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R&D and Innovation Collaboration between Universities and Business—A PLS-SEM Model for the Spanish Province of Huelva

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A B S T R A C T

In the last decade we have witnessed a growing amount of interest for developing better 'exchange' between universities, research centres and technology parks and companies, governments and other institutions. The biggest aim of those projects is, on the one hand, to make sure that valuable research does not stay hidden in the ivory tower of academia, and, on the other, that there are clear indications for what kinds of solutions are needed in the market. Due to the lack of empirical research in the topic, the focus of this paper is to establish and explain which factors determine the demand for technological services and how they can contribute to the promotion of greater university–business collaboration in R&D and innovation. To achieve that goal, we applied the PLS- SEM (Partial Least Squares Structural Equation Modelling) method in order to create a theoretical model, which was then verified through the application of the CTA (Confirmatory Tetrad Analysis) with the purpose of evaluating whether the specification of the chosen measurement model based on the theoretical rationale was supported by data. The test run was performed on 96 companies from the Spanish region of Huelva. It showed that only four of the considered factors, namely influence of the environment, market conditions, technology adoption decision and economic characteristics of the company, constituted 65.76% of the variance of the endogenous latent Demand for Technological Services. We believe that thanks to the proposed model and its adaptivity, it is possible to design relevant policies and undertakings aimed at promoting the research-business collaboration at the regional, national and international levels.

A R T I C L E I N F O

Keywords:
technology demand; technology adoption; R&D collaboration; university; business

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1. INTRODUCTION

The last decade has witnessed the increase of activities undertook by the scientific and research institutions in the developed countries (such as R&D centres, universities and technology parks) with the objective of presenting their latest research results and practical solutions to governments, companies, and other institutions around the world, in order to find more sources of investment for the continuation of the projects and research. The issue of broadly understood collaboration between business and science is one of the key issues constituting the foundations for the modern knowledge-based economy (Doman´ska 2018). One of the examples is the MINATEC Campus in France, where an approach to micro- and nanotechnology research based on the triple helix of higher education–research– industry has been adopted. The MINATEC innovation campus is home to 3000 researchers, 1200 students, and 600 business and technology transfer experts on a 20-hectare state-of- the-art campus with 13,000 m2 of clean room space where it generates up to 350 patents and 1600 scientific articles every year (Allan et al.2019). The main reason for this kind of actions is not only the willingness of the scholars and researchers to path the way for their work beyond the so-called Ivory Tower of Academia (Coulter1999), but also the fact that public spending and investment in R&D is not sufficient and is not allowing the desired progress. The case of Spain seems to reflect this latest change quite clearly.

According to the latest Cotec report (Cotec Foundation for Innovation2020), invest- ment in R&D has reported its fifth consecutive year of growth, surpassing, for the very first time, the amount of EUR 15 million. It is important to highlight that the main con- tributor to this growth was not public administrations, but rather companies that drove the advance in research spending by increasing their investment by 8.2%. Even though Spain has recovered to the levels of investment in R&D achieved prior to the crisis of 2008, the percentage of GDP dedicated to R&D is still below the average for European Union countries, which are currently at the level of 2.12%, compared with 1.8% in 2006 (Europe Press Agency2018). For Spain, the highest level was reported in 2010, at 1.36%, and in 2018 it reached only 1.24% (and 1.21% in 2017). From 2010 to 2018, investment in R&D in Spain decreased by 8.82%, placing the country in the third quartile of the EU-28, very far from the target of 2% set for 2020 agreed by the Government of Spain with the EU (Maqueda 2019), and the 3% target set by the EU in its Europe 2020 strategy (European Commission 2010). With the ongoing consequences caused by the global pandemic and the efforts that must be undertaken in order to facilitate the economic revival of the economy, it seems quite possible that spending on R&D will not increase significantly.

Another observation made for the case of Spain with respect to research and knowl- edge transfer from Spanish universities points out a slight increase in expenditure R&D hires, reaching an average price of EUR 77,000 per contract (compared to EUR 71,000 per contract in 2016). However, at the same time, a downward trend in average prices in R&D contracts can be observed, particularly for technical support and service provision—from EUR 15,000 per contract in 2010 to EUR 3800 per contract in 2017. Similarly, the average prices of R&D on request (hiring for R&D projects, characterized by the generation of new knowledge), has fallen from EUR 44,000 per contract in 2010 to EUR 32,000 per contract. This is a reflection of the reduction of the scientific–technical scope of R&D contracts and services, and its replacement, in many cases, by agreements with consulting and advisory purposes. Therefore, the expenditure on R&D with a certain level and scope seems to take place only within the framework of "subsidized grants". Quite striking is also the fact that the exchange is very 'local'—67% of contracts are carried out with entities whose head- quarters are in the same Autonomous Community, 27% with entities whose headquarters are in other parts of Spain, 6% with companies located in Europe (4%) and only 2% with companies on other continents (Conde-Pumpido Touron and Cerezo García2019).

Given the lack of empirical studies on the subject, the objective of this work is to fill in the knowledge gap by discovering and explaining which factors determine companies' demand for technological services, and in what way, and how this could contribute to the promotion of greater university–business collaborations in R&D. Based on the authors' previous work, in which the complex initial theoretical model was developed using the PLS-SEM methodology, this paper examines and tests its practical implementation and pre- dictive relevance using a sample of companies from the Huelva region of Andalusia, Spain. For the design, evaluation and predictive relevance of this model, the Structural

Equation Models based on Variance (PLS-SEM) methodology (Hair et al.2019a) and the statistical software SmartPLS, version 3.2.9 was used (Ringle et al.2015). Out of 13 initially considered factors (constructs), just four of them, namely the influence of the environment, market conditions, technology adoption decisions and, to a lesser extent, the economic characteristics of the company, explain 65.76% of the variance of the central construct of this research, that is, demand for technological services.

The authors believe that the implementation of this type of study can be an important step and act as a basis for designing relevant policies and actions aimed at promoting research–business cooperation at regional, national and international levels.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Technological development is one of the factors that has a significant effect on the economic development of enterprises and countries. One of the most important reasons for organisations commencing R&D cooperation is to obtain an innovative product that allows them to obtain a competitive advantage (Cygler and Wyka2019), and therefore it can be claimed that innovation capability plays an important role in international competitiveness (Klein et al.2021). Technological collaboration makes it possible for companies to overcome the complexity of international markets, thus boosting the internationalisation of the firm (Serrano et al.2021).G ónzalez Hermoso de Mendoza(2011), focusing on the importance of innovation, highlighted how companies in Spain can benefit from contracting part of their

R&D from universities and public research centres, but despite the boost that the Spanish Public Administration has given to promote relations between the scientific and business sectors, only 2% of Spanish companies collaborate regularly with universities and public research centres. The reasons for such a low exchange 'rate' include the great differences in mentality between researchers from public centres and businesspeople, which often makes these relationships difficult. Since the prestige of a university or a research centre, as well as the professional careers of the researchers themselves, is dependent on the number and quality

of publications, the objective is to publish and popularize the research as fast as possible. However, it is often crucial for a company's competitiveness to keep its R&D activities confidential, so it is imperative that the researchers do not publish their results without having first protected the research through a patent or other form of industrial protection. On top of that, the civil servant status of most Spanish public researchers is, in many cases, an added difficulty for collaborations with the private sector. The internal organization of research centres, rather than facilitating engagement, makes it difficult for researchers to engage in collaborative projects with companies.

However, overcoming these obstacles and developing the technological cooperation agreements with universities (or other type of research centres) can directly translate into important strategic advantages being obtained, especially for small companies (Chastenet et al.1990). Although the pace of change is slower than desired, important advances have been made, and collaboration between universities and public R&D centres and companies has been increasing. Undoubtedly, the restrictions on public funding for universities and public centres contribute to this, as they are forced to seek funding in other ways— one of those being collaboration with companies through research contracts. This gives the companies a competitive edge and helps to improve innovative processes, while, at the same time, providing the universities with the resources necessary for the constant modernization of laboratories and for the gratification and incentivisation of its agents (Nieto Antolín and Rodríguez Duarte1998). However, according to a report from the Spanish Chamber of Commerce(2020), the financing of university R&D by companies has been falling since 2008 (with a turning point in 2017). The uptake of resources as a result of university–company collaborations via licenses decreased between 2016 and 2017 (the most recent data available when the study was prepared), and the number of spin-offs (companies born in the university) created was at its lowest between 2007 and 2017. This occurred despite the abundant "production" of 453,489 articles in the last four years, placing Spain as one of the main research states, with 3.3% of the world's total academic publications. The report highlights that the number of applications for patents owned by universities was at the level of 327 in 2018, 25% less than a year earlier, although these data may be influenced by legal changes. It is, according to the Spanish Chamber of Commerce, "the reality of considerable excellence in publications and, on the contrary, a scarce transfer to the productive sector" (Spanish Chamber of Commerce2020).

López Hurtado(2014) examined an interpretive model of relationships in which he highlighted the need for the three main axes of the economy, State–Company–University, to be interrelated. He reviewed the theoretical approaches regarding said interactions and the impact they have on society, highlighting the concepts of the scientific–technological triangle and the triple helix model. The former, known also as the Sábato Triangle Approach, reflects the relationship between the government, the scientific–technological infrastructure, and the productive structure (Sábato1997;Vega-Jurado et al.2007;Marone and Gonz ález del Solar2007). The later distinguishes between the academy, industry, and the government (Etzkowitz and Leydesdorff2000;Etzkowitz2003;Gonz ales2009;Leydesdorff2011). The intent of both theories is to describe innovation systems, and although they differ in their approach with respect to knowledge generation and the interpretation of innovation (in linear and non-linear terms), they agree that innovation does not depend solely on the capabilities that the public sector, industry and universities possess, but rather that it results from mutual relationships between agents and interactions that are established within the framework of National Innovation Systems (López Hurtado2014). Due to the aforementioned scarcity of empirical research on the topic of interaction among companies and scientific and research organizations, we embarked on the task of investigating the factors on which the demand for technological and scientific solutions by companies depends, using a sample of companies form the Spanish province of Huelva.

