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PLS-SEM MODEL ON BUSINESS DEMAND FOR TECHNOLOGICAL SERVICES AND R&D AND INNOVATION ACTIVITIES

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Abstract. The aim of the current study is to search for the elements that determine the companies' demand for technological services, and by doing so, to contribute to the advancement of a closer University-Company partnership in the sphere of activities in research, development and innovation. Based on the PLS-SEM methodology, an explanatory-predictive model was drawn up, which concluded that the four most influential variables are: the influence of the environment, market conditions, the technology adoption decision and the economic characteristics of the company. The originality and main contributions of this work lie in the construction and design of the proposed model, particularly the application of both the Confirmatory Tetrad Analysis and the Global Goodness-of-Fit measures adapted for the scope of PLS-SEM, both aiming to elaborate on its use and to provide a model that could be used by other researchers in different regions. By implementing this type of analysis, it is possible to better understand the drivers that push the choice of enterprises concerning the demand for technological services and, subsequently, policymakers, academy, and R&D agencies, as well as corporations leading to better strategies for closer and stronger cooperation and collaboration among themselves.

Keywords: technology demand, technology adoption, R&D&I, PLS-SEM, CTA-PLS.

JEL Classification: C39, C43, D81, O14.

Introduction

Cooperation among science and business is a major factor comprising the grounds for a knowledge-based economy (Domańska, 2018), becoming a key reason for the development of an inventive product that provides a competitive advantage (Cygler & Wyka, 2019). Consequently, the capability to innovate is a major factor in international competitiveness (Klein et al., 2021).

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During the last decade, there has been a growing performance of actions in developed countries whose main objective is to showcase practical solutions and the latest research results developed by research and scientific institutions, such as universities, R&D centres, and technology parks to companies, governments and, other institutions (e.g. Jirčikova et al., 2013; Liu et al., 2019).

According to the latest Eustat data (Basque Institute of Statistics, 2020), Spain currently is 16th in the ranking, still below the EU-28 average, but progressing two positions from the previous year. The countries of Central and Northern Europe are those with the highest intensity of spending on R&D. Sweden, Austria, Germany and Denmark – all above 3% – have met the EU target in their Europe 2020 strategy. Next, Belgium stands at 2.76% and Finland at 2.75%, both close to achieving the 3%. France, with 2.20%, and the Netherlands, with 2.16%, are above the EU-28 average. Slovenia and the Czech Republic have 1.95% and 1.93% respectively, while the United Kingdom and Hungary invest 1.71% and 1.53% of their GDP. Estonia, Italy and Portugal exceed 1.3%. Below Spain (1.21%) are the rest of the countries, closing the list with Cyprus, Malta and Romania, which record expenditure on R&D of a little more than 0.5% (Europa Press, 2018).

In their report on research and knowledge transfer in Spanish universities, Conde-Pumpido Touron and Cerezo García (2019) pointed out a minor rise in hired R&D, attaining an average price of €77,000 per contract (€71,000 in 2016). Nevertheless, the relevant downward trend in average prices in R&D contracts and, mainly, in those for technical support and service provision stands out, which has gone from having an average price in 2010 of €15,000 per contract to an average price in 2017 of €3,800 per contract. Another striking fact is the evolution of the regular cost of R&D on request, which has been reduced from €44,000 in 2010 to €32,000 per contract. The reduction of the scope of those services and contracts is justified and it is replaced by consulting and advisory agreements. Consequently, to a greater extent, in Europe, R&D of a specific scopes occur within the framework of "subsidized grants".

Due to the limited amount of empirical studies using the PLS-SEM methodology in this topic, the objective of this work on the basis of this approach is to discover and explain which factors, and in which way, determine the demand for technological services, and how they can contribute to the promotion of greater University-Business collaboration in R&D. Based on the works of García-Machado et al. (2021) in which the complex initial theoretical model has been developed using PLS-SEM methodology, this paper develops a PLS-SEM model on business demand for technological services and R&D & Innovation activities, examining, and carrying out a Confirmatory Tetrad Analysis (CTA-PLS) in order to have an empirical foundation for modelling measurement models with a sample of companies from the Andalusian region of Huelva, Spain. The business factors that are presented as latent exogenous and endogenous variables that form the basis of this theoretical model are: the economic characteristics of the company, the attitude towards the performance of the technology, the marketing actions, the technological attributes, the perceived usefulness, the perceived ease of use, market conditions, demand for technological services, the decision to adopt technology, the ease of conditions, the behavioural intention towards the adoption of technology, the influence of the environment and the business willingness towards technology adoption. By implementing this type of study, it is possible to design relevant policies and actions targeted at endorsing this behaviour at the local, domestic and global levels. For the design, assessment and predictive significance of this model, the Structural Equation Models based on Variance (PLS-SEM) methodology (Hair et al., 2019a) and the statistical package SmartPLS, version 3.2.9 were used (Ringle et al., 2015).

This work is divided into five main sections. First, and after this introduction, a review of the literature and the theoretical framework is carried out. Next, the methodology is described, including the description and characteristics of the potential sample, the data collection, as well as the estimation of the theoretical model with the PLS analysis. Finally, discussion of the results, the main conclusions and limitations associated with the research carried out are exposed.

1. Literature review and theoretical framework

In their work on technological strategy and research demand, Dutrénit et al. (2003) analysed the nature of R&D activities carried out by companies in Mexico and the demand for basic research that they generate for universities and R&D centres. Based on the empirical evidence they found, they reflected on the fundamental research demanded by two different types of companies that they took as a case, and on the consequences of establishing a demand-oriented model for the development of science. According to these authors, companies occupy a central place in national innovation systems, and the university-company link constitutes one of the most relevant relationships.

