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Knowledge Management: *Human Intellectual Capital* (HIC) Measurement by *Item Response Theory* (IRT)

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Abstract

Man is always in search of knowledge; the discoveries of fire, animals' domestication and agricultural procedures, astronomy or navigation, all allowed at their time important leaps in Humanity' evolution. Today, Knowledge is fully present in our daily lives, as in the way we work, socialize or spend our free time. In economy, it is undeniable that it is the true worth of today's organizations, which compete in each day more globalized market. Every day we witness companies that emerge to satisfy needs that we didn't feel until recently, where the incorporation of knowledge is condition for competitiveness and wealth generation. And due to the conditions that this new knowledge economy has been imposing on market, also the professional's profile is evolving. Now, it is the workers themselves who carry their means of production, their own intellectual capacities. On the other hand, this change brings new and deep challenges also to *higher education institutions* (HEI), committed on training those who will be the pillars of technological innovation and economic development, the knowledge workers. In this context, *Human Intellectual Capital* (HIC) is defined as the tools for knowledge put into practice for wealth generation. But are companies aware of their intellectual assets? Can it be measured and managed? Since the middle of the 20th century, companies have begun to understand the value of knowledge for their economic sustainability, and different methodologies have been tested for their evaluation, however complex and of difficult implementation, and none applied to HIC. The aim of this work is to build an HIC measurement tool based on *Item Response Theory* (IRT), whose results are consistent with the theoretical framework, demonstrating this way to be a reliable tool for the management of Knowledge processes, as well as a contribute to better understand the components of intellectual capital (IC) and its impact on the organization performance.

Keywords

Knowledge Measurement, Management, Organization Performance, Human Intellectual-Capital (IC), *Item Response Theory* (IRT)

1. Introduction

What is *Knowledge*? From Latin *cognoscere*: the act or effect of knowing, it takes vastly different meanings, whereby must be contextualized (Lewin, 2004). Since the 18th century Industrial Revolution, we have seen an increase in cognitive content applied to products and processes. More recently, with the growing use of *information and communication technologies* (ICT), Knowledge, which was traditionally a private good, (almost) suddenly becomes a public good (Santos, 1999), leading us to the *episteme* of today (Crozon, 2004). In this work, Knowledge refers to individual intellectual and experiential skills, as well as the attitude to work in an organizational context.

For Caraça (2003: p. 21), knowledge evolves by "jolts" in the cultural component of the community in which is inserted, such as the rules of social organization, values and perceptions, or information codes, and Costermans (2001) describes knowledge as all the intangible assets of an organization, applied to value creation. In turn, Sveiby (1997) argues that all tasks are accomplished using two forms of knowledge: tacit, which is built from each individual experience, and explicit, acquired through information, where one does not exist without the other.

It is this tacit knowledge, commonly unnoticed by managers and which often supports decision-making, that constitutes the main distinguishing factor of organizations, and its competitive advantage, staying "stored only in the organization's memory" (Arasaki et al., 2017). It is, therefore, this knowledge "the greatest wealth of organizations" (Sveiby, 1997), of the utmost value to manage (control, manipulate and improve), from a perspective of organizational excellence, while cultivating the motivation, commitment, and capabilities of workers (Timsal et al., 2016).

But are companies aware of their intellectual assets? Can it be measured and managed? Since the middle of the 20^{th} century, different methodologies have been built to understand the value of knowledge on economic sustainability, and evaluation. However complex and of difficult implementation, and none applied to HIC (Matošková, 2016). In this field, Bontis (1998) developed a method to assess the impact of knowledge on the creation of value, showing a strong causal link between intellectual capital and business performance, which has been replicated in different scopes and realities.

The main objective of this work is to build a HIC measurement model through

Item Response Theory (IRT), based on data collected in a survey by questionnaire applied to students in the final year of *Instituto Superior de Engenharia de Lisboa* (ISEL) degree courses. The concepts under study are introduced in part 1. Tools and methods used for data collection and analysis are presented in part 2, and the results are discussed in part 3. In final part 4 it is concluded that the tested method produces reliable and reproducible results, consistent with the theoretical framework studied, allowing to accurately estimating the psychological trait under investigation, which makes this a suitable tool for the management of knowledge processes.

2. Theoretical Framework

In 1997, Sveiby warned for a social paradigm shift about to happen, with Drucker later in 2012 arguing that it has already begun. We are living changing times, whose signs are perceived both in the way of being and thinking, but also in how we understand traditional cultural values. Also in the economy, is noted the new professions that appear every day to meet needs that did not exist until recently, in such different sectors or activities, but all with a common aspect: they are based on intensive knowledge. In this new framework concentration is no longer done economically, but through intellectual resources. Schwab (2017: p. 5) says that:

> "Among the many and diverse and fascinating challenges we face, the most intense and important is how to understand and define the new technological revolution, which implies nothing less than the transformation of all humanity".