To design an explanatory model of the demand for scientific and technological services by companies in the province of Huelva, we used the works ofGarc ía-Machado et al. (2012), who empirically examined an extension of the Technology Acceptance Model in the context of online financial commerce,Rold án and Sánchez-Franco(2012), who applied it to the context of social networks, andGarc ía-Machado(2017), who proposed a PLS-SEM model for the study of secure online trading services. The results presented show that there is a positive, direct, and statistically significant relationship between the expectations of personal results, the perceived relative advantages, a shared vision and mutual trust based on the economy gains, and the quality of knowledge provided. Another work we used for the design of the initial theoretical model was the study of Magotra et al.(2018), which analysed the relationship between the perception of customer value and technology adoption behaviour with reference to online banking customers. Furthermore, this relationship was examined through the development of an Integrated Technology Adoption Model through the application of the Structural Equation Models (SEM) approach. The extrapolation of the factors gathered in these studies, regarding the demand for technological services, led to the creation of a first study model, made up of 13 latent variables (or constructs):

- Facilitating Conditions (FC):Venkatesh and Zhang(2010) placed the Facilitating Conditions as one of the factors that directly affect the final construct of the demand for technological services.Yu(2012), on the other hand, defined the Facilitating Conditions as the degree to which

an individual believes that there is an organizational and technical infrastructure supporting the use of technology.

- Behaviour Intention towards Technology Adoption Decision (BITA): Several authors have considered this "Intent" from various perspectives. For example,Lee(2009) in- vestigated a model that measures the factors affecting the adoption of online banking from a risk/benefit perspective, integrating two techniques: TAM (Technology Accep- tance Model) and TPB (Theory of Planned Behaviour). In this model, the "Intention" is considered to be "Intention of Use", placing the variable as a final endogenous construct.Venkatesh and Davis(2000) extended the TAM model to the TAM2, also applying the model in other fields of study. Regarding the variable addressed in this work, they placed the "Behavioural Intent" as an intermediate variable that collects relationships of various constructs with the final construct. These authors defined it together with the "Facilitating Conditions" as the direct determinant of adoption behaviour.Legris et al.(2003) defined BITA as an intermediate variable that gathers information from the constructs: beliefs and evaluations, attitude towards behaviour, normative belief and motivation to comply, and subjective norms.Alsajjan and Dennis (2010) explained that attitude and behaviour are so closely related that they could be considered in certain studies to be the same variable. Attitude should predict actual behaviour, as should intentions, but attitude avoids the bias that often marks mea- surements of intentions.Sharma and Govindaluri(2014), in their structural equations model, placed this variable as one more construct that may or may not influence the relationship with another construct, the so-called "Technology Adoption Decision", making it a step variable towards final adoption. These studies, enriched by the work ofRawashdeh(2015), were used as a basis for the preparation of the questionnaire.
- Attitude towards Technology Performance (ATP):Lai and Li(2005) focused on the attitude of the different agents towards the adoption of Internet banking.Rogger (2003) specified this as the "disposition of the individual to experience an innovation" and indicated that it could be considered the disposition of an individual towards experiencing the acquisition of new technology.
- Perceived Utility (PU); and
- Perceived Ease of Use (PEU):Legris et al.(2003) used a model in which both "Perceived Ease of Use" and "Perceived Utility" appear—two variables that are quite interesting and important in any model of adoption of technology.Alhassany and Faisal(2018) used both variables in their model, framing it within what they referred to as the "technology dimension". They defined "Perceived Utility" as the beliefs of users that the adoption of technology will improve their productivity and performance. The "Perceived Ease of Use" is based on the entrepreneur's perspectives and the evaluations of facilities/difficulties in the execution of the product.
- Technological Attributes (TAT): According toMagotra et al.(2018), the construct "Tech- nological Attributes" can be defined by the two previous constructs, PU and PEU. "Technological Attributes", in turn, influences the "Technology Adoption Decision" and the "Demand for Technology Services", because if a
- technology has perfect at- tributes for reinforcing or improving a certain area, and it is also easy to use, a company will consider adopting it. This attribute influences the decision-making process of the responsible person. In their study,Sharma and Govindaluri(2014) also confirmed that PU and PEU define TAT.
- Business Predisposition Towards the Adoption of Technology (BPTAT):Yu(2012) exposed the idea of the adoption of online banking through the Unified Theory of Acceptance and Use of Technology (UTAUT), showing that, among other factors, it is influenced by the "Perceived Financial Cost" and the "Performance Expectation". These, although not directly, would contribute to what would come to be "Business Predisposition Towards the Adoption of Technology". In principle, it is assumed that the higher the financial cost, the less business predisposition, or the higher the expectation of performance, the greater the predisposition.
- Economic Characteristics of the Company (ECC): This is mentioned, inter alia, in the study byMagotra et al.(2018). It suggests that the economic attributes of the company could be an essential factor to consider in our research.Labra Lillo(2015) confirmed this by stating that one of the most important factors for investment in R&D is the size and the economic nature of the company, which are always related.
- Technology Adoption Decision (TAD):Magotra et al.(2018) designed a model where FC, TAT and BPTAT were related to this construct. However, it also depends on two more relationships: those of ATP and ICAT. Therefore, in some way, this endogenous latent variable could be

understood as being "intermediate" or "regulatory" when it comes to relating all the model variables with the final construct. Following the expla- nation ofPorras Bueno(2016), the adoption decision is the core of several variables, and it is within a cause–effect system that ranges from the antecedents of the adoption decision to the impact of the business owners. Other authors consulted wereVerhoef et al.(2009) and their construct "Self-Service Technology".

- Demand for Technological Services (DTS): This is the final dependent variable at which all of the relationships of the model will arrive. At first, no references were found that included this final construct, neither as such nor from another perspective that could be subject to adaptation, as in the case of the previous constructs. However, every technology acceptance model has a final dependent variable. For example, Sharma and Govindaluri(2014), with, among others, questions about the customers' intentions as a measure to know whether they would be willing to demand a variety of services, better defined the DTS construct. Other items used were collected from Verhoef et al.(2009).
- Marketing Actions (MKTA):Figueroa-Garc ía et al.(2018) pointed out that government organizations, through their marketing actions, are main actors in the education and dissemination of the information to promote a sustainable consumer behaviour. Kollmuss and Agyeman(2002) noted that institutional factors, that is, how the actions of institutions affect caring for the environment, are located among the external fac- tors. Transferred to our study, marketing actions that can be carried out by different scientific and research organizations should have an impact on the Demand for Tech- nological Services by companies. Taken to the field of DTS, this would mean: "How do the actions of institutions outside the organization affect this demand?"
- Influence of the Environment (IE):Figueroa-Garc ía et al.(2018) stated that there are external aspects to the person (such as education and sociodemographic variables, among others) that have an influence on environmental sustainability. Contextualizing it for this research, this could be defined by aspects such as education, socio-economic, demographic, geographical and even political variables among many others, which also might influence the demand for technological services.
- Market Conditions (MKC): as stated byFrancis(2010), the market is volatile and changes quickly. As such, it will affect the final decision regarding new products, new marketing actions and new technological resources that lead the company to decide to adopt technical services or to lag behind its competitors.

3. METHODOLOGY

3.1. Sample Characteristics

This study is based on a sample of 96 companies from the Spanish province of Huelva. Initially, a database was prepared from a list of companies provided by the Office for the Transfer of Research Results (OTRI) of the University of Huelva and the SABI database, completed with a direct search by municipalities through Google Maps. Out of a total of 467 companies, those that were not operational were eliminated (145). The remaining ones that provided contact information (email, telephone, fax or postal address) were invited to participate in the investigation. A total of 96 valid questionnaires were received, which represents a response rate close to 30%.

The most relevant characteristics of the companies that make up the sample, according to their location, type of company, number of employees, seniority, turnover, and activity sector are shown in Figures1–5. In general, most companies are based in the Huelva area (47%) and are private limited companies (59%). Most of the companies have been run for 20 years or more (46%) and were rather small in size, with a turnover of less than EUR 500,000 per year (41%). As for the sector of activity, agriculture and food industry companies constituted 18% of the sample, followed by wholesale trade (6%), specialized construction (6%), and building construction (5%).

3.2. Data Collection

The data were collected from May to November 2019. For a company to become part of the study, two requirements had to be met: first, they had to be based in the province of Huelva, and second, the responsible person (entrepreneur, manager, technical or administrative director) had to fill in an online questionnaire regarding the demand for technological services on behalf of the company. This stage of the investigation was the most challenging due to the reluctance of companies to provide identifying information, opinions, or lack of time, so we consider a response rate of 30% to be a great achievement. Furthermore, as we will show later, a sample of 96 companies represents a sufficient size to validate the results.

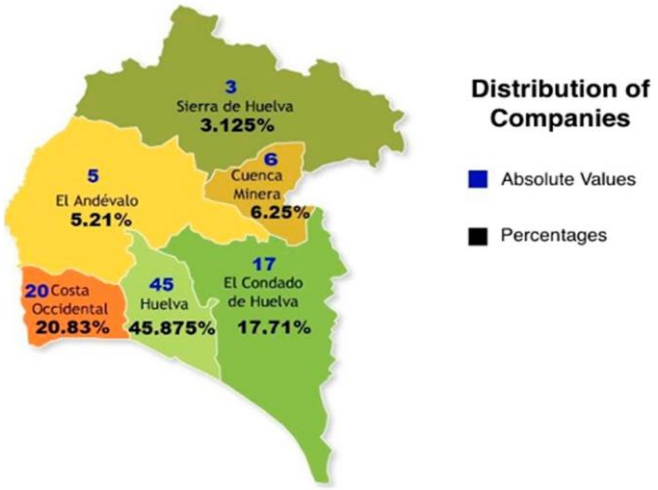

Figure 1. Geographic distribution of the companies.

