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Research Article

Complexity in the Acceptance of Sustainable Search Engines on the Internet: An Analysis of Unobserved Heterogeneity with FIMIX-PLS

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This paper analyses the complexity of user behaviour when facing the challenge of using sustainable applications, such as Internet search engines. This paper analyses an acceptance model using extended TAM (Technology Acceptance Model) with Trust as an added external variable. It was suggested that Trust indirectly influences the final Intention to Use with the perceptions of Utility and Ease of Use. To test the proposed model, a survey was carried out with users from different geographical areas of Spain ($n = 445$). The second aim of this study was to understand the complexity of marketing segmentation by separating the application users into different user groups. Users were grouped by their preference of favorite Internet search engine. Unobserved heterogeneity was studied using FIMIX-PLS, and three different user behaviours with search engines were identified. These corresponded to the number of inhabitants who live in the user area. In this way, the impact that the environment has on user choice, acceptance, and use of this type of sustainable applications was shown. The results were checked using PLS-SEM and showed that the model for the adoption of sustainable search engines is explanatory and predictive because confidence and acceptance for this TAM were validated. The conclusions are interesting for developers of environmentally sustainable and responsible applications which want to coincide with current trends to ensure that users prefer them.

1. Introduction

Many companies have had to adapt their business organizations to new technological developments in the Internet [1]. In a world that is increasingly global and interconnected, finding information that can enrich a company and allow it to obtain a competitive advantage is becoming increasingly important [2]. In addition, these technological changes have also affected users and have significantly changed consumers' lives.

In this global context, the increasing complexity of business environments has led to the introduction of new business models, an improvement in global contacts and relationships, with easier access to information. Businesses need to know how to take advantage of these new opportunities. One way to do this is for companies to use Internet search engines to find information about different products, services, activities, or any information that is required. The use of these technological advances has changed users' habits and ways of accessing information as well as increasing creativity when solving strategic marketing problems [3, 4].

Companies have realized that they need to develop effective marketing strategies in order to take advantage of new trends in consumer behaviour. One of the tools that can be used to do this is the search engine. Search engines are websites that index information on the Internet and organize it according to its quality for a user's search criteria. Today, the most widely used search engines worldwide are Google with 78.78% of the total market share, Bing with 7.65%, Baidu with 7.33%, and Yahoo with 4.70% [5]. Each of these

Table 1: Related works.

Authors	Descriptions
Chao et al. [21]	Present an investigation of the participating agents when users search for information with search engines, especially studying the beliefs and risks that are taken in their searches
Palos-Sanchez and Saura [5]	Analyse the Ecosia sustainable search engine using the Unified Theory of Acceptance and Use of Technology (UTAUT) and then analysing the results with PLS-SEM (Partial Least Squares-Structural Equation Modelling)
Rangaswamy et al. [22]	Research the different strategic perspectives of search engines from the point of view of sustainability and sustainable development
Keirstead [23]	Investigates the searches made with sustainable search engines and the user behaviour
Liaw et al. [24]	Use the TAM with PLS to find what the users feel about the information found with different search engines
Kamis and Stohr [25]	Develop a PLS model to determine the importance of search engines when an online purchase is made, using factors such as purchase decision, trust or perceived utility, and the behaviour of different users

search engines has different features that can be used to analyse and improve marketing strategies.

As well as considering global developments when creating new business models, companies are also trying to use the planet's resources more sustainably and use niche-marketing strategies. The complexity of these marketing strategies must be analysed in order to understand the new consumer [6, 7]. Research has been done on various sustainable search engine initiatives called Green Search Engines in some studies, which are a strategic micro niche within the sector [5, 8, 9].

Many energy-consuming computing resources are needed for a search engine to be able to find information from anywhere in the world. These resources generate high temperatures that can be mitigated with air conditioning that also consumes electricity. In fact, Google says that each query requires around 1 kJ or 0.0003 kWh of energy [10].

Sustainable search engine is the name given to a search engine that gives part or all of its profits to sustainable social and environment projects. A search engine's profits usually come from advertising in the search results [5, 11].

