

The unidimensional model M1 addresses more manifestations (items) than the M2A model, but includes all those of M2A, except the two that make up the "customer economic evaluation analytics capability" factor. This indicates that the underlying attribute in the unidimensional model captures the essence of the factors "customer acquisition analytics capability" and "customer maintenance analytics capability" of the M2A model, which is logical considering that these can summarize most of the organization's interactions with the customer.

6. Conclusions and future studies

Regarding the research question that guided this study, it was possible to identify a main model that allows for the empirical measurement of CAC in the organizational context, meeting criteria for fit, validity, reliability, and fairness. The developed model consists of three factors: customer acquisition analytics capability; customer maintenance analytics capability; and customer economic evaluation analytics capability. This factorial composition represents the essence of the issues that organizations must address to operationalize CAC and, through them, reconfigure marketing operational routines and other related business domains, aiming to achieve competitive advantages.

The customer acquisition analytics capability is empirically manifested through five practices in organizations: examining different marketing mixes (pricing, promotion, placement, product) considering customer data analysis; monitoring the impact of marketing campaigns on company performance based on data analysis; evaluating the market performance of new products/services before, during, and after their launch on the market; making decisions about how to reconfigure the value offer based on results derived from customer data analysis; and defining commercial strategies to implement based on customer-related data analysis.

The customer maintenance analytics capability has three manifestations: evaluating customer experience at all

https://doi.org/10.25100/cdea.v40i78.13227

touchpoints with the help of data analysis methods; assessing the performance of loyalty strategies based on evidence derived from data analysis; and designing cross-selling strategies (exploitation of complementary products) based on customer consumption pattern data.

The customer economic evaluation analytics capability is manifested through the practices of analyzing transactional data to identify the best customers for the company; and examining the level of customer retention based on data analysis.

In addition to the three-dimensional model, a unidimensional model is also provided, which meets the criteria of fit, validity, reliability, and equity. This model is useful when entrepreneurs or scholars aim to capture the essential trait of CAC without delving into the dimensions that compose it. This trait combines capabilities to capture and retain customers within the organization.

The developed scales allow researchers to capture reliable and valid data on CAC in a more efficient way. Furthermore, by being able to measure the construct, researchers will be able to relate CAC to other constructs, such as organizational performance, in future studies. Likewise, it enables business owners to make organizational diagnoses on CAC and provides a basis for configuring or reconfiguring analytics departments by proposing an agenda of content to be addressed by them.

7. Limitations

The fieldwork conducted for the development of the measurement model was limited to Colombian organizations. Future studies are suggested to contrast the results with empirical evidence from other geographical contexts. Additionally, the sample size of respondents was small and not strictly random, as it was selected from a group of professionals with LinkedIn profiles who responded to invitations. Furthermore, while the existence of a factor with two items in the proposed scale was argued, this fact constitutes an opportunity for future research to incorporate new empirical manifestations into this factor.

8. Conflict of interest

No potential conflict of interest was reported by the authors.

9. Source of financing

This work was supported by Universidad de Antioquia and IDINNOV, SAS.

10. References

AERA, APA, & NCME. (1999). The Standards for Educational and Psychological Testing. *AERA Publications Sales.* https://www.scirp.org/reference/ReferencesPapers?ReferenceID=1779513

Boldosova, V. (2019). Telling stories that sell: The role of storytelling and big data analytics in smart service sales. *Industrial Marketing Management, 86,* 122-134. https://doi.org/10.1016/j.indmarman.2019.12.004

Cao, G., Tian, N. (2020). Enhancing customer-linking marketing capabilities using marketing analytics. *Journal of Business & Industrial Marketing, 35*(7), 1289-1299. https://doi.org/10.1108/JBIM-09-2019-0407

Carbone, L., Haeckel, S. (1994). Engineering customer experience. *Marketing Management, 3*(3), 8-19. https://www.researchgate.net/publication/265031917_Engineering_Customer_Experiences