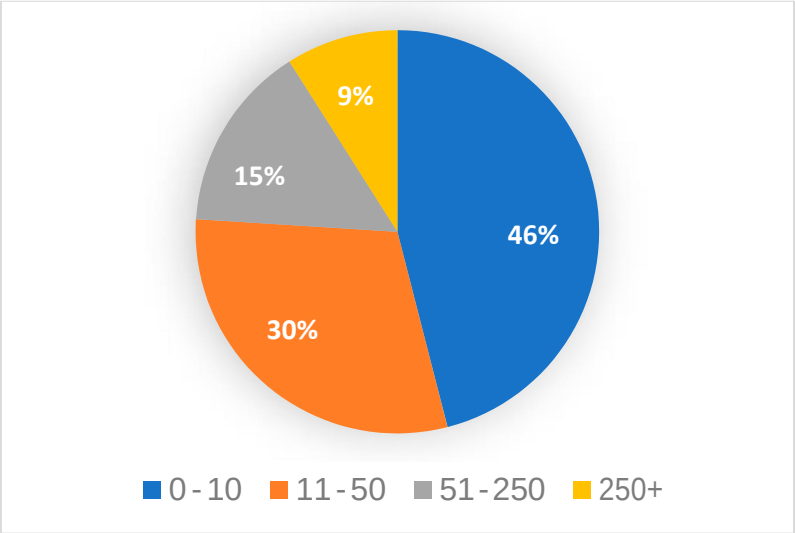

Figure 2. Distribution of companies by number of employees.

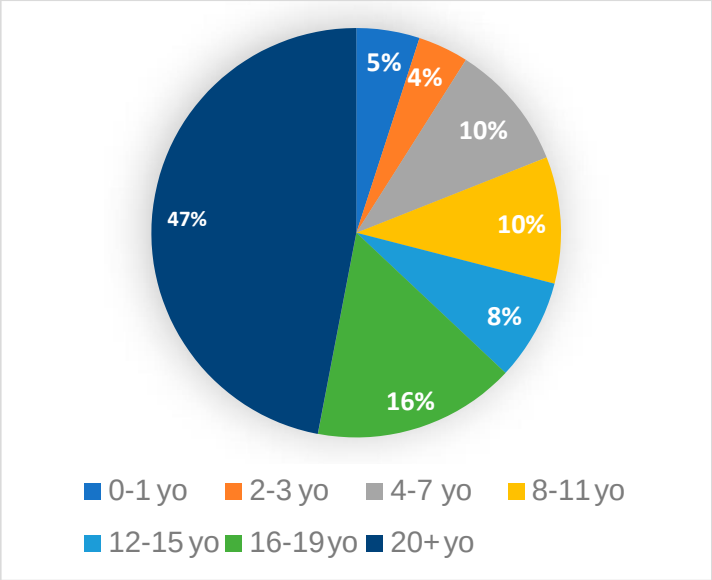

Figure 3. Distribution of companies by age of the company.

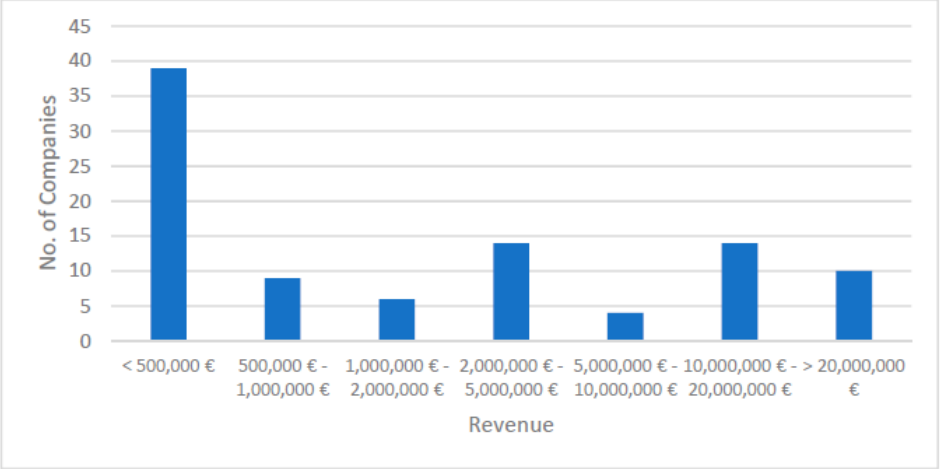

Figure 4. Distribution of companies by revenue.

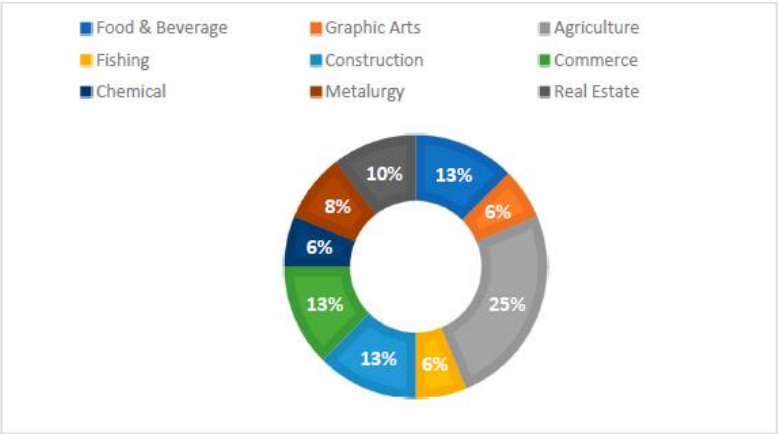

Figure 5. Distribution of companies by economic sector.

We constructed a very complete data set that initially included 77 indicators or mani- fest variables and a size of 96 observations from companies in the province of Huelva. In total, they added to 7392 datapoints. The questions included manifest variables at the mi- croeconomic level of the company (location, type, seniority, number of employees, turnover, etc.) and items that have been taken and/or adapted from previous studies. All the items were measured with a Likert scale of 1 to 7 points, from 1 = strongly disagree to 7 = strongly agree, where 4 is interpreted as a point of indifference. The detailed questionnaire can be seen in Table1.

All the indicators and data were computed in an Excel spreadsheet and then converted into CSV format to be able to run it using SmartPLS v.3.2.8 software (Ringle et al.2015) to apply PLS-SEM modelling.

3.3. Estimation of the Theoretical Model

An initial theoretical model was developed concerning the possible determinants of the demand for technological services by companies. The latent exogenous and endogenous variables, as well as their relationships, are represented in the initial proposed model (Figure6) and are summarized in Table1.

Table 1. Constructs and indicators of the measurement models.

Indicator	Definition
Identification data	
Company name	
Address	
E-mail	
Website	
Contact person	
Economic Sector	
Economic Characteristics of the Company (ECC)	
ECC1	Business Type
ECC2	Scope
ECC3	Number of employees
ECC4	Age of the Company
ECC5	Turnover
Attitude Towards Technology Adoption (ATTA)	
ATTA1	In my opinion, it would be very convenient to incorporate Technological Advances.
ATTA2	I would like to use the Technological Advances in my company.
ATTA3	I have a positive evaluation in relation to the performance of Technology in the company.
ATTA4	Incorporating Technology is a good idea.
ATTA5	In general, my attitude towards the performance of Technology is favourable.
Marketing Actions (MKTA)	
MKTA1	National and regional governments and other institutions do enough to motivate the incorporation of Technological Services by companies.
MKTA2	National and regional governments and other institutions are responsible for doing what is necessary for companies to develop or acquire Technological Resources.
MKTA3	Scientific and research organizations offer courses or workshops on the incorporation and mastery of Technological Advances to companies.
MKTA4	I have enough information about the various Technological Services offered by scientific and research organizations, and their possible advantages and disadvantages.
Technological Attributes (TAT)	
TAT1	In my opinion, it is desirable for my company to use Technology Resources.
TAT2	I think it is good for my company to use Technology.
TAT3	In general, my attitude towards Technological Advances is favourable.
TAT4	In general, I think that Technological Resources increase the performance of my company.
Perceived Utility (PU)	
PU1	The adoption of Technological Resources improves the performance of my company.
PU2	I believe that the use of Technological Advances will increase the productivity of the processes and tasks in my company.
PU3	I think that the use of Technology will improve the effectiveness and quality of the products and services offered in my company.
PU4	The Use of Technology will allow me to carry out operations more quickly.
PU5	The incorporation of Technological Resources is very useful for my company.

Table 1. Cont.