2.1. Knowledge Transfer and Acquisition

Family is no longer the natural environment for knowledge transfer and acquisition, but the company itself, argues Sveiby (1997). For this author, knowledge plays an important role in organizations, that traditionally carry out their training of workers:

1) By information: oral communication (explicitly) where the receiver is a passive recipient of information (Cicuto & Torres, 2016).

2) By assimilation: on job training, with technical and behavioral perception (tacitly) of action (Brito, 2019).

In this processes, Nonaka (1994) says that the transfer of explicit knowledge takes place by absorption or combination, through the analysis, categorization and reconfiguration of information. By its side, tacit knowledge assimilation is a long-term process, which may or may not incorporate scientific fundamentals, where the receiver is involved in the activity, making use of analysis, synthesis and communication skills, building up his own knowledge (Brito, 2019).

Says Drucker (2012), that because it is largely made up of an experimental component, as people often prefer to reach their conclusions than to be given, knowledge transfer and acquisition are essentially tacit, through exposure (*epis-*

temological dimension) to the conditions (*ontological dimension*) it is applied. It is this knowledge what Sveiby (1997) claims to be the true wealth of organizations, their main competitive factor, but which is often dispersed and neglected, hidden only in the organization's memory.

2.2. Knowledge Measurement

The growing demand for information to the study of human attitudes has been promoting the development of new methodologies to measure individual ways of thinking and behaving, yet complex and of difficult implementation. As Edvinsson and Malone (1997: p. 123) point out "it is not easy to measure what goes on in the heads and hearts of managers and workers". Although the cost of a product today largely consists of R&D (Stewart, 1999), intangible resources are generally disregarded for return on investment, just because they are not easily measurable. We can know how much money and time is spent on training, but not how much knowledge has been acquired (Stewart, 1999).

Regarding to the measurement theory (Pasquali, 2017), any instrument to assess a psychological trait must guarantee that measures what it proposes (principle of legitimacy), as well represents the true magnitude of the property under study (principle of sensitivity). In this field, *Item Response Theory* (IRT) has been successfully used to represent a property not directly observable (latent variable) through a set of questions (manifest variables) placed in a questionnaire (measuring instrument), postulating that the category of response will be determined only by the individual's ability (Vidotto et al., 2017). IRT designates a type of mathematical models, that also allows the comparison between groups of different populations (samples), or the variation of the skill under study over time (Andrade, Tavares, & Valle, 2000).

2.3. *Human Intellectual Capital* (HIC)

Edvinsson and Malone (1997) refer to *intellectual capital* (IC) as the company's intangible assets, structured in two dimensions:

- *Human capital* (HC), individual capabilities, talent and skills as social relationships of workers, that "never belong to the organization", and
- *Structural capital* (SC), which includes machinery and processes, that "stays in the company when employees go home at the end of the day".

By his side, Bontis (1998) defines IC as what it isn't: "it is not intellectual property like copyrights, patents, design rights, or trade and service marks". For this author, the SC is the support for intellectual activities to be effective, or, as he says, "without structural capital, intellectual capital would just be human capital" (Bontis, 1998: p. 66). Stewart (2001: p. 13) adds to this "value platform" all the company external relations, as clients and suppliers' relationships, government rulers and industrial associations, or market and marketing orientations, calling it *customer capital* (CC).

In this work is defined *Human Intellectual Capital* as the proactive combination of cognitive capacities and attitudes to produce value (**Figure 1**).

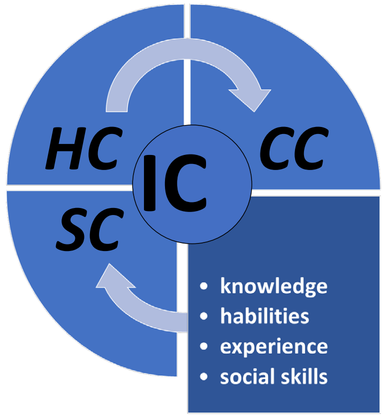

Figure 1. Structure of intellectual capital (IC).

2.4. Knowledge Economy

Unlike other economic goods, knowledge is not a scarce resource (Sveiby, 1997). Against all the classical laws of economics, when applied it doesn't decrease, but instead grows and expands. Says Drucker (2012: p. 165) that modern companies exist to value "hundreds, sometimes thousands, of specialized types of knowledge", where "the innovative recombination of different types of knowledge generates new knowledge", in what he calls the *economization of knowledge*. Being today the main resource for many companies, not only in new sectors but also in more traditional ones, knowledge is already classified by (OCDE, 2017) as the 4th factor of production, alongside labor, capital or land.