Dinh, T. L., Vu, T. M., Dam, N. A., & Nguyen, C.N. (July, 2022). *Trivi: A Conceptual Framework for Customer Intelligence Systems for Small and Medium-sized Enterprises.* Conference: Pacific Asia Conference on Information Systems (PACIS). Association for Information Systems, Taipei, Australia. https://www.researchgate.net/publication/361613382_Trivi_A_Conceptual_Framework_for_Customer_Intelligence_Systems_for_Small_and_Medium-_sized_Enterprises

Dubey, R., Gunasekaran, A., & Childe, S. (2018). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. *Management Decision, 57*(8), 1-38, https://doi.org/10.1108/MD-01-2018-0119

Ediger, D., Appling, S., Briscoe, E., McColl, R., & Poovey, J. (9-11 September 2014). *Real-time streaming intelligence: Integrating graph and NLP analytics*. IEEE High Performance Extreme Computing Conference (HPEC), Waltham, USA. https://ieeexplore.ieee.org/document/7040990

https://doi.org/10.25100/cdea.v40i78.13227

Egaña, M. , Barrios S., Núñez M., & Camus, M. (2014). Optimal methods for content validity. *Revista Cubana de Educación Medica Superior, 28*(3), 547-558. https://www.researchgate.net/publication/282374966_Optimal_method_for_content_validity

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, *69*(2), 897-904. https://doi.org/10.1016/j.jbusres.2015.07.001

Fernández, A. (2019). Artificial intelligence in financial services. *Economic Bulletin*, *2*. https://repositorio.bde.es/handle/123456789/9047

Fox-Rushby, J., Cairns, J. (2005). *Economic Evaluation.* Open University Press.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S., Childe, S., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *Journal of Business Research*, *70,* 308-317. https://doi.org/10.1016/j.jbusres.2016.08.004

Hallikainen, H., Savimäki, E., & Laukkanen, T. (2020). Fostering B2B sales with customer big data analytics. *Industrial Marketing Management*, *86,* 90-98. http://dx.doi.org/10.1016/j.indmarman.2019.12.005

Hanaysha, J. R., Shaikh, M. E., & Alzoubi, H. M. (2021). Importance of Marketing Mix Elements in Determining Consumer Purchase Decision in the Retail Market. *International Journal of Service Science, Management, Engineering, and Technology*, *12*(6). https://doi.org/10.4018/IJSSMET.2021110104

Hays, R.D., Schalet, B.D., Spritzer, K.L., & Cella, D. (2017). Two-item PROMIS® global physical and mental health scales. *Journal of Patient-Reported Outcomes, 1*(1). https://doi.org/10.1186/s41687-017-0003-8

He, W., Tian, X., & Wang, F.-K. (2019). Innovating the customer loyalty program with social media: A case study of best practices using analytics tools. *Journal of Enterprise Information Management*, *32*(5). https://doi.org/10.1108/JEIM-10-2018-0224

Hinkin, T. R. (1995). A review of scale development practices in the study of organizations. *Journal of Management*, *21*(5), 967-988. https://doi.org/10.1016/0149-2063(95)90050-0

Holland, C. P., Thornton, S. C., & Naudé, P. (2019). B2B analytics in the airline market: Harnessing the power of consumer big data. *Industrial Marketing Management, 86,* 52-64. https://doi.org/10.1016/j.indmarman.2019.11.002

Hossain, M. A., Akter, S., & Yanamandram, V. (2020a). Revisiting customer analytics capability for data-driven retailing. *Journal of Retailing and Consumer Services*, *56*. https://doi.org/10.1016/j.jretconser.2020.102187

Hossain, M. A., Akter, S., & Yanamandram, V. K. (2020b). Customer Analytics Capabilities in the Big Data Spectrum: A Systematic Approach to Achieve Sustainable Firm Performance. *Sydney Business School Papers*, 1-17. https://ro.uow.edu.au/cgi/viewcontent.cgi?article=1616&context=gsbpapers

Kolsarici, C., Vakratsas, D., & Naik, P. A. (2020). The Anatomy of the Advertising Budget Decision: How Analytics and Heuristics Drive Sales Performance. *Journal of Marketing Research*, *57*(3). https://doi.org/10.1177/0022243720907578