Indicator	Definition
Perceived Ease of Use (PEU)	
PEU1	Interacting with the Technological Resources does not require much effort for my company.
PEU2	I find the Technological Resources to be easy to use.
PEU3	My interaction with Technology is clear and understandable.
PEU4	It would be easy for me to be proficient in the use of Technology Resources.
PEU5	In general, I consider the use of Technological Resources to be more advantageous than current technology.
Market Conditions (MKC)	
MKC1	The market has caused us to focus more on new products, incorporating innovative Technological Advances.
MKC2	We are aware of the advertising campaigns of new products and the incursion of the Technological Services that it entails.
MKC3	I think there are many places where you can find diverse interesting technologies for the company.
MKC4	I choose Technological Resources over traditional resources, even if it is more expensive.
Demand for Technological Services (DTS)	
DTS1	How often have you introduced Technology Enhancements in your company in the last 5 years?
DTS2	How would you classify the frequency of demand for Technology Services?
DTS3	Rate your level of demand for Technological Resources in the future
DTS4	Given your experience, will you incorporate Technological Resources in the future?
DTS5	How much would you be willing to invest in the acquisition of Technological Resources?
Technology Adoption Decision (TAD)	
TAD1	Technological Advances offer me alternatives to solve possible problems that may arise in my company.
TAD2	Technology has economic advantages for my company.
TAD3	My company staff feel more valued/fulfilled when they use Technology Resources.
TAD4	I feel relaxed/calm when my company uses Technology Resources.
TAD5	The use of Technology by my company allows me to feel good.
TAD6	The use of Technological Resources can satisfy my desire to improve the productive processes of my company.
TAD7	The use of Technological Advances can satisfy my desire for new products.
TAD8	The use of Technological Resources offers my company timely communication with my clients and suppliers.
Facilitating Conditions (FC)	
FC1	The guide for the use of the different Technological Resources is available to my workers.
FC2	My company has specialized instructions on the Technological Resources.
FC3	A specific person (or group) is available to help my company with difficulties that may occur through the use of Technology.
FC4	I would carry out Technological Advances, if they were compatible with all the processes of my company.
Behaviour Intention Toward Technology Adoption (BITA)	
BITA1	I intend to use (or continue to use) Technological Resources in my business in the future.
BITA2	I intend to continue my current use of Technology Resources but will change the current provider of these.
BITA3	My company plans to use Technological Advantages in the future.
BITA4	I highly recommend other companies to use Technology Services.
BITA5	I intend to increase the use of Technology in my company in the future.
BITA6	I hope that my company's investment in Technology increases in the future.

Table 1. Cont.

Indicator	Definition
Influence of the Environment (IE)	
IE1	Someone from the company or the environment (other companies in the sector), motivates/forces me to follow a series of steps on the subject of Technological Resources.
IE2	My company has participated as a volunteer in a new Technology test.
IE3	My company has taken advantage of the social appeal of new products to incorporate Technological Advances.
IE4	The use of Technology is a tradition in my company.
IE5	In my company it is normal to incorporate Technological Resources.
IE6	My company has Technological Services.
IE7	I have felt pressured by other companies when it comes to incorporate Technological Resources.
IE8	My company uses Technological Resources due to the large proportion of companies that use them.
Business Predisposition Towards the Adoption of Technology (BPTAT)	
BPTAT1	The use of Technological Resources gives my company more control over its day-to-day professional affairs.
BPTAT2	Other people and companies come to me for advice on the use and benefits of Technological Advances.
BPTAT3	The use of Technological Advances offers my company more agility, both productive and decisive.
BPTAT4	The values of my company reside in the adoption of Technological Resources.
BPTAT5	Technology provides my company with more independence.
BPTAT6	I would use Technological Resources if I had support.
BPTAT7	I would use Technological Advances, if someone showed me how to use them.

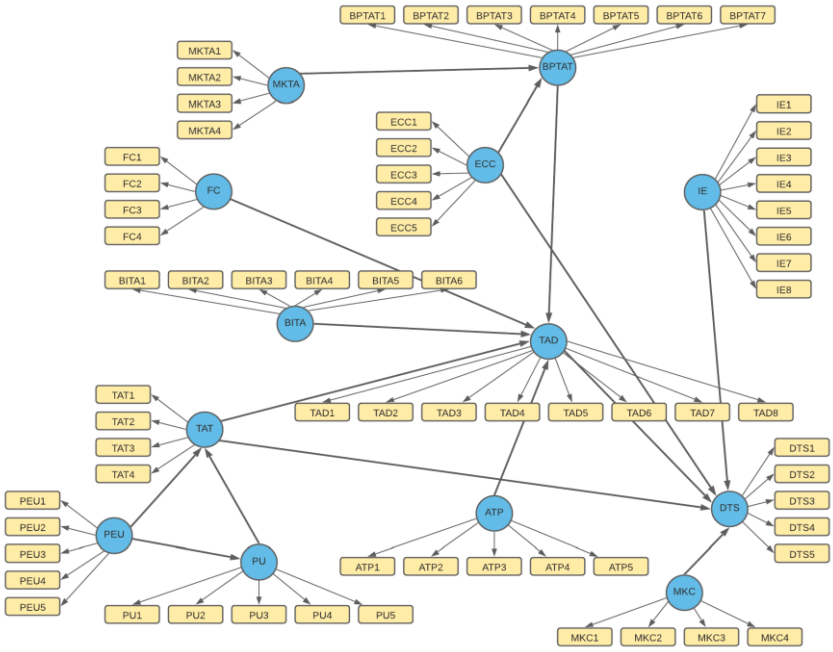

Figure 6. Initial theoretical model.

The objective of this analysis is to explain the final endogenous construct "Demand for Technological Services" (DTS), employing a PLS-SEM model through eight exogenous constructs (MKTA, ECC, IE, FC, ICAT, PEU, ATP and MKC) and four intermediate endoge- nous constructs (BPTAT, TAT, PU and TAD). Initially, all the constructs were modelled as reflective (Mode A). These variables, and the relationships between them, were included in the initial model based on the extrapolation of the factors collected in previous studies.

These indicators were included in a questionnaire and sent by email or fax to the companies. Subsequently, they were transferred to an Excel sheet, where further analysis and data debugging was carried out.

After creating the model, the SmartPLS software was run for the first time, provid- ing three key results: the outer loadings of the indicators, the path coefficients, and the coefficients of determination of the endogenous latent variables (R2) (Ringle et al.2015).

4. RESULTS

4.1. Evaluation of the Measurement Models in Mode A (Reflective)

Following the recommendations ofChin(2010) andHair et al.(2017,2018), to guaran- tee the reliability and validity of the measurements of the constructs and, therefore, support the suitability of their inclusion in the model (Hair et al.2017), we performed an evaluation of the measurement models. The evaluation of mode A (or reflective measurement models) was carried out by examining the reliability of the indicators, the composite reliability, the convergent validity (using the outer loadings and the average variance extracted, AVE), and the discriminant validity.

The first step was to confirm that the PLS algorithm converges properly. If the algorithm's stopping criterion is reached before the maximum number of iterations (for example, 300) defined in the parameter settings of the PLS-SEM algorithm, convergence has been achieved properly. In our model, the algorithm converged after just 13 iterations.

To evaluate reflective measurement models (Hair et al.2019a), the outer loadings of the indicator should be greater than 0.708. Indicators with outer loadings between 0.40 and 0.70 should be considered for purification only if the elimination leads to an increase in the composite reliability or to an AVE above the minimum values and does not present problems for content validity.

Table2shows the results for the reliability and validity of the reflective measurement models (Mode A). These results give evidence of the validity and reliability according toHair et al.(2017,2019a) andRingle et al.(2015). All loads exceed the set threshold of 0.70. Regarding Cronbach's Alpha and composite reliability, they are also above the established parameter. However, values higher than 0.95 may indicate redundancy of the indicators used (Hair et al.2017). The results suggest that there may be a slight redundancy between the TAT + ATP (0.959) and PU (0.969) indicators. The mean variance extracted (AVE), as a measure of convergent validity, which is the degree to which a latent construct explains the variance of its indicators, also exceeds the established threshold of 0.5. Regarding the discriminant validity, Table3shows the results according to the Fornell- Larcker criterion, and Table4, the heterotrait–monotrait ratio (HTMT), whose results are below the established parameter of 0.85 or 0.9 (Henseler et al.2015).

4.2. Evaluation of Measurement Models in Mode B (Formative)

The evaluation of the B-mode (or formative measurement models) was performed by analysing the convergent validity, the possible multicollinearity, the magnitude of the outer weights, and their significance (Hair et al.2019a). The analysis of the convergent validity of a formative measurement model was carried out by means of a separate redundancy anal- ysis for each construct that evaluated the correlation between the formative measurement and a global reflective measure (or of a single element) for the same construct, which must be observed and be greater than 0.7. In this case, the data was not available for a reflective (or single-element) measurement of the two formative constructs. To demonstrate how feasible it is to conceive the MKTA and ECC constructs as formative, it is necessary to verify that there are no collinearity problems between the indicators, for which it is necessary to calculate the variance inflation factor (VIF) that provides an index measuring the point at which the variance of an estimated regression coefficient increases due to collinearity. A collinearity value indicates critical problems when it has a VIF value greater than or equal to 3.3 (Diamantopoulos and Siguaw2006) or greater than 3 (Hair et al.2019c). If the VIF of certain indicators in the formative measurement model exceeds these critical values, then the possibility of eliminating the corresponding indicator or combining the collinear indicators in a new composite indicator could be considered (Avkiran2018). Given that we can expect a high correlation between reflective indicators, Table5shows the VIF values ob- tained for the indicators of the two formative constructs. As can be observed, all the values are below the threshold value of 3.3 (only ECC5 is slightly above the other, more restrictive, threshold of 3), with a range between 1.019 and 3.089, which means that the criterion has been met, and there are no multicollinearity problems between the formative indicators.

Table 2. Reliability and validity of reflective measurement models.