There is a curious parallelism in this area between Mexico and Spain, as these same authors emphasize that in Mexico there has not been a clear, congruent and scientific technology policy persistent over time. The policy has had some effect on the creation of research infrastructure and the training of human resources, although not a significant influence on the behaviour of companies. Furthermore, they suggest that universities should establish two lines of action: on one hand, transfer knowledge and technology to companies and, on the other, carry out basic research on the frontier of scientific knowledge. As Cohen et al. (2002) suggest, basic research should be carried out and aimed at current users: the targeted companies. We must ensure that the basic and applied research needed will contribute to their strategy of replacing technology in the short term. In this sense, works such as the one done by Bellini et al. (2019) show that there should be a balance between pure, oriented and applied basic research.

On the other hand, the university must carry out basic frontier research in order to train high-capacity human resources, which can be agents of change within the companies themselves, and for the generation of scientific capacities to take advantage of the scientific and technological opportunities that may arise (Iqbal et al., 2022). The university must anticipate market needs and, in a sense, to contribute to generate a more developed market (Etzkowitz et al., 2000). However, the success of the effort the country can make will depend to a greater extent on the companies assuming their role and becoming more dynamic in their R&D activities and being able to benefit from the knowledge generated (Dutrénit et al., 2003; Acebo et al., 2021). Duque (2020) suggests that it is not possible to understand academic institutions without research as an intrinsic part of their training activity and points out that most of the scientific research is carried out in university institutions.

In Spain, Gónzalez Hermoso de Mendoza (2011) highlights how public research centres and universities are becoming gradually important partners for companies to hire part of their R&D. Nevertheless, it has been difficult to achieve the desired levels, despite the support that the Spanish public administration gives to promote cooperation among the companies and the scientific sector. Currently, only 2% of Spanish companies cooperate with public research centres and universities regularly.

Regardless, noteworthy improvements have happened, and partnerships are increasing. Certainly, public funding restrictions for universities and public centres are compelling them to pursue funding by alternative means, one of which is partnerships through research contracts. Nevertheless, since 2008, the funding of university R&D by enterprises has been on a downwards trend (Fernández, 2019). The usage of resources due to university-private industry collaborations through licenses decreased between 2016 and 2017, and the quantity of spin-offs generated was at its lowest in the period 2007–2017.

In an interpretive model of relationship, López-Hurtado (2014) emphasised the need for the three principal axes of the economy, State-Company-University, to interrelate by reviewing the theoretical approaches, among which the following stand out:

– The Scientific-Technological Triangle (also known as the Sabato Triangle). This triangle exposes the association between Government, Scientific-Technological Infrastructure and Productive Structure (Sábato, 1997; Vega Jurado et al., 2007; Marone & Gonzales del Solar, 2007).
– The Triple Helix Model consists of three elements: the Academy, the Industry, and the Government (Etzkowitz & Leydesdorff, 2000; Etzkowitz, 2003; González de la Fe, 2009; Leydesdorff, 2011).

Both the Scientific-Technological Triangle and the Triple Helix Model are models that express a singular structure regarding the organization of the actors that are involved in the innovation and knowledge development. The models agree on the need to arrange the actors and organizations in a way such that the innovation depends on technological innovation processes given from joint associations among agents. The National Innovation Systems was established within this framework (López-Hurtado, 2014).

García-Machado et al. (2012), analytically studied a continuation of the Technology Acceptance Model (TAM) in digital financial trade; Roldán and Sánchez-Franco (2012) used it for social networks context, and García-Machado (2017) proposed a PLS-SEM model for e-trading services that allow investors to use secure Internet commerce. These studies were used as a base to design a descriptive framework of the demand for scientific and technological services. These results revealed that a direct, positive, and statistically noteworthy correlation among expectancies of individual results, perceived relative advantage, shared vision and trust based on the economy, with the quality of knowledge. Considered for the proposal of the preliminary theoretical model were also the works by Magotra et al. (2018), that analysed the association amid the perception of customer value and technology adoption behaviour concerning digital banking clients. Additionally, this correlation was studied through the elaboration of an Integrated Technology Adoption Model through the use of the Structural Equation Modelling (SEM) approach.

The factors collected in these studies were extrapolated, to study the demand for technological services, proposing 13 latent variables or constructs for the creation of a first study model. These variables are more precisely defined and described in greater detail in García-Machado et al. (2021).

1.1. Ease of Conditions (EC)

Applying the so-called "Unified Theory of Acceptance and Use of Technology" to arrive at the "Behaviour of Use" of an item (which in the case that concerns this research would be the Technological Services), it would be necessary to act on the "Behavioural Intention", which, by itself would be produced by several factors, among which is the "Ease of Conditions (EC)". See for example Venkatesh and Zhang (2010) and Yu (2012).

1.2. Behavioural Intention toward Technology Adoption (BITA)

Although for the previous variable (EC) the possibility was considered that the "Behavioural Intention" was the variable that collected all the information, and was the construct that followed, for the model defined for this study, the Behavioural Intention is towards the "Technology Adoption Decision" and will be treated as one more exogenous construct of the model. Several authors consider the "Intention" from different viewpoints. Lee (2009) studied a model wherein to measure the aspects that affect the acceptance of digital banking from a risk/benefit angle, incorporating TAM and TPB (Theory of Planned Behaviour). More information can be found at Venkatesh and Davis (2000), Legris et al. (2003), Alsajjan and Dennis (2010), and Sharma and Govindaluri (2014). In accordance with this and given that said authors provided the indicators that contributed to its measurement, it was decided, together with those offered by Rawashdeh (2015), to use these works as a foundation for outlining the survey.

1.3. Attitude towards Technology Performance (ATP)

Lai and Li (2005), to understand the predilection of the diverse individuals concerning the acceptance of e-banking proposed alternative analyses of the invariance in the constructs of the model. Rogger (2003, p. 33) identifies it as the inclination of the subject to experience an innovation, and that it might be assessed as the inclination that the subject must experience the procurement of modern technologies.

1.4. Perceived Usefulness (PU) and Perceived Ease of Use (PEU)

These two variables that are fairly fascinating and significant, and appear in any model of technology adoption. See for instance Legris et al. (2003) and Alhassany and Faisal (2018).