With the amount of information that exists on the Internet, new sustainable business models have been developed for search engines in recent years [12]. It is important to note that the well-known techniques of SEO, Search Engine Optimization, and SEM, Search Engine Marketing, are widely used. The first technique optimizes the information given in the results of any search request, and the second technique is used to produce economic benefits. These economic benefits are earned from sponsored search results (paid search) that are financed by advertisers using CPC (cost per click) or CPM (cost per thousand impressions) or any other type of payment method [13, 14]. This type of advertising also allows effective marketing strategies to be used, since it collects usage and navigation data about new consumer trends, which can be used to modify marketing.

As a general rule, SEM-sponsored search results finance and sustain different types of sustainable projects [15]. Some sustainable search engines are described below. Ecosia allocates 80% of SEM advertising revenue to tree reforestation projects around the world. Solydar helps sustainable development projects as well as sectors of the socially disadvantaged population. Goodsearch encourages users of their search engine to accumulate $5 units of credit that they can later donate to sustainable development projects. Lilo is a search engine that donates drops of water that are accumulated by users every time they search using this search engine. Benefind makes a donation of 0.5 cents each time someone searches using their search engine. Forestle donates 90% of its profits to sustainable and social development agencies or projects such as Treeho, which is similar to the Ecosia model of planting trees as a result of using the search engine [5, 16, 17].

The purpose of this study is to use the TAM with Trust as an external variable to identify different groups of sustainable search engine users. A FIMIX-PLS analysis and a post hoc analysis are carried out in order to identify different behaviour when users adopt a sustainable search engine and to detect new trends in consumer behaviour. In this way, a large amount of information can be used to comment on how marketing can face future technological challenges as users take advantage of environmentally sustainable technologies.

2. Theoretical Background

Over the last decade, researchers have followed various lines of research in the areas of search engine acceptance, users' feelings about different search engines, and the different options available in the market (see Table 1 [18]).

Sánchez et al. [19] investigated the evolution of search, the number of searches made, and the consistency of any expected result when using different sustainable search engines. Likewise, Martínez-Sanahuja and Sánchez [20] carried out research on search engine sustainability to discover how sustainable programs affect the users' opinion and also review the main initiatives of sustainable search engine since 1994.

In the research by Hahnel et al. [26], both traditional and sustainable search engines were studied to find the factors which influence users' choice of search engines. Liaw and Huang [27] suggested a model to investigate the methods used to find information with search engines and identify how these searches can be made more efficient.

Fortunati and O'Sullivan [28] showed the importance of new media and new technologies that are provided by digital alternatives. Sustainable social development was studied with special importance placed on how users behave with these new digital alternatives in order to find ways to improve them

[29]. Jaca et al. [30] showed the importance for businesses of considering society and users' respect for the environment. They pointed out that sustainable development can be understood by analysing user behaviour for sustainable organizations [23].

In addition, Hirsu [29] investigated the cultural factors that influence the choice of search engine for different searches made by users. The behaviour of different types of users of search engines was investigated in order to determine behaviour patterns and consequently predict them [28].

3. Research Model and Hypotheses Development

After analysing different models and theories of technological acceptance, the TAM with Trust as an added external variable was chosen for this investigation. TAM was chosen because it has been shown to be a reliable model for measuring the acceptance and use of technologies as well as for the behaviour of users. The main constructs in the model explain users' attitudes towards using technology, and the TAM has been used to investigate users' attitudes towards alternative technologies. Reviewing different research that used the TAM, with added external variables, to accept theories helped in the choice of this model. In the next section, there is an explanation of each of the variables and relationships used in the model to analyse the hypotheses.

4. Technology Acceptance Model (TAM) Variables

The TAM establishes casual relationships between perceived usefulness (PU), perceived ease of use (PEOU), attitude toward using (ATU), and intention to use (USE) [31]. Following the research of Davis [32], in which the model was proposed for the first time, perceived usefulness (PU) and perceived ease of use (PEOU), that are not implicitly included in TAM, are expected to influence attitude toward using (ATU) and behavioural intention to use [33]. In this study, the external variable Trust was also included. Trust is defined as the confidence that users have in technology and links the reliability of their implicit actions with technology when they use it [5]. ATU refers to a user's positive or negative feelings toward the use of any given technology, while BUSE is the amount of prior use given to the technology [34]. PU is defined as how much an individual believes that using a particular system will improve their performance [32]. It is a measure of the subjective likelihood that a potential user will increase their work performance in an organization when using the technology [35]. The PEOU variable measures how much an individual believes that using a particular system is effort-free. Different authors have also previously used the external variable, Trust, in the TAM [36]. Trust is an external variable to the model and has been defined by previous research in a variety of ways, both theoretically and operationally.