Latent Variable	Indicators	Convergent Validity			Internal Consistency Reliability			Discriminant Validity
		Loadings	Indicator Reliability	Average Variance Extracted (AVE)	Cronbach's Alpha	rho A	Composite Reliability	HTMT Confidence Interval Does Not Include 1
		>0.70	>0.50	>0.50	>0.70	>0.70	>0.70	
Technological Attributes + Attitude towards Technology Adoption (TAT + ATTA)	TAT1	0.920	0.846	0.855	0.943	0.948	0.959	Yes
	TAT3	0.875	0.766					
	TAT4	0.960	0.922					
	ATTA1	0.941	0.885					
Market Conditions (MKC)	MKC1	0.818	0.669	0.673	0.841	0.860	0.891	Yes
	MKC2	0.800	0.640					
	MKC3	0.844	0.712					
	MKC4	0.818	0.669					
Technology Adoption Decision (TAD)	TAD2	0.865	0.748	0.729	0.906	0.909	0.931	Yes
	TAD3	0.798	0.637					
	TAD5	0.899	0.808					
	TAD6	0.902	0.814					
	TAD7	0.801	0.642					
Demand for Technological Services (DTS)	DTS1	0.811	0.658	0.767	0.898	0.904	0.929	Yes
	DTS2	0.886	0.785					
	DTS3	0.926	0.857					
	DTS4	0.876	0.767					
Facilitating Conditions (FC)	FC1	0.939	0.882	0.802	0.876	0.917	0.924	Yes
	FC2	0.931	0.867					
	FC3	0.811	0.658					
Perceived Ease of Use (PEU)	PEU2	0.717	0.514	0.661	0.841	0.913	0.886	Yes
	PEU3	0.863	0.745					
	PEU4	0.859	0.738					
	PEU5	0.803	0.645					
Influence of the Environment (IE)	IE3	0.762	0.581	0.762	0.894	0.915	0.927	Yes
	IE4	0.926	0.857					
	IE5	0.937	0.878					
	IE6	0.854	0.729					
Behaviour Intention Toward Technology Adoption (BITA)	BITA3	0.925	0.856	0.858	0.835	0.835	0.924	Yes
	BITA4	0.928	0.861					
Perceived Utility (PU)	PU1	0.967	0.935	0.912	0.952	0.956	0.969	Yes
	PU3	0.965	0.931					
	PU4	0.932	0.869					

Table 3. Discriminant validity: Fornell-Larcker Criterion.

	MKTA	TAT + ATTA	ECC	MKC	TAD	DTS	FC	PEU	IE	BITA	PU
Marketing Actions (MKTA)											
Technological Attributes + Attitude towards Technology Adoption (TAT + ATTA)	0.104	0.925									
Economic Characteristics of the Company (ECC)	0.419	0.040									
Market Conditions (MKC)	0.262	0.510	0.129	0.820							
Technology Adoption Decision (TAD)	0.018	0.570	0.027	0.697	0.854						
Demand for Technological Services (DTS)	0.225	0.514	0.344	0.672	0.653	0.876					
Facilitating Conditions (FC)	0.303	0.403	0.284	0.518	0.480	0.560	0.896				
Perceived Ease of Use (PEU)	0.189	0.669	−0.001	0.697	0.699	0.613	0.420	0.813			
Influence of the Environment (IE)	0.127	0.553	0.147	0.560	0.619	0.672	0.656	0.499	0.873		
Behaviour Intention Toward Technology Adoption (BITA)	0.044	0.441	0.026	0.651	0.740	0.572	0.383	0.567	0.592	0.927	
Perceived Utility (PU)	0.026	0.850	0.078	0.555	0.650	0.602	0.357	0.670	0.500	0.486	0.955

Table 4. Discriminant validity: Heterotrait–Monotrait Ratio.

	MKTA	TAT + ATTA	ECC	MKC	TAD	DTS	FC	PEU	IE
Technological Attributes + Attitude towards Technology Adoption (TAT + ATTA)									
Market Conditions (MKC)	0.567								
Technology Adoption Decision (TAD)	0.613	0.787							
Demand for Technological Services (DTS)	0.551	0.741	0.716						
Facilitating Conditions (FC)	0.445	0.587	0.532	0.631					
Perceived Ease of Use (PEU)	0.672	0.825	0.787	0.691	0.511				
Influence of the Environment (IE)	0.597	0.623	0.684	0.740	0.742	0.564			
Behaviour Intention Toward Technology Adoption (BITA)	0.496	0.773	0.849	0.653	0.449	0.701	0.681		
Perceived Utility (PU)	0.891	0.607	0.698	0.645	0.384	0.668	0.532	0.543	

Table 5. Collinearity assessment: VIF values of the formative measurement models.

Formative Constructs	Indicators	VIF
Marketing Actions (MKTA)	MKTA1	1.655
	MKTA2	1.174
	MKTA3	1.992
	MKTA4	1.803
Economic Characteristics of the Company (ECC)	ECC1	1.019
	ECC2	1.034
	ECC3	2.925
	ECC4	1.139
	ECC5	3.089

To determine the relevance and significance of the outer weights, Tables6and7 show the results of the bootstrap analysis for the measurement models of the formative constructs, in which the importance of the magnitude of the outer weights can be evaluated, which indicate the relative contribution of an indicator to the construct (regression weight), and outer loadings that represent the absolute contribution of an indicator (correlation weight). In it, we look for outer weights that are significantly different from zero.

Table 6. Significance and relevance of outer weights.

Formative Constructs	Indicators	Outer Weights	*t*-Value	*p*-Value	95% BCa Confidence Interval	Is It Significant? ($p < 0.05$)
Marketing Actions (MKTA)	MKTA1	0.402	1.392	0.164	[−0.200; 0.962]	No
	MKTA2	0.672	2.498	0.013	[0.228; 1.014]	Yes
	MKTA3	0.158	0.473	0.636	[−0.587; 0.760]	No
	MKTA4	0.044	0.137	0.891	[−0.653; 0.616]	No
Economic Characteristics of the Company (ECC)	ECC1	0.287	1.919	0.055	[0.014; 0.586]	No
	ECC2	0.577	3.108	0.002	[0.256; 0.894]	Yes
	ECC3	0.221	0.613	0.54	[−0.496; 0.865]	No
	ECC4	0.076	0.249	0.804	[−0.552; 0.780]	No
	ECC5	0.679	1.67	0.095	[−0.170; 1.364]	No

Note: Bias-Corrected and Accelerated (BCa) bootstrap confidence intervals for 5000 subsamples, no sign changes, and two-tailed test.

According toAndreev et al.(2009), the weights of the indicators must be higher than 0.1, a requirement that is not fulfilled for the MKTA4 and ECC4 indicators. In addition, they do not present statistical significance, so we would go directly to eliminate them from the measurement models. For the rest of the indicators, where the value is greater than 0.1, but not too significantly, the next step is to analyse their outer loadings and determine whether they are significant or not. FollowingHair et al.(2017), when the weight of an indicator is not significant, but its corresponding outer loading is relatively high (for example, greater than or equal to 0.5), or statistically significant, the indicator must generally be maintained. Otherwise, it should be removed. Table7shows the relevance and significance of the outer loadings, where we can see how the already-eliminated MKTA4 and ECC4 indicators do not meet this criterion either. Of those remaining, only ECC1 does not meet it, since its load is less than 0.5 and it also does not present statistical significance. Therefore, we eliminated it from the ECC measurement model.

Table 7. Significance and relevance of outer loadings.

Formative Constructs	Indicators	Outer Loadings	*t*-Value	*p*-Value	95% BCa Confidence Interval	Is It Significant? ($p < 0.05$)
Marketing Actions (MKTA)	MKTA1	0.764	4.153	0.000	[0.425; 0.972]	Yes
	MKTA2	0.868	4.126	0.000	[0.679; 0.997]	Yes
	MKTA3	0.569	2.387	0.017	[0.070; 0.899]	Yes
	MKTA4	0.435	1.799	0.072	[−0.071; 0.822]	No
Economic Characteristics of the Company (ECC)	ECC1	0.181	0.967	0.334	[−0.198; 0.540]	No
	ECC2	0.417	2.080	0.038	[0.023; 0.767]	Yes
	ECC3	0.682	4.000	0.000	[0.389; 0.908]	Yes
	ECC4	0.304	1.079	0.281	[−0.313; 0.805]	No
	ECC5	0.786	4.527	0.000	[0.526; 0.970]	Yes

Note: Bias-Corrected and Accelerated (BCa) bootstrap confidence intervals for 5000 subsamples, no sign changes, and two-tailed test.

For the measurement models of the MKTA and ECC formative constructs formed by MKTA1, MKTA2, MKTA3, ECC2, ECC3 and ECC5, it was found that both present convergent validity and their retained indicators do not present collinearity problems. As such, they are relevant and statistically significant. After debugging the items, the PLS algorithm was run again, converging after nine iterations, thus finding a faster and more stable solution.

4.3. Evaluation of the Structural Model

Once it has been verified that both the validity and the reliability of the measurement models meet the requirements indicated above, and once the non-significant indicators of MKTA and ECC have been refined, the next step consisted of evaluating the structural model, which represents the relationships hypothesized between the constructs (García- Machado2017). This involved examining the predictive capacity of the model, for which

PLS-SEM was originally designed, as well as the relationships between the constructs. The key criteria for evaluating the structural model are the algebraic sign, the significance and relevance of the path coefficients, the level of the values of R2, the effect size f 2, the predictive relevance Q2, and the effect size q2 (Hair et al.2011,2017,2019b). However, before doing so, it is advisable to examine the possible multicollinearity between the constructs of the structural model. Table8shows the results of the VIF values of all the sets of predictors. For this analysis, most authors recommend that the FIV values should be below 5, or what is the same, a tolerance greater than 0.20, although, recently,Hair et al. (2019a) recommended a threshold of 3 for assessing the VIF. In any case, for the proposed model, there are no collinearity problems, since all the VIFs are below these thresholds.

Continuing with the evaluation of the structural model, we analysed the coefficients of determination or the R2 values of the endogenous latent variables. This value measures the amount of variance in the endogenous constructs explained by all the exogenous constructs linked to them, and it is the most frequently used measure for checking the predictive power of the model (Hair et al.2019a). While several authors argue that a valid R2 should be greater than 0.1 (Hair et al.2017;Falk and Miller1992), the interpretation of R2 will depend on the model and field of study. In general, R2 values can be described as substantial, moderate and weak, depending on whether their value is 0.75, 0.5 or 0.25 (García-Machado2017). To avoid the bias produced by the increase in the number of exogenous constructs, it is usually also used in adjusted coefficient of determination (R2adj).

Table 8. Collinearity assessment: VIF values in the structural model.