1.5. Technological Attributes (TAtt)

This construct will influence because, if high tech has flawless characteristics to emphasise or improve some areas, and is easy to use, it encourages the business to contemplate its implementation. This attribute will impact the decision of the individual in charge. For futher details see Sharma and Govindaluri (2014) and Magotra et al. (2018).

1.6. Business Predisposition towards the Adoption of Technology (BPAT)

Technology acceptance and its implementation, amid other factors, is affected, albeit not directly, but “indirectly”, by perceived cost and performance expectation (Yu, 2012). It is presumed that the greater the monetary charge, the lower the entrepreneurial tendency or, the higher the performance expectation, the greater the susceptibility.

1.7. Economic Characteristics of the Company (ECC)

Economic features of the business might be an important element to ponder in the study. By asserting that one of the crucial elements for R&D investment is the financial nature and size, which tend to be related. Labra Lillo (2015) confirmed the notion.

1.8. Technology Adoption Decision (TAD)

Magotra et al. (2018) devised a diagram with EC, TAtt and BPAT associated with this endogenous latent variable. Nevertheless, it relies on two relations, ATP and BITA. This construct may be assumed as “intervening” when it relates all the constructs of the model to the target construct. In line with the above, this can also be found in the works of Verhoef et al. (2009) and Porras Bueno (2016) in the design of their path models and constructs.

1.9. Demand for Technological Services (DTS)

Any model of acceptance of technology has a end-point target variable. Some of the previously cited works were used to propose the measurement model for this construct. See for example, Sharma and Govindaluri (2014) and Verhoef et al. (2009).

1.10. Marketing Actions (MKTA)

Public bodies are key players in the dissemination of messages that promote sustainable customer behaviour (Figueroa-García et al., 2018; Kollmuss & Agyeman, 2002). Transferred to the current work, the marketing activities that can be performed by the various scientific and research organizations ought to influence the business demand for technology services.

1.11. Influence of the Environment (IE)

External aspects to the human being (for instance, socio-demographic variables and schooling, and so on) that impact on sustainability (Figueroa-García et al., 2018).

1.12. Market Conditions (MKC)

The market volatility will affect the final decision in the adoption of innovative products, new commercial activities and modern technical equipment, leading the business to choose whether to require specialist services or remain behind its peers (Francis, 2010). For this reason, the elements by Figueroa-García et al. (2018) were adjusted and extrapolated to the demand for technology.

2. Methodology

2.1. Research design and scope

Based on the theory and the literature review, an preliminary theoretic model was conceived regarding the possible factors of the request for technological services by businesses. The indicators (represented as yellow squares), the exogenous and endogenous constructs (represented by blue circles), as well as their connections through arrows, are showed in the initial proposed model (Figure 1). Regarding all the indicators that make up the measurement models for all the latent variables, a more detailed description can be found in García-Machado et al. (2021). The construct measurement of exogenous and endogenous latent variables included in the theoretical model consisted of both established scales and were based on the work of several scholars. "Ease of Conditions (EC)" was based on Venkatesh and Zhang (2010) and Yu (2012). "Behavioural Intention toward Technology Adoption (BITA)" was derived from Sharma and Govindaluri (2014) and Rawashdeh (2015). "Attitude towards

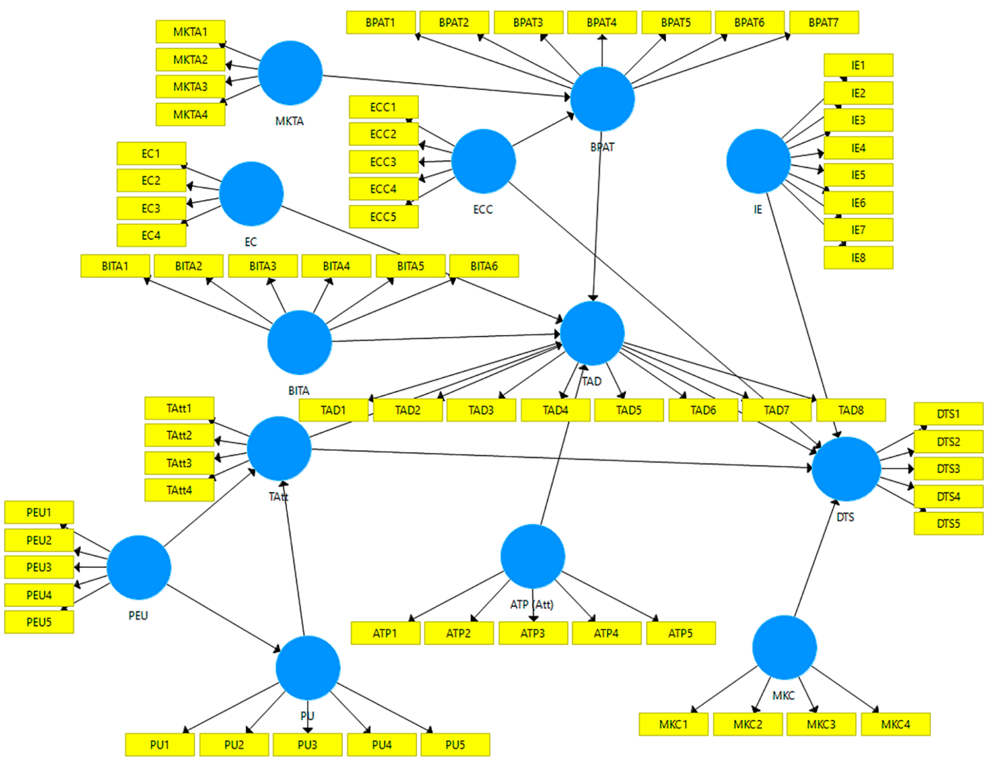

Figure 1. Initial theoretical path model (source: own research)