Palanisamy [37] demonstrated and developed a model for the acceptance of different search engines and linked the influence of PU with USE. Liaw and Huang [27] studied the influence of PU on ATU to understand users' attitudes towards using search engines and the perceived utility of the different search engines. Using the studies above, we propose the following hypothesis.

H1 Perceived usefulness (PU) influences intention to use (USE) sustainable search engines on the Internet.

Lim and Ting [38] developed a technology acceptance model for search engines that are used in e-commerce web pages. A clear relationship was found between PU and ATU when using the search engine. Koufaris [39] studied user behaviour when making queries with these search engines and investigated the relationship between PU and ATU when accessing a web page as a result of using a search engine. Using these studies, we propose the following hypothesis.

H2 Perceived usefulness (PU) influences attitude towards using (ATU) for sustainable search engines on the Internet.

Morosan and Jeong [40] used the TAM to study the adoption of search engines for booking hotels and restaurants and researched the influence of the PEOU and PU variables when using these search engines to achieve travellers' goals. Yang and Kang [41] showed the influence of USE and PU variables for search engines in Thailand and used them in the UTAUT (Unified Theory of Acceptance and Use of Technology) model. Using this literature, we propose the following hypothesis.

H3 Perceived ease of use (PEOU) influences perceived usefulness (PU) of sustainable search engines on the Internet.

Hsu and Walter [42] investigated the relationship of the ease of use and the perceived usefulness of search engines when looking for content on web pages. They proposed a relationship between PEOU and ATU using the technology acceptance model. Chi-Yueh et al. [43] explored the intention of users to use search engines to find audio and video content on the Internet and analysed the influence of PEOU on ATU. Using these investigations, we propose the following hypothesis.

H4 Perceived ease of use (PEOU) influences attitude toward using (ATU) sustainable search engines on the Internet.

Moon and Kim [44] and Gefen et al. [45] used the TAM to study search engines and online stores on the Internet. In this research, the influence of attitude toward using (ATU) on intention to use (USE) Internet search engines was studied. Following these investigations, in which the TAM was adapted for search engines, we propose the following hypothesis.

H5 Attitude toward using (ATU) influences intention to use (USE) sustainable search engines on the Internet.

Hsu and Walter [42] adapted the TAM for search engine use by adding the Trust variable and then linking this to PU. To do this, the influence that attitude has on use, when a user trusts the search engine, was measured [44]. Palanisamy [37] also included the Trust variable in the model, in order to find the reliability of search engines and their technological acceptance. Using this research on search engines, we propose the following hypothesis.

H6 Trust influences perceived usefulness (PU) of sustainable search engines on the Internet.

Lim and Ting [38], Palanisamy [37], and Hsu and Walter [42] also analysed the influence that Trust, as an external variable, has on PEOU in acceptance models and revealed the influence of both variables for search engines [5, 45]. Therefore, the following hypothesis was proposed.

H7 Trust influences perceived ease of use (PEOU) for sustainable search engines on the Internet.

5. Heterogeneity and Segmentation

In Social Sciences, it is difficult to guarantee that the whole sample fits the same probabilistic distribution. However, with PLS, segmentation can be used with the structural model, which means that different parameters are used to separate the sample into groups [46].

Heterogeneity in the data may or may not be observed. Heterogeneity is observed when the differences between two or more groups of data are caused by observable characteristics, such as sex, age, or country of origin. On the other hand, unobserved heterogeneity arises when the differences between two or more data groups do not depend on any observable characteristic or combinations of characteristics. However, there can still be significant differences in the relationships between data groups in the model, when the origins of these differences cannot be attributed to any observable variable such as age, gender, educational level, or any other type [47].

In our study, these observable characteristics were used to divide the data into separate groups for investigation and then analysed with a group-specific PLS-SEM method. To do this, the variables used for the grouping of the sample had to be found. Once these were identified, the relationships between these groupings could be established and analysed.