Le, T. M., Liaw, S.-y., & Bui, M.-T. (2020). The role of perceived risk and trust propensity in the relationship between negative perceptions of applying big data analytics and consumers' responses. *WSEAS Transactions on Business and Economics, 17,* 426-435. http://dx.doi.org/10.37394/23207.2020.17.41

Liao, S.-H., Hsu, S.-Y. (2020). Big data analytics for investigating Taiwan Line sticker social media marketing. *Asia Pacific Journal of Marketing and Logistics*, *32*(2), 589-606. https://doi.org/10.1108/APJML-03-2019-0211

Louro, A., Brandrão, M. M., Jaklič, J., & Sarcinelli, A. (2019). How can Customer Analytics Capabilities influence organizational performance? A moderated mediation analysis. *Brazlian Business Review*, *16*(4). https://doi.org/10.15728/bbr.2019.16.4.4

Madhavan, R., Shah, R. H., & Grover, R. (1994). *Motivations for and theoretical foundations of relationship marketing* (pp. 183-190). In AMA Winter Educators' Conference , Chicago, USA.

Mariani, M. M., Wamba, S. F. (2020). Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. *Journal of Business Research*, *121,* 338-352. https://doi.org/10.1016/j.jbusres.2020.09.012

Martínez, M., Hernández, M., & Hernández, M. (2006). *Psychometry.* Editorial Alliance. https://dialnet.unirioja.es/servlet/libro?codigo=284004

Maya-Restrepo, M. A. (2023). *Design, development and psychometric validation of a measurement model of the client's analytical capabilities under a theory/data guided approach*. [Thesis Universidad de Antioquia].

https://doi.org/10.25100/cdea.v40i78.13227

Nethravathi, P. S., Bai, G. V., Spulbar, C., Suhan, M., Birau, R., Calugaru, T., Hawaldar, l. Thonse., & Ejaz, A. (2020). Business intelligence appraisal based on customer behavior profile by using hobby based opinion mining in India: a case study. *Economic Research, 33*(1). https://doi.org/10.1080/1331677X.2020.1763822

Nicholas, M. K., McGuire, B. E., & Asghari, A. (2015). A 2-item short form of the Pain Self-efficacy Questionnaire: development and psychometric evaluation of PSEQ-2. *Journal of Pain*, *16*(2), 153-163. https://doi.org/10.1016/j.jpain.2014.11.002

O'Neill, M., Brabazon, A. (2019). Business analytics capability, organizational value and competitive advantage. *Journal of Business Anal*ytics, *2*, 160-173. https://doi.org/10.1080/2573234X.2019.1649991

Pavlou, P. A., Sawy, O. A. (2011). Understanding the Elusive Black Box of Dynamic Capabilities. *Decision Sciences*, *42*(1), 239-273. https://doi.org/10.1111/j.1540-5915.2010.00287.x

Pérez-Rave, J. I. (2021a). *Data/Text Mining – Structural – Multicriteria as a strategic resource in personnel selection.* https://repositorio.unal.edu.co/bitstream/handle/unal/80145/71225056.2021.pdf?sequence=2

Pérez-Rave, J. I. (2021b). *MinerConstructo: intelligent framework to learn, update and practice construct mining with scientific rigor* (pp. 10-986-55). https://www.idinnov.com/terminos-y-condiciones-idinnov-s-a-s/

Pérez-Rave, J., Guerrero, R. F., Vallina, A., & González-Echavarría, F. (2022). A measurement model of dynamic capabilities of the continuous improvement project and its role in the renewal of the company's products/services. *Operations Management Research*, *16*. https://link.springer.com/article/10.1007/s12063-022-00281-9

Pérez-Rave, J. I., Figueroa, G. A., & Echavarría, F.G. (2022). A scale for measuring healthcare service quality incorporating patient-centered care and using a psychometric analytics framework. *Journal of Health Organization and Management, 36*(6). https://doi.org/10.1108/JHOM-10-2021-0387