Technology Performance (ATP)" and "Technological Attributes (TAtt)" were devised from Lai and Li (2005), Rogger (2003), and Sharma and Govindaluri (2014). "Perceived Usefulness (PU)" and "Perceived Ease of Use (PEU)" were based on Legris et al. (2003) and Alhassany and Faisal (2018). "Business Predisposition towards the Adoption of Technology (BPAT)" was built on the work of Yu (2012). "Economic Characteristics of the Company (ECC)" was based on Labra Lillo (2015) and Magotra et al. (2018). "Technology Adoption Decision (TAD)" was founded on Verhoef et al. (2009), Porras-Bueno (2016), and Magotra et al. (2018). "Marketing Actions (MKTA)", "Influence of the Environment (IE)", and Market Conditions (MKC) were adopted from Figueroa-García et al. (2018). Finally, the measurement model for the latest endogenous variable "Demand for Technological Services (DTS)" was designed on the basis of Verhoef et al. (2009) and Sharma and Govindaluri (2014). All items were measured on a seven-point Likert scale from 1 "totally disagree" to 7 "totally agree". Scale measurement was on different response categories to avoid response bias.

The objective of the current work is to describe the target latent variable "Demand for Technological Services" (DTS), using a PLS-SEM scheme over eight exogenous constructs (MKTA, ECC, IE, EC, BITA, PEU, ATP and MKC) and four intermediate endogenous constructs (BPAT, TAtt, PU and TAD). Initially, they were modelled as mode A (reflective) (Dijkstra & Henseler, 2015b; Sarstedt et al., 2016; Hair et al., 2019a).

The variables, and its interactions were encompassed in the original path diagram grounded on the extrapolation of the determinants gathered in earlier works.

2.2. Sample

The indicators were included in a survey and sent to businesses of different type and size in diverse economic sectors. The model was developed with a sample of 96 businesses from Huelva, Spain (García-Machado et al., 2021). Originally, a databank was arranged from a catalogue composed of 467 companies, from which those that were not in operation were removed (145). The remaining businesses that provided contact details (such as email, phone number or address) were encouraged to take place in the research. In the end, a result of 96 valid surveys was collected, which represents a rate of response of 29.81%.

Afterwards, the responses were analysed and data debugging was performed. They were prepared for execution with the SmartPLS software and thus be able to apply a PLS-SEM path model (Ringle et al., 2015).

The most significant features of the businesses from the sample are based on their type of company, location, staff, revenue, seniority and activity sector (see García-Machado et al., 2021 for a more detailed description about the sample characteristics).

2.3. PLS analysis

For the evaluation of the proposed theoretical model, the modelling of structural equations by partial least squares (PLS-SEM) was used. This is a technique to estimate compound models based on composites that, over the last few years, has become increasingly used in the disciplines of social sciences, information systems and business (Hair et al., 2017). Hence, PLS-SEM makes possible to work with mode A (reflective), mode B (formative) and mixed (composite) models (Valdivieso Taborga, 2013; Dijkstra & Henseler, 2015b), and as Henseler (2018) points out, it is often applied in a variety of research settings (descriptive, exploratory, confirmatory, explanatory and predictive).

For its execution, we used the SmartPLS v.3.2.8 software. As stated in the works of Figueroa-García et al. (2018) and García-Machado (2017), this software has the advantage of being able to operate "Big Data style", that is, to operate many complex data and models at the same time, such as constructs, their indicators and the relationships between them. In addition, it allows evaluating both the relationships between indicators and their constructs (measurement models) and the relationships between the latter (structural model).

For this study, a mixed model has been used, since it is the one that best adapts to the research problem as constructs have been modelled as composites in mode A, mode B and common factor.

For the empirical analysis with PLS-SEM, a database of 96 observations was used. Initially, to determine the minimum sample size, the so-called "ten times rule" was applied (Barclay et al., 1995; Kline, 1998). The maximum number of arrows (5), pointing to a specific construct, occurs in the structural model in TAD (Technology Adoption Decision) and in DTS (Demand for Technological Services). Therefore, according to the heuristic "rule of thumb" (Barclay et al., 1995), $5 \times 10 = 50$ signifies the minimum number of observations necessary to estimate the path of PLS model of Figure 1. Alternatively, following the recommendations of Cohen (1992) for an OLS multiple regression analysis, it would be needed between 58 and 70 observations to find out R^2 values around 0.25, assuming significance levels of 10% or 5%, with a statistical power of 80%. Additionally, following the recommendations of Nitzl (2016), at least between 75 and 92 observations would be required to detect a mean effect size of 0.15 with the same levels of significance and statistical power. Besides, Green (1991, p. 503) recommends between 89 and 91 observations, depending on whether "the sample size based on power analysis or the sample size based on a new rule-of-thumb" is used, for the same level of previous analysis and with a significance level of 5%. On the other hand, using GPower (Faul et al., 2009), an analysis program for statistical tests commonly used in social and behavioural research, it would need 55 observations given the same statistical power, effect size, and significance level.

Consequently, by using any of the five guidelines as a baseline for defining the sample size, this study fully meets all five recommendations. Additionally, for the same aim, other procedures such as either the inverse square root methods or the gamma-exponential method can also be applied (Kock & Hadaya, 2018).

3. Results

After estimating the model, the SmartPLS package provided three key results after the first iteration (see Figure 2): indicator's outer loadings for outer models, the path coefficients for inner model relationships and the coefficients of determination of the endogenous latent variables (R^2). After a first debugging of items and constructs that did not meet the minimum requirements, the initial results of the model show the variables with the most important influence on DTS. For instance, ECC seems to have the strongest effect with the endogenous variable (0.289), followed by IE (0.238), MKC (0.233), TAtt (0.203), and TAD (0.184). Similarly, these five constructs explain 66.8% of the variance for the endogenous dependent variable DTS.