Schwab (2017) distinguish two types of *knowledge companies*: those that provide the product, and those that develop the process. For Drucker (2012: p. 153), this new *knowledge economy* is an economy of organizations, where they "do not exist for themselves, but to play a role, for the individual and for society". In this scenario, Stewart (2001) alerts that only those most aware of their knowledge are prepared for the changes to come, and it is by perceiving and anticipating social needs and desires that these organizations can secure their place in society.

2.5. Knowledge Worker

The Industrial Revolution in Europe, with the intensification of knowledge in industry, gave rise to the concept of modern company (Caraça, 2003). The most valuable production factor today is no longer property, but the workers themselves (Drucker, 2012), and due to these changes in labor market, also workers are facing new and deep challenges these days (Stewart, 2001). Although still needing support equipment, the worker today carries his own tools, that is his knowledge (Stewart, 1999). Performing with increasing levels of autonomy (planning, innovation and supervision), the *knowledge worker* is now more attached to the task itself than to the company that employs him.

But although the focus on knowledge is a factor of greater productivity, and synonymous with economic development, what can be observed is that the creation of new jobs has not followed this expanding market, becoming more flexible and transitory (Schwab, 2017). In modern companies the focus is not on *how to do*, but on *what should be done*, and workers are expected to have the necessary competences to do it (Drucker, 2012). Schwab (2017) defines today's worker by having:

1) Explicit knowledge, through education;
2) Proficiency, demonstrating capabilities;
3) Experience, acquired from practice;
4) Social skills;
5) Learning competences.

2.6. *Higher Education Institutions* (HEI)

João Caraça (2003) points out the fundamental role to be played by HEI in the transition to this knowledge society, to train those who will be the pillars of the new social order. But Drucker (2012: p. 173) alerts that "never before have these organizations been faced with the task of managing knowledge", arguing they need to start by identify the distinctive factors that will give them place in society. In turn, Christensson and Staaf (2019) argues that the main challenge that HEIs will face is a cultural change, with the redefinition of learning processes, involving teachers and students in the rationalization of knowledge.

By his side, Khalid (2018) says that a change always come through the development of competences, where Drucker (2012: p. 360) argues that "the most effective way of managing knowledge is creating it".

According to Bass (1999), the problematization of teaching must be centered on the discussion of learning theories, with Brame (2016) defending the concept of active learning, where students are involved in cognitive and social activities, building knowledge and understanding. HEIs should guide their educational strategies to the development of talents, valuing those who demonstrate the highest levels of potential to make a difference in the overall performance of an organization, exploring their own areas of expertise (Khalid, 2018).

3. Methodology

The empirical research in this work focused on data collected through a questionnaire survey, built from the work of Bontis (1998) to study the impact of *intellectual capital* (IC) on busyness performance. Data analysis was performed through *Item Response Theory* (IRT). This technique accepts different types of data entry, automatic or not, even in complex universes, allowing individuals and groups to be compared, punctually or over time, in the same or different universes (Baker, 2001).

Other approaches such as performance indicators analysis (Colauto & Beuren, 2005) or the *Structural Equation Modeling* (SEM) (Schumacker & Lomax, 2016) of latent variables were not explored.

Human Intellectual Capital (HIC) is a latent variable, not directly observable, but which can be inferred through other manifest variables, such as questions in a questionnaire (Schumacker & Lomax, 2016). The applied questionnaire (*see* Annex A) includes 20 Likert questions with 7 categories, providing this way a greater extent of the latent variable under study, appropriate for the study of abilities (Barbetta, 2010).

When not practical to consult the entire universe under study, the characteristic of interest can be observed in a smaller group of cases (work sample), guaranteed the representativeness of all population (Nunes & Primi, 2005), following one of two approaches:

- Definition of boundaries of the universe, collecting information for all cases in this group, or
- Use a formal sampling method, distinguishing between probabilistic (random) and non-probabilistic (*non-random*) methods.

While random sampling methods allow for greater sample representativeness, non-random methods have advantages, as producing more reliable results and saving time and effort in the process (Reis et al., 2016). By other side, knowing that larger samples are less prone to sampling errors (Nunnally & Bernstein, 1994), the sample size determination must be based on a cost-benefit assessment, being most common the heuristic (*thumb rules*) or statistical methods (Lenth, 2001).