There are established techniques for this process, but previous research has shown that traditional grouping techniques do not work very well for the identification of grouping differences [48]. Methodological research with PLS-SEM has resulted in a multitude of different techniques, commonly referred to as latent class techniques, to identify and treat unobserved heterogeneity. These techniques have proved to be very useful for identifying unobserved heterogeneity and grouping the data accordingly [47].

TAM was used for this investigation into the adoption of sustainable search engines on the Internet, and the number of segments was established so that it was small enough to guarantee parsimony and large enough to guarantee strategic relevance [49].

The technique chosen to study unobserved heterogeneity was FIMIX-PLS [50], extended by Sarstedt et al. [51]. FIMIX-PLS is the most used latent class approach for PLS-SEM [52] and is an exploratory tool that results in the appropriate number of segments into which the sample should be divided. The FIMIX-PLS technique allowed decisions to be made about the number of segments using pragmatic reasoning and practical issues identified in current research [53].

FIMIX-PLS is the most widely used technique and has been used in various areas of research, such as environmental positioning of businesses [46], Internet usage by SMEs [54, 55], tourism management [56], strategic marketing management [57], corporate reputation [48, 58], mobile shopping [59], and learning systems [60].

FIMIX proposes an estimated path model using the PLS-PM algorithm. The resulting latent variable values are used in the FIMIX-PLS algorithm to find any unobserved heterogeneity in the estimated parameters of the internal model (relationships between latent variables).

6. Data and Methodology

Table 2 shows the demographic characteristics of the sample ($n = 445$). It can be seen that most of the sample are young people aged 19–30 (81.3%) who are students (75.3%) at university (73.0%) and use search engines with smartphones (91.2%). The percentages of men (41.6%) and women (56.8%), as well as the habitats, were more equally proportioned.

The data collection technique chosen for this study was the survey, which is a quantitative technique. In this case, it allowed us to identify the users' attitudes and behaviour when using sustainable and unsustainable search engines on the Internet. A 15-item questionnaire about attitudes and behaviour and 5 classification questions were used. The classification questions were about gender, age, job, habitat, education level, and the device used for Internet access. The questionnaire was divided into 3 sections.

The first section dealt with the questions for the TAM [32] about Internet search engine technology and the users' feelings, attitudes, and behaviour for the adoption and use of sustainable search engines. This section was composed of 12 questions about PU (3), PEOU (3), ATU (3), and USE (3). The TAM variables were measured using adapted item scales [32].

The second section consisted of a block of questions on different aspects of Trust and sustainable search engines. These questions were grouped into the 3 items in the Trust construct. The behavioural items about sustainable search engines on the Internet were adapted from previous research on Trust, in which the Trust variable refers to how much a user believes in the safety, reliability, efficiency, competence, and validity of a sustainable search engine [5]. The behavioural items for sustainable search engines refer to the moment when a user finds a service to be unreliable and interacts less with the search engine, content, or information.

Table 2: Demographic characteristics of the sample ($n = 445$).

Classification variable		Frequency	Percentage
Gender	Female	253	56.8%
	Male	185	41.6%
	Others	7	1.6%
Age	18–30	362	81.3%
	31–45	49	11.0%
	46–55	27	6.1%
	56–65	6	1.4%
	>65	1	0.2%
Job	Unemployed worker	13	2.9%
	Self-employed worker	24	5.4%
	Contracted worker	58	13.7%
	Student	335	75.3%
	Housewife	8	1.8%
	Retired	4	0.9%
Habitat	Town with more than 100,000 inhabitants	142	31.9%
	From 20,000 to 100,000 habitants	153	34.4%
	Less than 20,000 habitants	149	33.7%
Education level	Basic studies (O-levels)	77	17.3%
	Professional training/A-levels	40	8.7%
	University degree	325	73.0%
Access to Internet from	Smartphone	406	91.2%
	Tablet or iPad	117	26.3%
	Laptop	270	60.7%
	Personal computer	47	10.6%

In the study of the behavioural intention to use a search engine, Trust is defined as the general belief that these searches will be made [37, 38, 42, 44, 45].

There were 20 items in the research questionnaire (see Table 3). All the items, except for the classificatory questions, were measured using a Likert 5-point scale that ranged from total disagreement [61] to total agreement [62].