	MKTA	TAT + ATTA	ECC	MKC	TAD	DTS	FC	PEU	IE	BITA	PU
Marketing Actions (MKTA)			1.000								
Technological Attributes + Attitude towards Technology Adoption (TAT + ATTA)					1.349						
Economic Characteristics of the Company (ECC)						1.044					
Market Conditions (MKC)						2.082					
Technology Adoption Decision (TAD)						2.323					
Demand for Technological Services (DTS)											
Facilitating Conditions (FC)					1.273						
Perceived Ease of Use (PEU)											1.000
Influence of the Environment (IE)		1.333				1.742					
Behaviour Intention Toward Technology Adoption (BITA)					1.324						
Perceived Utility (PU)		1.333									

Table 9. Explained variance (R2).

Endogenous Latent Variables	R^2	R^2_{adj}
Technological Attributes + Attitude towards Technology Adoption (TAT + ATTA)	0.744	0.738
Economic Characteristics of the Company (ECC)	0.176	0.167
Technology Adoption Decision (TAD)	0.642	0.630
Demand for Technological Services (DTS)	0.657	0.642
Perceived Utility (PU)	0.449	0.443

To assess whether the omission of an endogenous construct has a substantial impact on the model, the effect size f 2 is used (Albort-Morant et al.2018;Hair et al.2017;Ali et al. 2018;Müller et al.2018). Values of f 2 above 0.02, 0.15 or 0.35 are considered to be a small, medium, or large effects, respectively (Cohen1988). Table10shows the results of the effect size f 2. For example, the largest effect size is PU on TAT + ATP (1.708), followed by PEU on PU (0.814) and BITA on TAD (0.677), which have large effects, and by MKTA on ECC (0.213), ECC on DTS (0.179) and IE over DTS (0.173), which have moderate effects.

Table 10. f 2 Effect Sizes.

	MKTA	TAT + ATTA	ECC	MKC	TAD	DTS	FC	PEU	IE	ICAT	PU
Marketing Actions (MKTA)			0.213								
Technological Attributes + Attitude towards Technology Adoption (TAT + ATTA)					0.135						
Economic Characteristics of the Company (ECC)						0.179					
Market Conditions (MKC)						0.116					
Technology Adoption Decision (TAD)						0.077					
Demand for Technological Services (DTS)											
Facilitating Conditions (FC)					0.056						
Perceived Ease of Use (PEU)											0.814
Influence of the Environment (IE)		0.086				0.173					
Behaviour Intention Toward Technology Adoption (BITA)					0.677						
Perceived Utility (PU)		1.708									

To analyse the significance and relevance of the relationships between the constructs in the structural model, we looked at the algebraic sign, which provided us with the path coefficients. In Figure7, it can be observed that all of the signs are positive, which indicates a direct relationship between them. The greatest relative importance among the constructs with a direct effect on the demand for technological services (DTS) is, in order of importance, the influence of the environment (IE), followed by market conditions (MKC) and the economic characteristics of the company (ECC). At first glance, it appears that technology adoption decisions (TAD) would rank fourth and last. Regarding the exogenous constructs that act on DTS, through the mediating variables ECC, TAD and TAT

+ ATTA, the greatest importance is perceived ease of use (PEU), followed by the intention to adopt technology (BITA) and marketing actions (MKTA). Facilitating conditions would also occupy the fourth and last place in this classification.

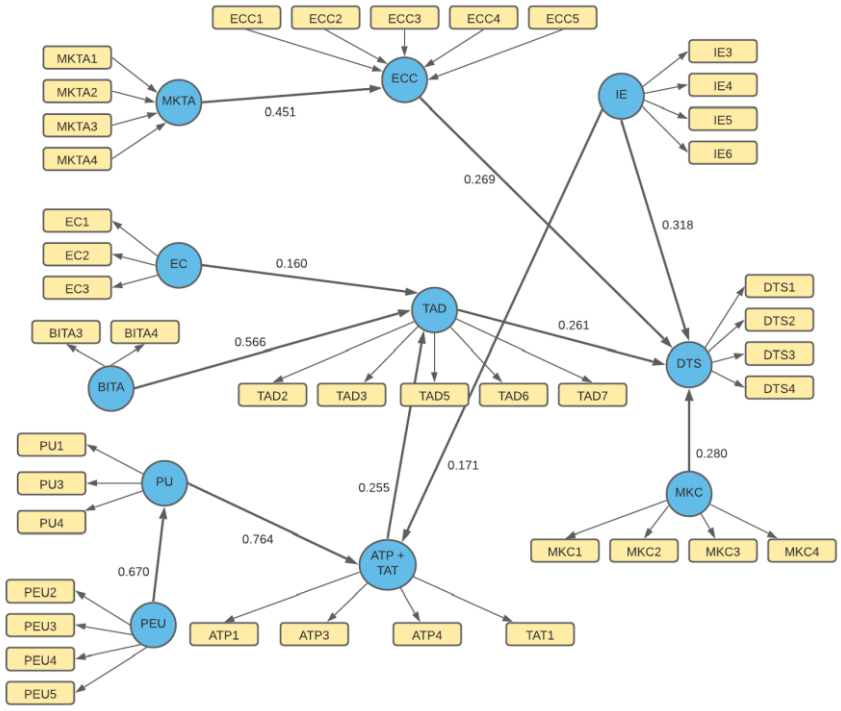

Figure 7. Debugged theoretical model.

To assess whether these relationships are truly significant, as well as to analyse the total, direct and indirect effects that a latent variable exerts on the key objective variable DTS, we ran a bootstrapping process with corrected and accelerated bias (BCa) for 5000 sub-samples, without sign changes, and a two-tailed test with a significance level of 0.05. Tables11and12show the results of the significance tests for direct effects and total effects (combination of direct effect plus indirect effects).

Table 11. Results of the significance test for the path coefficients (direct effects).

	Path Coefficients	*t*-Value	*p*-Value	95% BCa Confidence Intervals	Is It Significant? ($p < 0.05$)
MKTA → ECC	0.419	4.959	0.000	[0.178; 0.543]	Yes
TAT + ATTA → TAD	0.255	2.667	0.008	[0.091; 0.461]	Yes
ECC → DTS	0.253	3.334	0.001	[0.113; 0.408]	Yes
MKC → DTS	0.288	3.22	0.001	[0.097; 0.455]	Yes
TAD → DTS	0.247	2.206	0.027	[0.013; 0.448]	Yes
FC → TAD	0.160	2.244	0.025	[0.002; 0.284]	Yes
PEU → PU	0.670	10.146	0.000	[0.468; 0.765]	Yes
IE → TAT + ATTA	0.171	2.634	0.008	[0.043; 0.296]	Yes
IE → DTS	0.321	3.681	0.000	[0.149; 0.487]	Yes
ICAT → TAD	0.566	5.992	0.000	[0.354; 0.725]	Yes
PU → TAT + ATTA	0.764	10.527	0.000	[0.579; 0.872]	Yes

Table 12. Results of the significance tests for the total effects.

	Path Coefficients	*t*-Value	*p*-Value	95% BCa Confidence Intervals	Is It Significant? ($p < 0.05$)
MKTA → DTS	0.106	2.567	0.010	[0.032; 0.197]	Yes
TAT + ATTA → DTS	0.063	1.660	0.097	[0.010; 0.162]	No
FC → DTS	0.040	1.410	0.159	[0.000; 0.107]	No
PEU → TAT + ATTA	0.512	6.111	0.000	[0.265; 0.634]	Yes
PEU → TAD	0.131	2.211	0.027	[0.040; 0.272]	Yes
PEU → DTS	0.032	1.573	0.116	[0.006; 0.091]	No
IE → TAD	0.044	1.686	0.092	[0.009; 0.115]	No
IE → DTS	0.332	3.989	0.000	[0.167; 0.492]	Yes
ICAT → DTS	0.140	2.099	0.036	[0.020; 0.284]	Yes
PU → TAD	0.195	2.565	0.010	[0.068; 0.365]	Yes
PU → DTS	0.048	1.710	0.087	[0.009; 0.122]	No

As shown in Table11, assuming a significance level of 5%, all the relationships of the structural model are significant (with many even at a 1% level), which gives an idea of the robustness of our model. The most significant relationships, which show the great significance of the coefficients path, are found between the market actions and the economic characteristics of the company, the perceived ease of use with the perceived utility, the influence of the environment on the demand for technological services, the intention towards the adoption of technology with the decision technology adoption and the perceived utility with attitude toward technology adoption.

Regarding the total effects shown in Table12, of the exogenous variables MKTA, FC, IE, BITA and PEU on the endogenous constructs TAT + ATTA, TAD y DTS, it can be seen that the relationships MKTA ECC DTS, PEU PU TAT + ATTA, PEU PU TAT + ATTA TAD, IE TAT + ATTA TAD DTS,ICAT TAD DTS, and PU TAT + ATTA TAD are all significant at the 5% level, and in some cases even at a 1%.

After debugging the non-significant indicators and relationships, as well as performing a reorganization of the constructs, Figure8shows our final proposal for a more parsimo- nious explanatory model on business demand for technology services in the province of Huelva. Table13shows the contribution of each latent variable to the final construct (DTS) through the decomposition of the explained variance, where we verified that the variables that most influence the demand for technological services by the companies are the influence of the environment and market conditions, followed by the decision to adopt technology. It is important to highlight that the economic characteristics of the company variable has the least influence with 8.7% of R2.

Table 13. Decomposition of the explained variance of the endogenous latent variable DTS.