In social sciences, the concept of measurement gains special importance (Nunnally & Bernstein, 1994), requiring the verification of measurement legitimacy, i.e. that it really measures what is intended to, in terms of validity, that is the congruence between the psychological trait under study and its physical representation, and reliability, that it produces identical results when applied to the same cases in repeated measurements (Pasquali, 2017), stressing that these properties are specific to the context in which it is applied (Sireci, 2007).

To demonstrate its scientific validity, Nunnally and Bernstein (1994) argue that a measuring instrument must meet three criteria:

- Content validity—representativeness of the set of items used to describe the ability under study,
- Theoretical validity—theoretical support that defines both the latent variable (*construct*) and the manifest variables that describe it (*convergent validity*), and
- Predictive validity—correlation between observed and predicted behavior patterns (assessed outside of the measurement process).

But answering each item in a questionnaire resembles a succession of individual experiences, making the measurement susceptible to experimental errors. A measure of a variable is then said to be reliable if it is consistent, that can be estimated by *Cronbach*'*s* (α) method, being generally accepted values of α equal or greater than 0.7 to demonstrate test reliability (Pasquali, 2017).

Because an ability never occurs isolated in any cognitive process, being impossible to define a psychological trait by a single dimension, questionnaires usually include multiple questions to describe the same aspect (Andrade, Tavares, & Valle, 2000), leading to redundancy issues (Shlens, 2014). Often used as a first step in data analysis, condensation allows the removal of these redundancies without significant loss of information (Johnson & Wichern, 2007), being the most used techniques *principal components analysis* (PCA) and *exploratory factor analysis* (EFA). However, while Pasquali (2017) defends EFA for validation of latent variables, Jolliffe (2010) argues that PCA is descriptive by nature, and therefore more suitable for exploratory studies.

Data condensation focus on internal structures underlying raw data, where each factor or component (intermediate variable) is a weighted representation of latent variable, maximizing the unexplained variance of all system (Reimann et al., 2008). The main methodological issue with PCA concerns to define the smallest number of intermediates that describes the latent variable under analysis, without compromising data integrity (Jolliffe, 2010). Different approaches can be followed (Elvira, Chainais, & Dobigeon, 2017):

1) retaining those components that cumulatively represent a target explained variance (e.g., more than 70%),

2) retaining those that individually account for a significant variance (e.g., >1), or

3) by graphical analysis (*scree-plot*).

When not clear the number of intermediate variables to retain, a geometric rotation technique can be applyed, being most used the orthogonal *Varimax*, which maximizes variance loads, and the oblique *Promax*, which makes data projection on the dimensional space (Reimann et al., 2008). By other side, although being the covariance and correlation matrices directly related, Jolliffe (2010) warns that they can lead to quite different results, arguing that the covariance matrix in Varimax is affected by heterogeneous measurement scales and by sets of variables with high variance, which may cause interpretive errors.

Verified test legitimacy and data dimensionality, the next step is model parameter estimation (calibration), determining the data response function (Linden, 2010). Once item parameters and ability are in the same metric, the scale is thus a numerical representation of the psychological trait under study. Since 1990' different IRT models have been developed to describe the relationship between a latent variable ($\boldsymbol{\theta}$) and the probability of response (P_θ) to an item, as graduated and credit models (Pasquali, 2017). The *graded response model* (GRM) represents a family of mathematical models defined by the *discrimination* (**a**) and *difficulty* (**b**) parameters. It is assumed that the respondent in the decision-making process, successively surpasses each response category until reaching the one that he believes as correct (Linden, 2010).

Fumiko Samejima (2010) developed a GRM to integrate polytomous items, that ensures the IRT criteria for local independence and additivity of the response functions, as well the single maximum condition. In **Figure 2**, the *item characteristic curve* (ICC) represents the probability of a correct answer of an item with 5 categories. It is observed that individuals with an ability level of $\boldsymbol{\theta} =]-4; 0]$ are more likely to respond to category P3, the most selected answer, and individuals with $\boldsymbol{\theta} > 2$ will respond to category P5. By other side, the curve displacement to lower values of **θ**, is indicative of the ease felt by respondents in agreeing with statements (Baker, 2001). Chalmers (2015) claims that easy tests allow a more accurate characterization of individuals with lower levels of the skill under study.

As seen, IRT focus on the analysis of responses as a set, so each item contributes its own meaning (information) to the ability under study, that Fisher (*in* Baker, 2001: p. 104) defines as the "reciprocal of the estimated parameter precision". According to Baker (2001: p. 106), an "item measures the ability with greater precision at the level corresponding to parameter b" decreasing "as it approaches the limits of the **θ** scale", represented by its *item information curve* (IIC). In the same way, the *test information curve* (TIC) represents model's accuracy, or as stated by Bortolotti et al. (2012: p. 291), "how well a set of items evaluates the latent trait". In **Figure 3** it is observed a TIC showing better accuracy for **θ** ≈]−4.5; 3.2], with a maximum I for **θ** ≈ −0.8.