Overall, 445 questionnaires were collected from the users. Google Forms was used because the questionnaire could be produced online and then distributed on social networks. Nonprobabilistic and convenience sampling was used, and a pilot survey was carried out to check the validity and reliability of the scales. In this way, the questions could be refined and additional comments on the content and structure of the questionnaire were obtained. All the participants in the survey were asked to watch the video that accompanied the questionnaire.

The PLS-SEM method was used for the analysis. This is a statistical analysis technique based on the Structural Equation Model, which is a recommended method for exploratory research as it allows the modelling of latent constructs with indicators [63] to analyse the collected data. PLS is appropriate for the analysis and prediction of relatively new phenomena [64]. For this study, we used the SmartPLS 3 software [65]. The results were handled with the statistical package SPSS 24, which was used to calculate frequency tables, CHAID tree, ANOVA, and sample statistics.

To find the minimum sample size for PLS modelling, Hair et al. [66] recommend using the Cohen tables [67]. These tables were used with the G*Power software package [68] to find the dependent constructs, which are those that have the highest number of predictors. In this case, they were PU, ATU, and USE. The following parameters were used for the calculation: the test power (power = $1 - \beta$ error prob. II) and the size of the effect (f^2). Cohen [69] and Hair et al. [70] recommend a power of 0.80 and an average size of the effect $f^2 = 0.15$. In our case, there were 2 predictors, which were the constructs that have causal relationships with USE (see Figure 1). Therefore, from PLS, the USE construct established the minimum sample size as 107 for a power = 0.95 and critical F = 3.08. Therefore, the sample used is adequate because it is more than four times the recommended minimum for obtaining valid and reliable results with the established parameters.

7. Analysis of Results

7.1. Measurement Model Evaluation. Before the PLS analysis was carried out, the validity and reliability of the measurement model were calculated with the following tests: individual reliability of each item, internal consistency (or reliability) of each scale (or construct), convergent validity, and discriminant validity.

7.1.1. The Individual Reliability of the Items: Construct Loads (λ). In this phase of the investigation, the indicators' loads (λ) were calculated, with the minimum acceptance level for part of the construct $\lambda \geq 0.707$ [71]. Therefore, a value $\lambda \geq 0.707$ indicates that each measurement represents at least 50% ($0.7072 = 0.5$) of the variance of the underlying construct [72]. The indicators that did not reach the minimum level were disregarded [73].

The magnitude and importance of the relationships between latent variables were calculated using the standardized path coefficient. The rule established by Chin [74] states that this value must be at least 0.2 (see Figure 1).

Cronbach's alpha and the composite reliability (CR, composite reliability) were then calculated to find the reliability of each construct. This evaluation measures the consistency of a construct based on its indicators [75], that is, the rigor with which these items are measuring the same latent variable. The lower limit for the acceptance of the construct reliability using Cronbach's alpha is usually between 0.6 and 0.7 [76]. Causality is found from the loads of the indicators and the composite reliability (CR) [77] which must have a minimum level of 0.7 [62, 78, 79].

Table 4 shows the results for all the reliability coefficients. As can be seen, all the coefficients had much higher values than the necessary minimum limits, which confirms the high internal consistency of all the latent variables.

Table 3: Items and scale.

Construct	Items
Attitude toward using (ATU)	(ATU1) My favorite search engine provides access to most data. (ATU2) My favorite search engine is better than previous search engines. (ATU3) My favorite search engine provides accurate information. (ATU4) My favorite search engine provides integrated, up-to-date, and reliable information.
Perceived ease of use (PEOU)	(PEOU1) Interaction with my favorite search engine services is clear and easily understood. (PEOU2) Working with my favorite search engine does not require much mental effort. (PEOU3) My favorite search engine services are easy to use. (PEOU4) I can easily find what I want in my favorite search engine.
Perceived usefulness (PU)	(PU1) Using my favorite search engine allows tasks to be completed more quickly. (PU2) Using my favorite search engine improves work performance. (PU3) Using my favorite search engine increases work productivity. (PU4) Using my favorite search engine improves work effectiveness.
Intention to use (IU)	(IU1) I am going to use my favorite search engine. (IU2) I expect the information provided by my favorite search engine to be useful.
Trust (T)	(T1) My Internet search engine is trustworthy. (T2) My Internet search engine takes its users' ideas into account. (T3) My Internet search engine has good intentions.