Latent Variable	Path Coef.	Correlation	R^2
Economic Characteristics of the Company (ECC)	0.253	0.344	8.70%
Market Conditions (MKC)	0.288	0.672	19.35%
Technology Adoption Decision (TAD)	0.247	0.653	16.13%
Influence of the Environment (IE)	0.321	0.672	21.57%
Total R^2			65.76%

4.4. *Assessment of the Relevance and Predictive Power of the Model*

Until relatively recently, the Stone-Geisser (Q2) test was used to evaluate predictive relevance, by applying a blindfolding procedure to predict deliberately omitted data within a sample and then comparing the resulting estimates with the real values (Hair et al.2019a). In this case, it is possible to calculate the relative impact or the effect size q2 when omitting an exogenous construct and see its influence on the endogenous construct (Q2 inclusive and Q2 excluded). Tables14and15show the values of Q2 and q2.

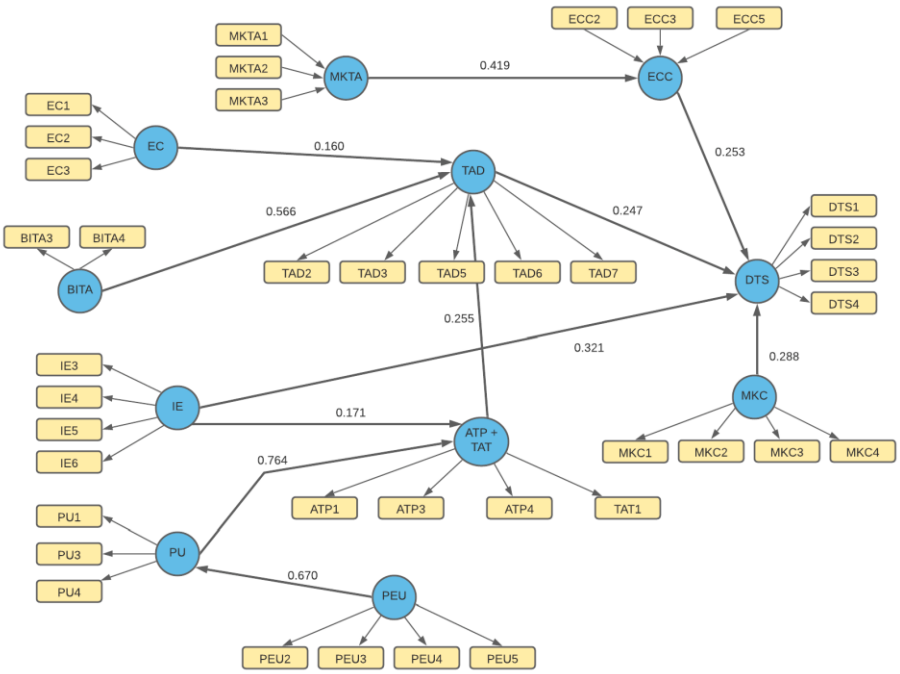

Figure 8. Proposed final model.

Table 14. Predictive relevance (Q2 values).

Endogenous Construct	Q^2
Technological Attributes + Attitude towards Technology Adoption (TAT + ATTA)	0.607
Economic Characteristics of the Company (ECC)	0.046
Technology Adoption Decision (TAD)	0.433
Demand for Technological Services (DTS)	0.490
Perceived Utility (PU)	0.391

Table 15. q2 Effect Sizes.

	MKTA	TAT + ATTA	ECC	MKC	TAD	DTS	FC	PEU	IE	ICAT	PU
Marketing Actions (MKTA)			0.048								
Technological Attributes + Attitude towards Technology Adoption (TAT + ATTA)					−0.055						
Economic Characteristics of the Company (ECC)						0.080					
Market Conditions (MKC)						0.057					
Technology Adoption Decision (TAD)						0.025					
Demand for Technological Services (DTS)											
Facilitating Conditions (FC)					0.023						
Perceived Ease of Use (PEU)											0.642
Influence of the Environment (IE)		0.051				0.086					
Behaviour Intention Toward Technology Adoption (BITA)					0.300						
Perceived Utility (PU)		0.504									

As can be seen, the Q2 values of all endogenous constructs are above zero, with TAT + ATP being the one with the highest value, followed by DTS, TAD and PU.Hair et al. (2019b) proposed a new rule of thumb for measuring predictive relevance according to the value of Q2: low (Q2 > 0), Medium (Q2 > 0.25) and high (Q2 > 0.5). Accordingly, TAT + ATP would have high relevance, DTS, TAD and PU medium, and ECC low.

Regarding the effect size q2, values of 0.02, 0.15 and 0.35 would indicate a small, medium or large predictive relevance of an exogenous construct over an endogenous one (Hair et al.2019a). In our case, the largest effect size is

PEU over PU (0.642) and PU over TAT + ATP (0.504). BITA over TAD (0.300) has a medium size effect, and the rest have a small effect.

Shmueli et al.(2016) pointed out that neither the value of Q2 nor that of q2 provides highly interpretable results in terms of the magnitude of the error, and they do not provide us with anything related to the precision of the model for predicting the values of new cases outside the sample. They recommend a procedure called PLSpredict (Shmueli et al. 2019), which has been implemented in the SmartPLS software since version 3.2.6 (Ringle et al.2015). For a better understanding of this and other procedures, the works ofShmueli et al.(2016,2019),Evermann and Tate(2016),Sharma et al.(2018,2019), andDanks and Ray(2018) can be consulted.

Following the procedure developed byShmueli et al.(2016), we applied the PLSpredict algorithm implemented in SmartPLS (Ringle et al.2015). The method uses training and hold-out samples to generate and evaluate predictions from the PLS path model estimates. In the settings, we select k = 3 folders or sections (96/3 = 32), since each folder must contain a minimum of 30 data points. The algorithm then predicts each section or folder (holdout sample) with the remaining k 1 = 2 subsets, which, in combination, become the training sample. This process is repeated 10 times by default. The number of repetitions indicates how often the PLS prediction algorithm performs k-fold cross-validation on random splits of the complete data set in k sections (folds). Traditionally, cross-validation only uses a random division in k-folds. However, a single random division can make predictions highly dependent on this random assignment of data (observations) in k-folds. Due to the random split of the data, runs of the algorithm at different points in time may vary in their predictive performance measures (for example, mean square error, mean absolute percentage error, etc.). Repeating the k-fold cross validation with different random data partitions and calculating the mean between the repeats ensures a more stable estimate of the predictive performance of the PLS path model.

Based on the procedures suggested byShmueli et al.(2016), the current implemen- tation of the PLS prediction algorithm (PLSpredict) in the SmartPLS software enables researchers to obtain cross-validated prediction error statistics and summaries of prediction errors such as the root mean squared error (RMSE), the mean absolute error (MAE) and mean absolute percentage error (MAPE) to assess the predictive performance of a PLS path model for manifest variables (MV or indicators) and latent variables (LV or constructs). These three criteria are available for the results of the indicators, whereas it is only possible to calculate RMSE and MAE for construct results. These criteria allow the predictive performance of alternative PLS path models to be compared.

Table 16. Q2predict values.

Indicator	PLS		
	RMSE	MAE	$Q^2_{predict}$
ATTA1	0.935	0.602	0.319
ATTA3	0.946	0.695	0.357
ATT1	0.968	0.656	0.395
ATTA4	0.913	0.582	0.315
ECC2	1.397	1.248	0.015
ECC3	0.971	0.765	0.039
ECC5	2.187	1.889	0.061
TAD6	0.944	0.722	0.470
TAD2	1.065	0.784	0.395
TAD5	0.929	0.744	0.548
TAD7	1.177	0.877	0.338
TAD3	1.214	0.917	0.414
DTS4	0.943	0.732	0.433
DTS1	1.22	0.998	0.324
DTS2	1.123	0.895	0.405
DTS3	1.019	0.8	0.480
PU4	1.039	0.744	0.322
PU1	0.991	0.68	0.371
PU3	1.083	0.763	0.357

Furthermore, to evaluate the results of a specific PLS path model, its predictive performance can be compared using two new indices:

1. The Q2 value in PLSpredict compares the prediction errors of the PLS path model with the simple mean predictions. To do this, we used the mean value of the training sample to predict the results of the holdout sample. The interpretation of the results of the Q2 value is similar to the evaluation of the Q2 values obtained by the blindfolding procedure in PLS-SEM. If the Q2 value is positive, the prediction error of the PLS-SEM results is less than the prediction error of simply using the mean values. In that case, the PLS-SEM models offer better predictive performance.

2. The linear regression model (LM) provides summary statistics and prediction errors that ignore the specified PLS path model. Instead, the LM approach returns all exogenous indicator variables with each endogenous indicator variable to generate predictions. Thus, a comparison with the PLS-SEM results provides information on whether using an established theoretical model improves (or at least does not worsen) the predictive performance of the available indicator data. Compared to LM results, PLS-SEM results should have a smaller prediction error (for example, in terms of RMSE or MAE) than LM. Consider, as mentioned previously, that the LM prediction error is only available for the manifest variables, and not for the latent variables.

In our solution, following the suggestions ofRold án and Cepeda(2020), we first run the algorithm and check that the values of Q2predict of the indicators of the dependent variables of interest are all positive (Q2predict > 0). The results of our analysis can be seen in Table16.

The next step was to check whether the prediction errors were symmetrically distributed—to do so, we analysed the skewness. If the asymmetry in the absolute value is less than 1, the RMSE should be used as a criterion for the prediction error; otherwise, the MAE should be applied. Table17shows the descriptive statistics of the indicators of the dependent variables of interest.

Table 17. Descriptive statistics and choice of the error prediction criterion.