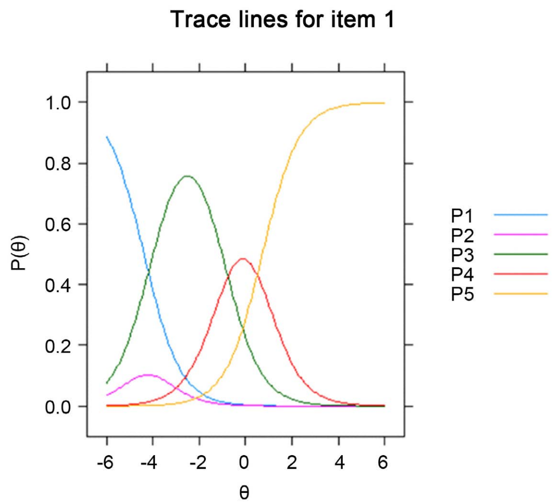

Figure 2. Item characteristic curve (ICC) with 5 categories, for 2 parameter model (PL2).

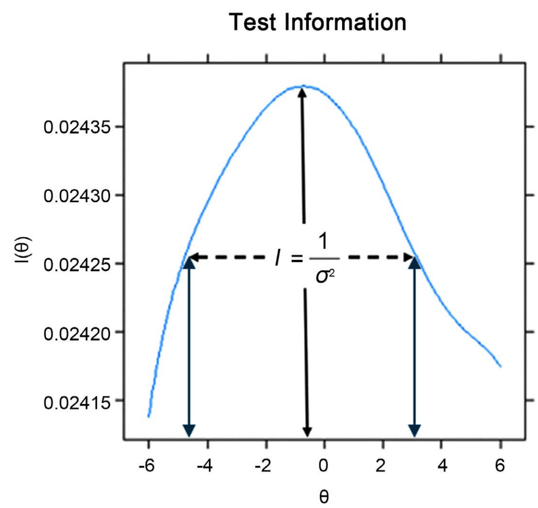

Figure 3. Test information curve (TIC), as test accuracy.

As the ICC describes the ability level achieved for each item, the *test characteristic curve* (TCC) represents the relationship between the accumulated *true score* (T_θ) and the ability $\boldsymbol{\theta}$, which allows the conversion of T_θ into $\boldsymbol{\theta}$ and vice versa (Baker, 2001).

4. Results and Discussion

The results obtained in this work allow to verify that collected data accurately describes target population and have consistency for component extraction, as also the applied questionnaire has scientific validity to measure the psychological trait under study. The Samejima's GRM shows robustness and individual discrimination power, being able to represent the latent variable under study in a numeric scale.

The identification of *anchor levels*, associated to an outcome or area of knowledge, was not performed (Wyse, 2017), as well as *differential item functioning* (DIF) for groups discrimination, such as familiarity or affection for the topics covered (Andrade, Laros, & Gouveia, 2010).

4.1. Data Collection

The academic structure at ISEL is a complex universe, which difficult sample representativeness. Thus, the questionnaire was applied to the entire target population, with 257 responses being validated, that represents a response rate of 62%. The questionnaire includes 4 questions for individuals' description, and 20 questions designed to assess 3 main aspects in *Human Intellectual Capital* (HIC):

- Workers' contribution to performance.
- Business perception and commitment.
- Role of organizations to task support.

To improve information quality, 6 questions were applied in negative phrasing, as proposed by Dilman (2000). Collected data shows that target universe is mostly composed by students under 25 years old (85%), as would be expected in this academic phase, with only 24 respondents (10%) having more than 3 years of labor experience. Most of applied items (13 out of 20) got answers in all 7 categories, although with greater tendency to agreement.

4.2. Test Validation

The test validity to measure the psychological trait under study, was verified by the relationship between the empirical property and the demonstrated behavior, following Nunnally and Bernstein (1994) criteria, that shows:

- Sensibility to describe the respondent's ability level;
- *Construct* coherence with the manifest variables.

Questionnaire reliability was then tested for internal consistency by Cronbach's α, *split-half* estimation and Guttman's $\boldsymbol{\lambda 6}$ coefficient. The results obtained (**Table 1**) shows good internal consistency, with a *split-half* identical to Cronbach's α, and lower than $\boldsymbol{\lambda 6}$ coefficient as would be expected (Maroco & Garcia-Marques, 2006).