Following the former obtained results, given the complexity of the model, the PLS algorithm and the non-parametric bootstrapping procedure were executed several times, which allowed determination of the statistical significance from several of the PLS-SEM results. After preliminary debugging of items and constructs, the possibility that some composites were merged, and others modelled as mode A or mode B (previously called reflective and formative) was analysed. The merger of some latent variables avoided redundancy and multicollinearity problems in both indicators and constructs, due to, among others, fallacies called "jingle-jangle" and conceptual haziness. Having considerably acceptable values in validity and reliability for reflective measurement models, when checking the values of the Heterotrait-Monotrait (HTMT) correlation matrix (Hair et al., 2017; Henseler et al., 2015), relationships that exceeded the limit value appeared, so it was decided to purify the items (Salgado Beltrán & Espejel Blanco, 2016) through three phases. The first phase was to check cross-loads and eliminate the largest heterotrait (HT) and smaller monotrait (MT) values (Figure 3), or sometimes merging constructs. Once this was done, the significant path coefficients were checked, and the non-significant ones were eliminated.

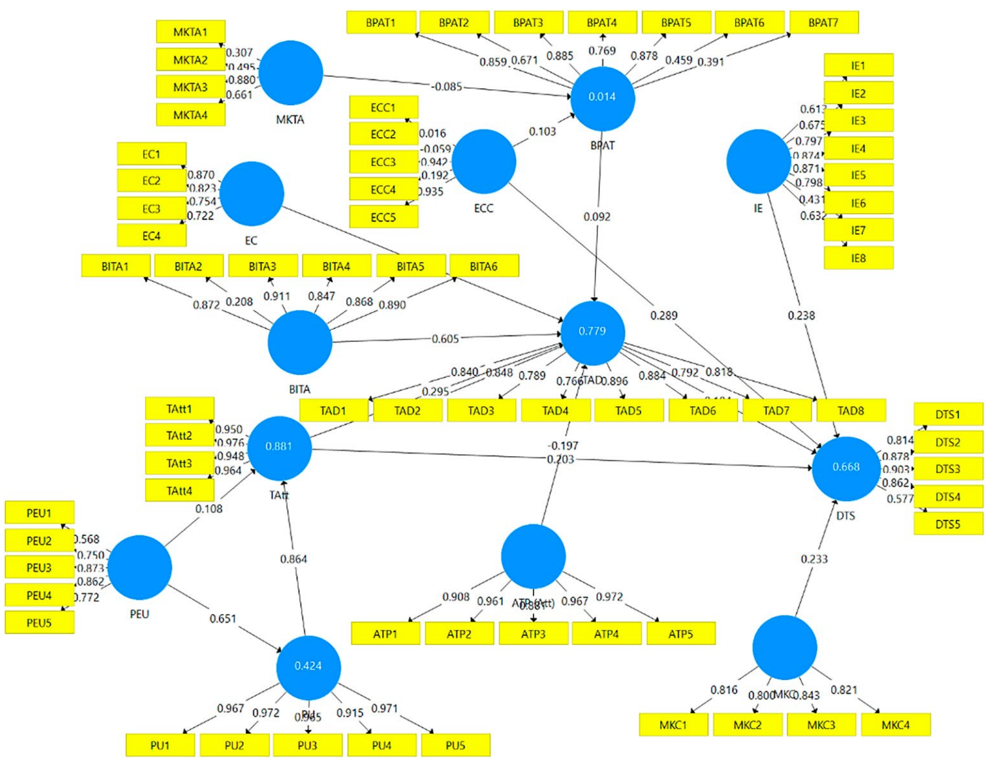

Figure 2. Initial theoretical model with results

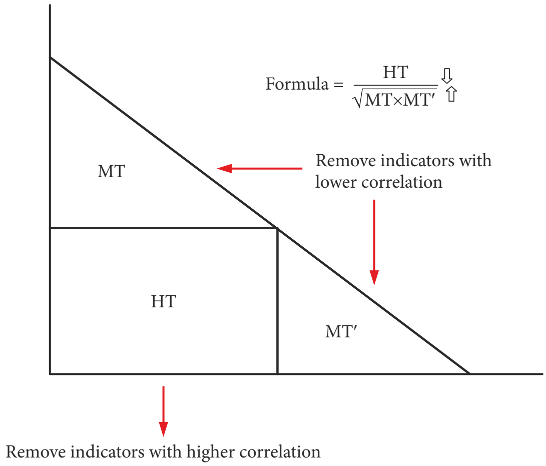

Figure 3. Reduction of HTMT ratios in the correlation matrix
(source: own elaboration based on Hair et al., 2017; Henseler et al., 2015
and Campbell & Fiske, 1959)

Additionally, deciding whether the constructs are measured as mode A (reflective) or mode B (formative) is a key point that can prevent the misspecification of measuring models. A poorly specified measurement model is a problem for the validity of SEM results (Jarvis et al., 2003). Nevertheless, the main way to decide whether to specify a measurement model reflexively or formatively is by its theoretical reasoning; so, any modification of the perspective of measurement should be based on the theoretical conditions (Hair et al., 2017). Therefore, after a more detailed study of the items of each latent variable, following the decision rules of Jarvis et al. (2003), it was decided to change the specification of the construct measurement models MKTA and ECC from reflective to formative. With that, the refined explanatory model on which we continue to work is the one shown in Figure 4.

Confirmatory Tetrad Analysis (CTA), introduced by Bollen and Ting (1993, 2000), adapted for the scope of PLS-SEM (CTA-PLS) by Gudergan et al. (2008), allows researchers to empirically evaluate whether the specification of the chosen measurement model based on the theoretical rationale is supported by data (Rigdon, 2005). Based on this, it was decided to carry out a Confirmatory Tetrad Analysis (CTA-PLS) to have an experimental base in addition to the theory of models of measurement, particularly those specified as formative or mode B (MKTA and ECC). A tetrad is the difference of the product of two pairs of covariances. In reflective measurement models, each tetrad is expected to have a value of zero and therefore to disappear. If only one value of a tetrad is significantly different from zero (if it does not disappear), the specification of the measurement model must be rejected as reflective and, instead, the alternative specification must be assumed as formative (Hair et al., 2017). Table 1 shows the results of the CTA-PLS analysis. With values of 0.037 (lower bound) and 2.490 (upper bound), the first MKTA tetrad, supports the specification of the measurement model of this latent variable as formative. The same occurs for DTS tetrads 1 and 2; however, following the recommendations of Jarvis et al. (2003), this construct was modelled as reflective.