Pérez-Rave, J. I., González-Echavarría, F., & Correa-Morales, J. C. (2022). A measure of dignified treatment for healthcare workers: design and psychometric properties. *Behaviormetrika, 50,* 287-316. https://link.springer.com/article/10.1007/s41237-022-00180-0

Petrescu, M., Krishen, A., & Bui, M. (2020). The internet of everything: implications of marketing analytics from a consumer policy perspective. *Journal of Consumer Marketing*, *37*(6). https://doi.org/10.1108/JCM-02-2019-3080

Pine, B., Gilmore, J. (1998). Welcome to the economic experience. *Harvard Business Review*, *78*(1), 97-105. https://hbr.org/1998/07/welcome-to-the-experience-economy

Ployhart, R. E., Schneider, B. (2012). The social and organizational context of personnel selection. In N. Schmitt (Ed.) , Oxford Library of Psychology, *The Oxford handbook of personnel assessment and* selection (pp. 48-67). https://doi.org/10.1093/oxfordhb/9780199732579.013.0004

Ramana, A. V., Rao, A. S., & Reddy, E. K. (2019). Applications of business intelligence and decision making for the customer behaviour analysis in telecom industry. *International Journal of Recent Technology and Engineering*, 7. https://www.ijrte.org/wp-content/uploads/papers/v7i6s2/F11150476S219.pdf

Real Academia Española. (s.f.). *Diccionario de la lengua española, 23° ed. [versión 23.7 en línea].* https://dle.rae.es

Rajan, A. P. (2019). The effectiveness of social media content marketing towards brand health of a company: Social media analytics. *International Journal of Scientific and Technology Research*, *8*(11). http://www.ijstr.org/final-print/nov2019/The-Effectiveness-Of-Social-Media-Content-Marketing-Towards-Brand-Health-Of-A-Company-Social-Media-Analytics.pdf

Rajendran, S. (2020). Improving the performance of global courier & delivery services industry by analyzing the voice of customers and employees using text analytics. *International Journal of Logistics Research and Applications*, *24*(5). https://doi.org/10.1080/13675567.2020.1769042

Rakhman, R. A., Widiastuti, R. Y., Legowo, N., & Kaburuan, E. R. (2019). Big data analytics implementation in banking industry - case study cross selling activity in indonesia's commercial bank. *International Journal of Scientific and Technology Research, 8*(9). https://api.semanticscholar.org/CorpusID:204901775

Rezaei, G., Hosseini, S. M., & Sana, S. S. (2022). Exploring the Relationship between Data Analytics Capability and Competitive Advantage: The Mediating Roles of Supply Chain Resilience and Organization Flexibility. *Sustainability*, *14*. https://ideas.repec.org/a/gam/jsusta/v14y2022i16p10444-d894732.html

Sackett, P. R., Putka, D. J., & McCloy, R. A. (2012). The Concept of Validity and the Process of Validation. In N. Schmitt (Ed.), *The Oxford Handbook of Personnel Assessment and Selection* (pp. 91-118). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199732579.013.0006

Slater, S. F. & Narver, J. C. (1999). Market-oriented is more than being customer-led. *Strategic Management Journal*, *20*(12), 1165-1168. https://doi.org/10.1002/(SICI)1097-0266(199912)20:12<1165::AID-SMJ73>3.0.CO;2-%23

Sohrabi, B., Vanani, I. R., Nikaein, N., & Kakavand, S. (2019). A predictive analytics of physicians prescription and pharmacies sales correlation using data mining. *International Journal of Pharmaceutical and Healthcare Marketing*, *13*(2). https://doi.org/10.1108/IJPHM-11-2017-0066

Sumbaly, R., Kreps, J., & Shah, S. (junio de 2013). *The "Big Data" Ecosystem at LinkedIn*. https://doi.org/10.1145/2463676.2463707

Sun, N., Morris, J., Xu, J., Zhu, X., & Xie, M. (2014). iCARE: a framework for big data based banking customer analytics. *IBM Journal of Research and Development*, *58*(5). https://ieeexplore.ieee.org/document/6964895