Table 1. Internal consistency.

Cronbach's α	*split-half*	*Guttman's λ6*
0.81	0.81	0.84
Average ($\bar{r}$)	0.17	
Median ($\underset{\cdot}{r}$)	0.17	

The values obtained for the average correlation ($\bar{r}$) and median of correlations ($\underset{\cdot}{r}$) confirm data homogeneity (Revelle, 2018).

Maroco and Garcia-Marques (2006) alert that Cronbach's α tends to underestimate reliability in multidimensional systems, but also for dichotomous items. For their part, Hill and Hill (2017) point out limitations of *split-half* method in small size questionnaires, as the arbitrariness in the questionnaire partition that may cause loss of internal consistency, contributing to the experimental error. Regarding this the *Spearman-Brown prophecy* method was also applied on calculations, in order to verify the reliability of a test (Hill & Hill, 2017).

Through response frequencies, it is also observed that all items contribute positively to internal consistency, although those placed in negative phrasing introduces greater bias. This could mean misinterpretation of questions, or lack of knowledge on concepts addressed, may contributing this way to the experimental error (Nunnally & Bernstein, 1994). Particularly, items CH13R and CH19R shows negative correlation with full scale, whereby they were score reversed, without any observed lost effect on data consistency (Revelle, 2018).

4.3. Component Extraction

To better define the IRT model to apply, raw data was tested using the *Kaiser-Meyer-Olkin* (KMO) criterion to evaluate strength for components extraction, and then data dimensionality analysis. The result of 0.81 (>0.6) for the *measurement index of sample adequacy* (MSA) demonstrate the expected data consistency, confirmed by *Bartlett sphericity test* with a *p*-value of $2.2e^{-16}$ (<0.05).

Principal component analysis (PCA) was then performed with *Promax* rotation, showing to be necessary 20 components (*manifest variables*) to explain initial data without any loss of information. Arbitrarily set the threshold of 20% for individual variance, first *principal component* (PC1) is represented by 13 items, while PC2 by all questions in negative phrasing excluding CH2R. In turn, PC3 is represented by items already repeated from the other two components (Revelle, 2018).

With an adjustment factor of 95%, it is observed that:

- First component (PC1) explains 25% of system variance, with 7 components being necessary to explain 62%, but 12 to reach 81%;
- The *scree-plot* distribution shows that 3 components explain 40% of the variance (**Figure 4**);
- Data projection for PC1 and PC2 (**Figure 5**) show a positive contribution of all items to the latent variable (HIC);
- The projection for PC2 and PC3 (**Figure 6**) shows a greater variance for items regarding the organization role;

• The subgroup *professional experience* (**Figure 7**) shows a clear association with acquired HIC.

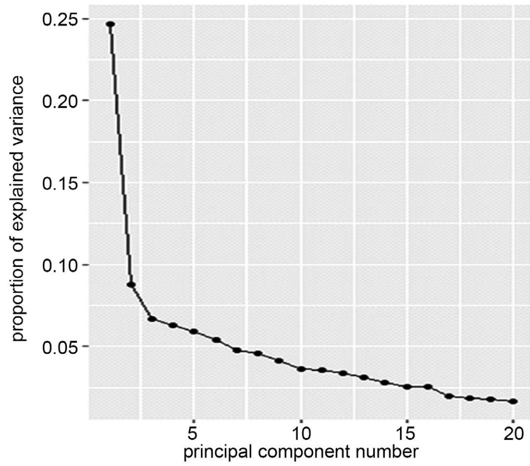

Figure 4. Scree-plot distribution.

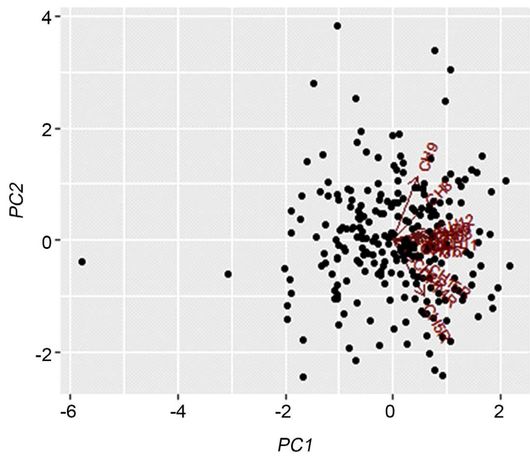

Figure 5. Data projection PC1/PC2.