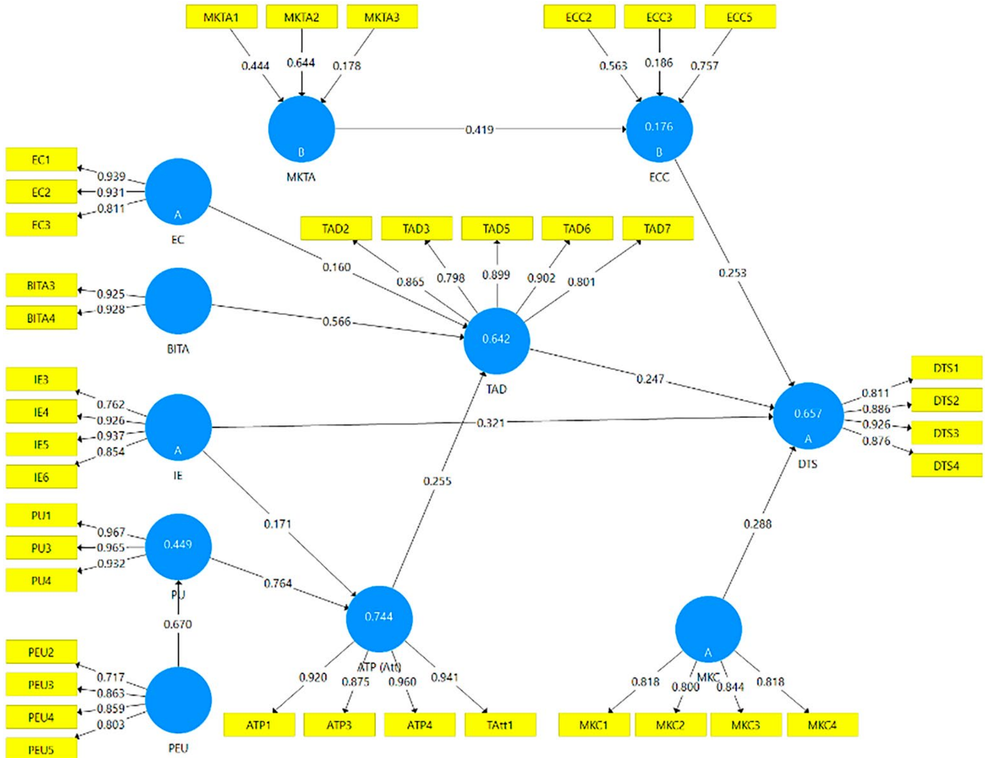

Figure 4. Debugged explanatory model (source: own research)

All other non-redundant tetrads disappear since all confidence intervals include zero. Therefore, it is assumed that all these measurement models from the rest of the latent variables are reflective.

3.1. Evaluation of measurement model

The CTA-PLS results indicate that the measurement models of the latent variables MKTA, TAD, MKC, TAD, PEU and IE would be well specified (the first as formative, and the rest as reflective). These results are contrary to the original specification of the ECC measurement models as formative, and DTS as reflective. However, a new revision of the conceptual foundations for these two constructs, following the qualitative decision rules of Jarvis et al. (2003), supports the initial specification of the measurement models for ECC and DTS.

3.2. Evaluation of structural model

Assessing the structural or inner model, signifies the relationships theorized among the latent variables (García-Machado, 2017). This encompasses scrutinising the model predictive capability, for which PLS-SEM was firstly designed, and the relationships amongst constructs. The critical measures to evaluate the structural model are in this order, the algebraic sign, the significance and relevance of the path coefficients, the values of R^2, the size of effect f^2, the predictive relevance Q^2, and the effect size q^2 (Hair et al., 2011, 2017, 2019b).

The values of R^2 or coefficients of determination of the endogenous constructs was examined. They represent a measurement of the amount of variance of an endogenous construct that is explained by its construct predictors. This is also considered a measure of the model's predictive power, which represents the amount of variance in the endogenous constructs explained by the exogenous constructs (Hair et al., 2019a). R^2 values of 0.75, 0.50, and 0.25 are considered strong, moderate, and weak respectively across many social science disciplines (Hair et al., 2014). To avoid the bias created by increasing the number of exogenous latent variables, the adjusted coefficient of determination is used. (R^2adj). Tatt + ATP, has a value close to 0.75. DTS, TAD and UP follow with 0.657, 0.642 and 0.449 respectively, leaving ECC with 0.176. The R^2adj values do not showcase much dissimilarity regarding the previous ones.

To evaluate if the exclusion of an endogenous construct has a considerable impact on the model, the effect size f^2 is applied (Albort-Morant et al., 2018; Hair et al., 2017; Ali et al., 2018). An f^2 with values ranging from 0.02, 0.15, and 0.35 represent small, medium, and large effects (Cohen, 1988). According to the study of García-Machado et al. (2021), the highest effect size is UP on TAtt + ATP (1.708), followed by PEU on PU (0.814), BITA on TAD (0.677), MKTA on ECC (0.213), ECC on DTS (0.179), and IE on DTS (0.173). Moreover, considering a significance level of 5%, all the relationships of the inner model are significant (some of them even at a 1% level) which provides an appreciation of how robust the model is. The greatest substantial relationships are observed among MKTA and ECC, PEU with PU, IE on DTS, BITA with TAD, and PU with TAtt+ATP. This concurs with those relationships, with greater consequence of the path coefficients.