Swanson, R. A., Holton, E. F. (2005). *Research in Organizations: foundations and methods of inquiry.* Barrett-Koehler Publishers. https://www.bkconnection.com/static/Research_in_Organizations_EXCERPT.pdf

Teece, D., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509-533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z

Vecchio, P. D., Mele, G., Passiante, G., & Fanuli, D. V. (2020). Detecting customers knowledge from social media big data: toward an integrated methodological framework based on netnography and business analytics. *Journal of Knowledge Management, 24*(4). https://doi.org/10.1108/JKM-11-2019-0637

Wilder, C. R., Ozgur, C. O. (2015). Business Analytics Curriculum for Undergraduate Major. INFORMS Transactions on Education, *15*(2), 180-187. https://pubsonline.informs.org/doi/10.1287/ited.2014.0134

Yaghmale, F. (2003). Content validity and its estimation. *Journal of Medical Education, 3*. https://api.semanticscholar.org/CorpusID:73134288

Yerpude, S., Singhal, T. K. (2019). "Custolytics": Internet of Things based customer analytics aiding customer engagement strategy in emerging markets – an empirical research. *International Journal of Emerging Markets, 16*(1). https://doi.org/10.1108/IJOEM-05-2018-0250

How to cite this paper?

Maya Restrepo, M. A., Pérez Rave, J. I. (2024). Design and psychometric validation of a Customer Analytics Capabilities (CAC) scale: empirical evidence in Colombian organizations. *Cuadernos de Administración, 40*(78), e2413227. https://doi.org/10.25100/cdea.v40i78.13227

Appendix 1. Items of the M2A (three-dimensional) model to represent CAC

Item	Description
cac5	Define commercial strategies to implement based on customer-related data analysis (e.g., needs, preferences, sociodemographic variables, recommendation intentions)
cac17	Make decisions on how to reconfigure the value offer based on results derived from customer data analysis
cac19	Evaluate the market performance of new products/services before, during, and after they are launched on the market
cac20	Monitor the impact of marketing campaigns on company performance, based on data analysis
cac21	Examine different marketing mixes (pricing, promotion, placement, product) considering customer data analysis
cac24	Evaluate the customer experience at all touchpoints with the customer, with the help of data analysis methods
cac25	Evaluate the performance of loyalty strategies, based on evidence derived from data analysis
cac28	Design cross-selling strategies (exploitation of complementary products) based on data on customer consumption patterns
cac10	Analyze business transaction data to identify the best customers for the company
cac11	Examine customer retention level from data analysis

Source: Authors' own elaboration after confirmatory factor analysis.

Appendix 2. Items of model M1 (one-dimensional) to represent CACs

Item	Description
cac5	Define commercial strategies to implement based on customer-related data analysis (e.g., needs, preferences, sociodemographic variables, recommendation intentions)
cac6	Design product and service personalization strategies based on results obtained from customer data analysis
cac7	Design customer relationship strategies, supported by the analysis of social network data
cac8	Monitor the variables that most influence customer commitment to the brand, with the support of data analysis methods
cac13	Measure psychological variables of consumers to complement customer segmentation criteria
cac15	Predict future customer purchasing behavior based on historical data analysis
cac17	Make decisions on how to reconfigure the value offer based on results derived from customer data analysis
cac19	Evaluate the market performance of new products/services before, during, and after they are launched on the market
cac20	Monitor the impact of marketing campaigns on company performance, based on data analysis
cac21	Examine different marketing mixes (pricing, promotion, placement, product) considering customer data analysis
cac22	Design new customer acquisition strategies supported by data analysis methods
cac24	Evaluate the customer experience at all touchpoints with the customer, with the help of data analysis methods
cac25	Evaluate the performance of loyalty strategies, based on evidence derived from data analysis
cac28	Design cross-selling strategies (exploitation of complementary products) based on data on customer consumption patterns

Source: Authors' own elaboration after confirmatory factor analysis.

https://doi.org/10.25100/cdea.v40i78.13227