	Mean	Median	Min	Max	Standard Deviation	Kurtosis	Asymmetry	Decision
ATTA1	−0.014	0.121	−5.452	1.888	0.935	10.03	−2.375	MAE
ATTA3	−0.01	0.151	−4.17	1.977	0.946	2.897	−1.284	MAE
ATT1	−0.013	0.16	−5.097	2.277	0.968	6.413	−1.902	MAE
ATTA4	−0.014	0.087	−5.37	2.441	0.913	10.957	−2.262	MAE
ECC2	−0.005	0.45	−3.301	2.48	1.397	−1.069	−0.439	RMSE
ECC3	−0.004	−0.177	−1.469	2.788	0.971	0.065	0.917	RMSE
ECC5	−0.003	−0.658	−4.178	5.905	2.187	−0.873	0.492	RMSE
TAD6	0.007	0.112	−2.597	3.458	0.944	1.189	−0.003	RMSE
TAD2	0.013	0.177	−4.77	4.667	1.065	4.017	−0.426	RMSE
TAD5	0.009	0.008	−2.675	2.583	0.929	-0.21	−0.144	RMSE
TAD7	0.008	0.183	-4.677	4.335	1.177	2.172	−0.596	RMSE
TAD3	0.013	0.257	-4.829	3.982	1.214	2.521	−0.976	RMSE
DTS4	0.004	0.06	−3.591	2.932	0.943	1.243	−0.486	RMSE
DTS1	0.004	0.234	−3.775	2.515	1.22	0.136	−0.631	RMSE
DTS2	0.003	0.033	−3.777	2.762	1.123	0.44	−0.548	RMSE
DTS3	0.002	0.034	−3.198	2.714	1.019	0.438	−0.464	RMSE
PU4	−0.009	0.15	−5.068	2.905	1.039	4.433	−1.148	MAE
PU1	−0.01	0.08	−5.084	2.128	0.991	5.888	−1.566	MAE
PU3	−0.009	0.104	−4.859	2.322	1.083	3.274	−1.182	MAE

Finally, we calculated the differences in the errors (as used as the RMSE or MAE criteria) between the predictions made using PLS and those of the linear regression model (LM) ignoring the specified path PLS model. For the predictions of PLS to be more accurate than those of LM, the errors of the latter must be greater, and, therefore, the differences when subtracting them from the former must be negative. Table18shows the differences in prediction errors between both models.

Table 18. The difference in RMSE or MAE errors between PLS and LM (predictive power).

Indicator	PLS			LM			PLS-LM		
	RMSE	MAE	$Q^2_{predict}$	RMSE	MAE	$Q^2_{predict}$	RMSE	MAE	Decision
ATTA1	0.935	0.602	0.319	1.05	0.763	0.141	−0.115	−0.161	MAE
ATTA3	0.946	0.695	0.357	1.053	0.821	0.204	−0.107	−0.126	MAE
ATT1	0.968	0.656	0.395	1.021	0.786	0.327	−0.053	−0.130	MAE
ATTA4	0.913	0.582	0.315	0.915	0.691	0.312	−0.002	−0.109	MAE
ECC2	1.397	1.248	0.015	1.918	1.558	−0.856	−0.521	−0.310	RMSE
ECC3	0.971	0.765	0.039	1.18	0.94	−0.42	−0.209	−0.175	RMSE
ECC5	2.187	1.889	0.061	2.645	2.258	−0.373	−0.458	−0.369	RMSE
TAD6	0.944	0.722	0.470	1.074	0.795	0.315	−0.130	−0.073	RMSE
TAD2	1.065	0.784	0.395	1.232	0.907	0.191	−0.167	−0.123	RMSE
TAD5	0.929	0.744	0.548	1.092	0.834	0.374	−0.163	−0.090	RMSE
TAD7	1.177	0.877	0.338	1.3	0.977	0.192	−0.123	−0.100	RMSE
TAD3	1.214	0.917	0.414	1.331	1.032	0.296	−0.117	−0.115	RMSE
DTS4	0.943	0.732	0.433	1.181	0.855	0.11	−0.238	−0.123	RMSE
DTS1	1.22	0.998	0.324	1.429	1.124	0.072	−0.209	−0.126	RMSE
DTS2	1.123	0.895	0.405	1.458	1.101	−0.003	−0.335	−0.206	RMSE
DTS3	1.019	0.8	0.480	1.326	0.983	0.12	−0.307	−0.183	RMSE
PU4	1.039	0.744	0.322	1.031	0.78	0.333	0.008	−0.036	MAE
PU1	0.991	0.68	0.371	1.02	0.764	0.333	−0.029	−0.084	MAE
PU3	1.083	0.763	0.357	1.126	0.874	0.306	−0.043	−0.111	MAE

Thanks to this, we can see that the model shows great predictive power for DTS, TAD and ECC. It has positive Q2 predict and negative differences for RMSE (recommended). It also has it for TAT + ATP and PU, and positive Q2 predict and negative differences for MAE. Therefore, the model meets all the criteria and has high predictive power, that is, the ability to predict new results.

5. DISCUSSION AND CONCLUSIONS

Due to the 2008–2014 crisis and its aftermath, Spain reduced its investment in R&D by 8.82% relative to its highest value of 1.36% of GDP in 2010. Despite that since 2016 it has been increasing (currently it is at a level of 1.24%), it is still far from the 3% target set by the EU in its Europe 2020 strategy and the countries of central and northern Europe that led this ranking (Spain occupies the 16th position). However, despite this decline in investment in R&D (Instituto Vasco de Estadística2020), we agree withYoldi(2016) and Ametic(2017) regarding the hopeful trend of cooperation with the aim of taking advantage of synergies between the public and private sectors.

However, although efforts have been made, the health crisis caused by COVID-19 unleashed a new scenario of total exceptionality that will most probably lead to future cuts to combat the subsequent economic crisis produced by the pandemic. It therefore seems even more important for companies to strengthen their cooperation with universities as the best mean to promote, share and complete basic and applied research developed by both, to attract talent, to hire researchers, to use specialized equipment and scientific instruments at a reduced cost, to gain experience in the field of project management and direction, and to keep up to date with international scientific developments.

To ease and contribute to the growth and promotion of closer collaborations between universities and companies in R&D, this research focused on exploring and discovering what factors of businesses (based in the province of Huelva) explained and determined the demand for technological services, and in what way. Through a cross-sectional study carried out on a sample of 96 companies, the most relevant characteristics of the same were analysed, according to their area, location, type of company, number of employees,seniority, turnover, and activity sector. First, based on the theoretical and literature review, we designed a complex initial theoretical model, using the PLS-SEM methodology, which posed eight exogenous constructs as possible determinants of the demand for technological services by companies (the economic characteristics of the company (ECC), the attitude towards the performance of the technology (ATP), the perceived ease of use (PEU), the market conditions (MKC), the marketing actions (MKTA), the facilitating conditions (FC), the intention of the behaviour towards the adoption of technology (BITA), and the influence of the environment (IE), as well as four intermediate endogenous constructs (the business predisposition towards the adoption of technology (BPTAT), the technological attributes (TAT), the perceived utility (PU), and the decision to adopt technology (TAD), which were modelled in mode A (previously reflective). This model was tested using a questionnaire with 77 indicators adapted to the Huelva context.

After successive phases of analysis and evaluation, both measurement models and the structural model, as well as the global adjustment of the model, different modifications were made, ranging from the purification of indicators and non-significant relationships, and reorganization of constructs, to changes in the measurement models of some latent variables that began to be modelled in mode B (previously formative). The later was carried out by means of a Confirmatory Tetrad Analysis (CTA-PLS) with an empirical foundation additional to the theoretical one on the measurement models, especially those modelled as B or formative mode (MKTA and ECC). The final model proposed for the business demand for technological services in the province of Huelva is a mixed model of factors and compounds, which is more parsimonious, and which is explained by four endogenous and six exogenous constructs. The variables that most influence the demand for technological services by companies were the influence of the environment (21.57%), market conditions (19.35%), and the technology adoption decision (16.13%). The economic characteristics of the company represented only 8.70% of the explained variance. These four variables alone explained 65.76% of the variance of the endogenous latent variable “Demand for Technological Services (DTS)”.

Other important relationships were also identified, showing that 74.4% of the variance of the construct “Technological Attributes + Attitude Towards Technology Adoption (TAT+ ATTA)” was also explained by the influence predictors of environment and perceived utility. Additionally, 64.2% of the variance of the construct “Decision to Adopt Technology (TAD)” was explained by the Intention Predictors of Behaviour Towards the Adoption of Technology, Facilitating Conditions, and TAT + ATTA.

As for the measure of goodness of global fit of the model, it shows a proper fit of the proposed model, both in the three statistics suggested in the context of PLS-SEM, and in the exact fit tests based on bootstrap.

The present study raises some interesting questions. Given that it is based on a sample of 96 companies in the province of Huelva, it would be interesting to analyse how the model would work in terms of predicting results for other companies and for those located in other geographical areas, especially those with a stronger presence of R&D centres. Additionally, further studies should be conducted to verify whether some of the economic characteristics of the companies, such as size, location, type of company, age, turnover, or activity sector, could act as mediating or moderating variables in the demand for technological services. It also seems justified to conduct a more qualitative

analysis regarding the variable of marketing actions to confirm that the flow of the "information" is as good as the questionnaire suggests.

An added benefit of conducting this kind of study is that it might help to analyse the supply of an institution's scientific and technological infrastructure by carrying out an inventory of available resources, an idea that was inspired by the Office for the Transfer of Research Results of the Geological and Mining Institute of Spain, which issues annual catalogues of Technological and Scientific Offers (Instituto Geológico y Minero de España 2013), and by the Fundación Campus Tecnológico de Algeciras, which has a website where they gather everything related to transfers, and which can be easily accessed.

We hope that the results presented in this study will help lead to a better understanding of the motivating forces that drive the decision making of companies regarding the demand for technology services. Consequently, public bodies, universities, agencies, and research centres, as well as companies interested in innovation, development, and adoption of new technologies, will be able to work together with the aim of designing strategies to obtain a more desirable and positive response in relation to basic and applied research for a better use of resources, University–Business cooperation, the economy, and society in general.

Conflicts of Interest:

The authors declare no conflict of interest.

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