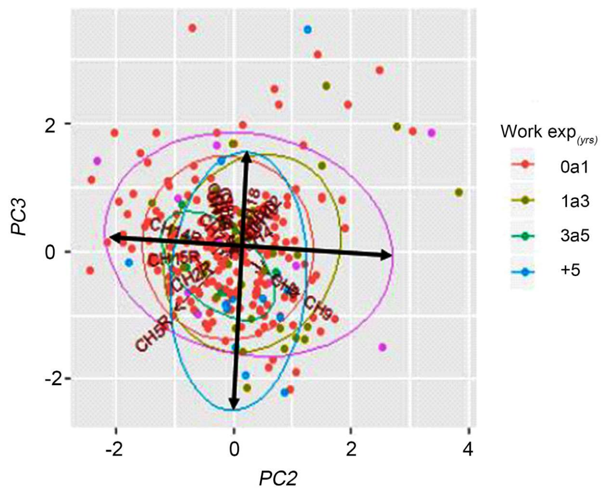

Figure 6. Data projection PC2/PC3.

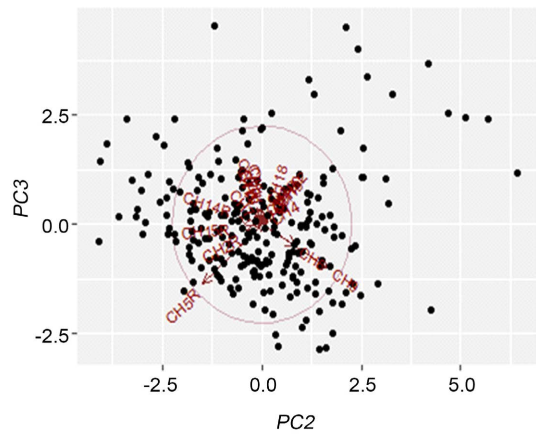

Figure 7. Subgroup analysis "prof exp".

4.4. Dimensionality Analysis

Data analysis show a dominant component with PC1 explaining alone 25% of system variance. By its side, the statistics *very simple structure* (VSS) attains a 0.26 maximum for 2 components, while Velicer's *minimum average partial* (MAP) reaches a 0.01 minimum with only 1 component (Revelle, 2018). These results are consistent with the validity analysis performed (see p. 15), demonstrating the good psychometric qualities of the test to access the psychological trait under analysis (Pasquali, 2017). However, even though the data structure can be adequately represented by only 1 manifest variable (Jolliffe, 2010), guaranteeing data representativeness with reduced susceptibility to experimental errors, as Maroco and Garcia-Marques (2006) warn, sets of high correlated items does not necessarily mean unidimensionality. Concerning this, a multidimensional analysis approach was followed.

4.5. *Item Response Theory* (IRT)

Knowing that any model is always a simplified simulation of reality, to assess the goodness of fit, or, how well this model represents initial data, 3 information criteria were applied: *Akaike* (AIC), *corrected Akaike* (AICc) and *Bayesian* (BIC). These results (**Table 2**) show a unidimensional model, without significant information gaining from adding greater complexity to the system (Chalmers, 2012).

Samejima's GRM was then performed for calibration with 1 dimension, through the *expectation maximization* (EM) method by the Gauss-Hermite algorithm (Chalmers, 2019), reaching convergence after 87 iterations, with $1e^{-04}$ of tolerance. Doing a pre-analysis of all ICC, it is observed that items CH1, CH3, CH4, CH6, CH7, CH10, CH11, CH12, CH16, CH17, CH18, CH20 have all high discriminatory power ($a > 1$), showing to be sensitive to variations in the skill under analysis (Pasquali, 2017), being therefore good representatives of main component CP1.

A second run was then performed with these 12 items, with convergence reached after 27 iterations ($1e^{-04}$ of tolerance) and the fit statistics (**Table 3**) *root* *mean square error of approximation* (RMSEA), *standardized root mean square residual* (SRMSR), *Tucker-Lewis's index* (TLI) and *comparative fit index* (CFI) indicating *a priori* good adjustment quality (Hooper, Coughlan, & Mullen, 2008).

Items good discrimination ***a*** has been confirmed, with difficult ***b*** obtaining negative values for the most categories in all items. Through the TIC in **Figure 8** it is observed that this model shows more information ($I_{(\theta)} \approx 8$) with greater precision in the interval $[-5.0 < \theta < 1.5]$, with maximums for $\theta \approx \{-3.2, 0.2\}$. The TCC in **Figure 9** shows a good discrimination power in the interval $[-4.0 < \theta < 1.0]$, noting also the relative ease felt by respondents in agreeing with the questions posed (Baker, 2001).