Table 1. Results of CTA-PLS analysis for non-redundant tetrads

Non-redundant Tetrads	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Bias	CI Low	CI Up	Alpha adj.	z(1-alpha)	CI Low adj.	CI Up adj.
MKTA1, MKTA2, MKTA3, MKTA4	1.223	1.181	0.626	1.954	0.051	–0.041	0.234	2.293	0.050	1.960	0.037	2.490
MKTA1, MKTA2, MKTA4, MKTA3	0.954	0.917	0.630	1.515	0.130	–0.037	–0.045	2.027	0.050	1.960	–0.244	2.225
ATP1, ATP3, ATP4, TATT1	–0.106	–0.103	0.068	1.553	0.121	0.003	–0.220	0.003	0.050	1.960	–0.242	0.025
ATP1, ATP3, TATT1, ATP4	–0.112	–0.108	0.074	1.516	0.129	0.004	–0.238	0.006	0.050	1.960	–0.261	0.029

End of Table 1

Non-redundant Tetrads	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Bias	CI Low	CI Up	Alpha adj.	z(1-alpha)	CI Low adj.	CI Up adj.
ECC1, ECC2, ECC3, ECC4	–0.173	–0.169	0.201	0.860	0.390	0.004	–0.508	0.154	0.020	2.327	–0.645	0.291
ECC1, ECC2, ECC4, ECC3	–0.191	–0.185	0.201	0.952	0.341	0.007	–0.528	0.133	0.020	2.327	–0.665	0.270
ECC1, ECC2, ECC3, ECC5	–0.610	–0.583	0.619	0.985	0.324	0.027	–1.657	0.381	0.020	2.327	–2.079	0.804
ECC1, ECC3, ECC5, ECC2	0.028	0.026	0.092	0.308	0.758	–0.002	–0.121	0.182	0.020	2.327	–0.183	0.244
ECC1, ECC3, ECC4, ECC5	0.210	0.199	0.835	0.252	0.801	–0.012	–1.152	1.596	0.020	2.327	–1.721	2.165
MKC1, MKC2, MKC3, MKC4	0.343	0.337	0.265	1.292	0.196	–0.006	–0.088	0.785	0.050	1.960	–0.172	0.869
MKC1, MKC2, MKC4, MKC3	0.070	0.072	0.348	0.201	0.841	0.002	–0.505	0.642	0.050	1.960	–0.614	0.751
TAD2, TAD3, TAD5, TAD6	0.421	0.404	0.302	1.396	0.163	–0.018	–0.057	0.936	0.020	2.327	–0.263	1.142
TAD2, TAD3, TAD6, TAD5	–0.088	–0.090	0.343	0.256	0.798	–0.002	–0.651	0.479	0.020	2.327	–0.885	0.713
TAD2, TAD3, TAD5, TAD7	0.546	0.524	0.353	1.547	0.122	–0.021	–0.013	1.148	0.020	2.327	–0.254	1.388
TAD2, TAD5, TAD7, TAD3	–0.602	–0.583	0.273	2.202	0.028	0.019	–1.071	–0.171	0.020	2.327	–1.257	0.015
TAD2, TAD5, TAD6, TAD7	0.199	0.192	0.192	1.033	0.302	–0.007	–0.111	0.522	0.020	2.327	–0.242	0.654
DTS1, DTS2, DTS3, DTS4	0.969	0.939	0.286	3.386	0.001	–0.030	0.528	1.470	0.050	1.960	0.438	1.560
DTS1, DTS2, DTS4, DTS3	0.820	0.797	0.297	2.761	0.006	–0.023	0.355	1.332	0.050	1.960	0.261	1.426
PEU2, PEU3, PEU4, PEU5	0.129	0.123	0.096	1.336	0.181	–0.005	–0.024	0.293	0.050	1.960	–0.055	0.324
PEU2, PEU3, PEU5, PEU4	0.105	0.102	0.201	0.525	0.600	–0.003	–0.222	0.439	0.050	1.960	–0.285	0.503
IE3, IE4, IE5, IE6	0.166	0.163	0.471	0.352	0.725	–0.003	–0.607	0.945	0.050	1.960	–0.755	1.093
IE3, IE4, IE6, IE5	–0.443	–0.406	0.887	0.500	0.617	0.037	–1.939	0.979	0.050	1.960	–2.219	1.258

Note: Bootstrap-based confidence intervals with corrected and accelerated bias and Bonferroni adjusted for a significance level of 10%.

3.3. Global goodness-of-fit evaluation

The global goodness-of-fit of the model is the starting point of its assessment to verify whether the model fits the data. The estimated model is the one that is graphically specified. The saturated model has the same pattern of measurement as the estimated model, but does not constrain the relationships among the constructs. For instance, in the saturated model all constructs are correlated. Three measures proposed in the PLS-SEM framework and bootstrap-based exact fit tests were used (Henseler et al., 2016). The first is the standardized root mean square residual (SRMR), described as the difference between the observed correlation matrix and what is inferred by the theoretic model. The SRMR quantifies how strongly the empirical correlation matrix differs from the implied correlation matrix, therefore the lower the SRMR, the better the fit of the theoretical model (Henseler, 2017). In the current case, as an absolute measure of fit, a value less than 0.08 (Hu & Bentler, 1998) or 0.10 (recommended by Ringle, 2016) is usually assumed to be a good fit. Next, two measures of discrepancy were assessed (Dijkstra & Henseler, 2015a): unweighted least squares discrepancy (d_{USL}) and geodesic discrepancy (d_G), which are compared to the 95% and 99% percentiles of their distribution (based on HI95 and HI99 bootstraps). This suggests that the upper bound of the percentile must be higher than the original value being compared. If the outcomes of these tests surpass these percentiles based on bootstrapping, the model's accuracy is not clear (Henseler, 2017). Table 2 suggests an appropriate global fit of the proposed model.