It is observed that for T_θ values close to zero correspond the lowest levels of θ, while to the right of the graph are the highest levels of the skill under study. As Chalmers (2015) claims, easy tests allow a more accurate characterization of individuals with lower levels of the skill under study.

Table 2. Dimension analysis by information criteria.

Criteria	1 *dimension*	2 *dimensions*	3 *dimensions*
AIC	**12311.17**	12220.36	12185.19
AICc	**12580.73**	12649.36	12853.96
BIC	12742.77	**12718.09**	12745.57

Table 3. Comparison of fit statistics, for 20 and 12 items.

Measure	1st *run*	2nd *run*	*Cut-off*
P	$1.83e^{-08}$	0.336	>0.05
RMSEA	0.082	0.024	<0.08
SRMSR	0.088	0.072	<0.08
TLI	−0.071	0.938	≥0.95
CFI	0.131	0.977	≥0.90

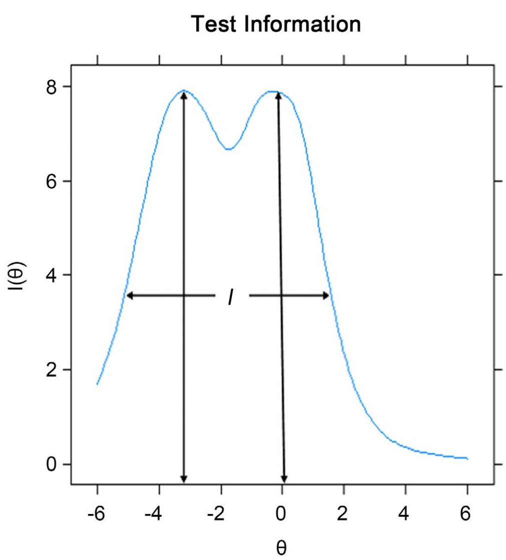

Figure 8. Test information curve (TIC).

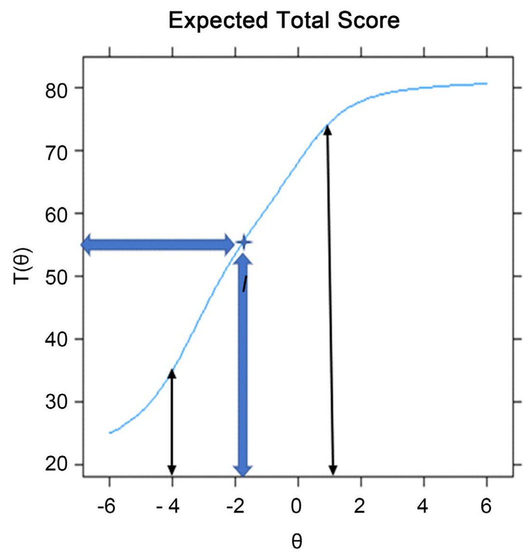

Figure 9. Test characteristic curve (TCC).

5. Conclusion

Data collection by questionnaire, being suitable for consulting complex and highly qualified academic populations, makes the tested methodology expeditious and flexible for the investigation, of punctual aspects of particular interest or over time for more in-depth studies, in the management of knowledge processes. The items used in the survey showed content and theoretical validity to describe the psychological trait under study, being yet necessary to assess the correlation between observed and predicted behavior patterns outside of the measurement process (predictive validity), as well as the development of new items in a broader scale, with a view to the construction of an item bank that allows the application in equalization processes, within the population or between different ones.

By its side, *Item Response Theory* (IRT) proved to be a robust statistical technique, able to discriminate individuals with different levels of acquired knowledge, as professional experience, which results are consistent with the theoretical framework. These results, which consider the entire extent of the information under study, are represented on a numerical scale, or graphically for qualitative analysis. The investigation of discriminant groups shall be carried out, such as through expansion studies, in a way to assess their own contribution to the psychological trait under study, and their impact on the measurement process.

The main objective of this work was to build a tool for the measurement of *Human Intellectual Capital* (HIC), as a contribution to the technical and academic development of management processes, aiming to better understand the components of *intellectual capital* (IC) and its impact on the organization's performance. The tested model proved to be a reliable tool for the best organizational practices of planning, execution and monitorization of Knowledge processes, in a look for the sustainability and the excellence of companies, and the leverage of competitive advantages.

Method Limitations

It is noteworthy that the construction of measurement scales by theory, the qualification and interpretation of psychological traits, and the complexity of the data under analysis can make the analysis process susceptible to deviations introduced by the researcher's subjectivity. In turn, the innovative statistical tools applied, associated with the limited bibliography consulted within the scope of this work, may have conditioned the exploration of alternative or complementary research methodologies.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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