Table 2. Global model fit measures

	Original Sample (O)	Sample Mean (M)	HI 95%	HI 99%
SRMR				
Saturated Model	0.084	0.064	0.078	0.085
Estimated Model	0.098	0.077	0.094	0.102
d_{ULS}				
Saturated Model	6.407	3.768	5.491	6.485
Estimated Model	8.608	5.397	7.902	9.315
d_G				
Saturated Model	3.447	3.659	5.208	6.121
Estimated Model	3.695	3.821	5.411	6.249

Note: Standardized root mean square residual (SRMR), unweighted least squares discrepancy (d_{USL}), geodesic discrepancy (d_G), bootstrap-based 95% (HI95) and 99 (HI99) percentiles.

4. Discussion

The goal of this study was to design a complex preliminary theoretical model, using the PLS-SEM methodology, which stood as potential drivers of business demand for technology services. Eight exogenous constructs were implemented: the economic characteristics of the company (ECC), the attitude towards technology performance (ATP), the perceived ease of use (PEU), market conditions (MKC), marketing actions (MKTA), the ease of conditions

(EC), behavioural intention toward technology adoption (BITA) and the influence of the environment (IE), and four intermediate endogenous constructs: the business predisposition towards the adoption of technology (BPAT), technological attributes (TAtt), the perceived usefulness (PU) and the technology adoption decision (TAD), which were modelled in mode A (previously reflective). This model was survey-tested with seventy-seven indicators adjusted to the Spanish situation.

After consecutive steps of assessment and evaluation, different alterations were performed, varying from the debugging of indicators and non-significant relationships, and rearrangement of latent variables, to changes in the measurement models of some construct that turned out to be shaped in mode B (formative). The latter was carried out employing a Confirmatory Tetrad Analysis (CTA-PLS) to have an experiential basis added to the theoretical one, particularly those specified as formative or mode B (MKTA and ECC). The latest proposed model is a mixed model of factors and composites, more parsimonious, which is explained mainly by four endogenous and six exogenous factors. The variables that most influence the business demand for technological services are in order of importance, the influence of the environment (21.57%), market conditions (19.35%) and the technology adoption decision (16.13%). The economic characteristics of the company, although also significant, represents only 8.70% of the explained variance. Only these four variables explain 65.76% of the variance of the endogenous latent variable "Demand for Technological Services (DTS)".

Other crucial linkages between other variables were also revealed, showing that 74.4% of the variance of the construct "Technological Attributes + Attitude towards Technology Performance (TAtt + ATP)" is also explained by the predictors, influence of the environment and perceived usefulness, which, in turn, is explained in 44.9% by perceived ease of use. Also, 64.2% of the variance of the construct "Technology Adoption Decision (TAD)" is explained by the predictor's behavioural intention toward technology adoption, ease of conditions and TAtt + ATP.

Spain, hit by the 2008–2014 crisis and its aftershocks, has decreased its level of investment in Research and Development by 8.82%, down from its maximum value of 1.36% of GDP in 2010. Although since 2016 has been rising (the current value is 1.24%), it is still far below the 3% target set by the EU in its Europe 2020 strategy and the Central and Northern European countries that used to lead this ranking (Spain is in 16th place). Notwithstanding the drop in investment in R&D, the authors agree with Yoldi (2016) and Ametic (2017) when they unveil an optimistic trend – that of collaboration with the aim of reaping the benefits of public-private collaboration-.

Nevertheless, while efforts have been made since 2016 (said investment has grown by 4.20% in three years), the COVID-19 crisis triggered a new situation of total exceptionality that produced cuts to tackle the economic crisis caused by the pandemic. It is, for this reason, important for enterprises to reinforce collaboration with universities as the best means to share, encourage and complement the basic and applied research carried out by both, recruit researchers, use specialised equipment and scientific tools at reduced cost, acquire expertise in the field of project management and leadership, and keep abreast of scientific developments worldwide.

Our results are consistent with Dutrénit et al. (2003) who concluded that university-company link constitutes one of the most relevant relationships in setting up a demand-oriented model for the development of science in national innovation systems. Furthermore, our results are also consistent with Acebo et al. (2021) in that its success will depend to a greater extent on the companies assuming their role and becoming more dynamic in their R&D activities. In addition, our results provide further empirical evidence to other studies, and they are aligned with the contributions of Gónzalez Hermoso de Mendoza (2011), López-Hurtado (2014) and Duque (2020). In this regard, it is also in line with various extensions of the Technology Acceptance Model (Legris et al., 2003; Lai & Li, 2005; García-Machado et al., 2012; Sharma & Govindaluri, 2014).

Conclusions

The CTA-PLS results indicate that the measurement models for the latent variables MKTA, TAD, MKC, TAD, PEU and IE would be well specified, the first as formative and the rest as reflective. On the contrary, these results oppose the original specification of the measurement models of CEE, as formative, and DST, as reflective. However, a further review of the conceptual foundations for these two constructs following the qualitative decision rules of Jarvis et al. (2003) supports the initial specification of the measurement models for ECC and DTS.

The measures of the goodness of overall model fit, show a good fit of the suggested final model, both in the three measures proposed and in the exact fit tests based on bootstrap. Finally, when it comes to its relevance and predictive power, the proposed final model fulfil all the criteria applied and has a significant power of prediction.

Nevertheless, the current work raises some fascinating questions. As it is grounded on a sample of ninety six businesses in Huelva, Spain, it might be noteworthy to examine how such a model could play in the forecasting of performance for other corporations and for those situated in other geographies, particularly those which are powerful in R&D. Also, supplementary research ought to be performed to confirm if certain economic business attributes, such as size, situation, company type, age, volume of business or sector of activity, could play a role as mediating or moderating variables in the demand for technological services. It seems quite reasonable to perform a more qualitative assessment concerning the marketing actions variable to check that the flow of "information" is as satisfactory as suggested by the respondents.

These results would help to deepen the knowledge on the motivating forces that drive firms interested in new opportunities for the adoption, innovation and development of new technologies, encouraging them to work jointly with public institutions, universities, agencies, and research centres in the design of well-targeted strategies to elicit a more willing and positive response concerning basic and applied investigation for a better use of its resources, university-business partnerships, and for economy and society in general.

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