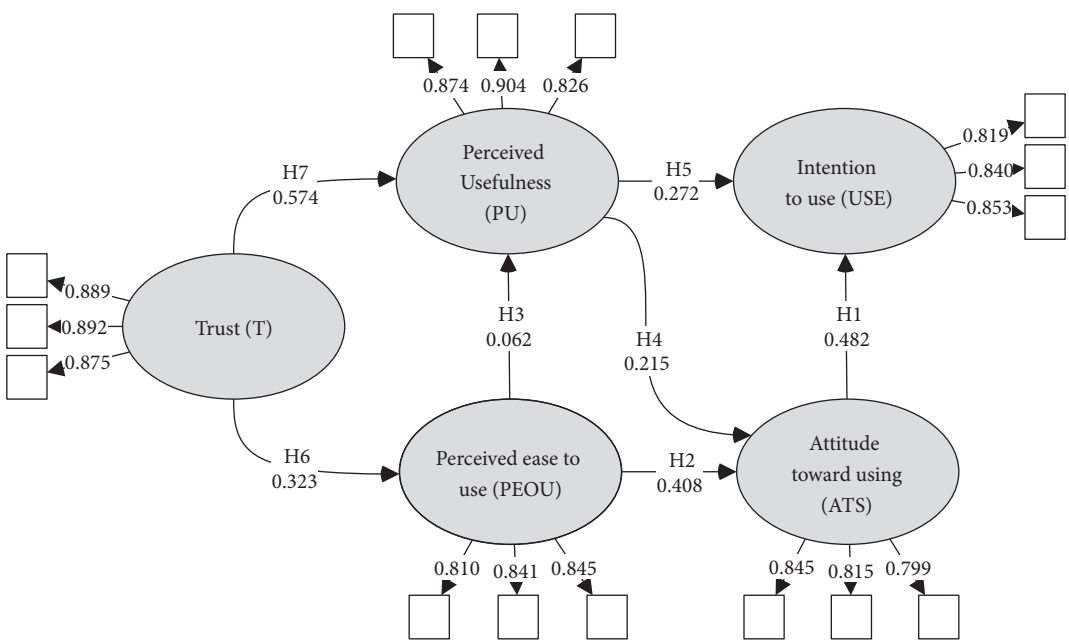

Figure 1: Proposed research model and PLS results.

Table 4: Measurement model.

Reliability of each construct					Fornell & Larcker criterion				
Constructs	Cronbach's alpha	rho_A	CR	AVE	ATS	USE	PEOU	PU	TRUST
ATS	0.756	0.757	0.860	0.672	0.820				
USE	0.830	0.833	0.898	0.746	0.572	0.864			
PEOU	0.703	0.700	0.828	0.616	0.535	0.461	0.785		
PU	0.756	0.756	0.860	0.673	0.383	0.496	0.325	0.820	
TRUST	0.862	0.862	0.916	0.784	0.386	0.423	0.364	0.637	0.885

7.1.2. Discriminant and Convergent Validity. AVE (average variance extracted) is defined as the mean extracted variance and measures how much variance the indicators of a construct have compared to the amount of variance due to the measurement error [80]. The recommendation of these authors is that AVE is ≥0.50. The rho_A coefficient [81] shows that in all constructs it is ≥0.7.

The discriminant validity shows how much one construct is different from another. A high value indicates weak correlations between constructs. For this test, the Fornell & Larcker [80] criterion is used, which verifies if the square root of the average variance extracted (AVE) for a construct is greater than that of the relationship between the construct and the rest of the model's constructs. This condition was met as can be seen on the right side of Table 2.

Table 5 shows the results that were obtained, where it can be seen that all the HTMT relationships for each pair of factors are <0.90 [82, 83]. The fulfilment of all these criteria and measurements means that the validity and reliability of the model are confirmed.

7.2. Assessment of the Structural Model. The following analyses were used to study the structural model, the explained variance of the endogenous constructs (R^2), the predictive capacity Q^2, the path coefficients (β), and the selection of critical values for the distribution of Student's t-value [84].

Henseler et al. [72] consider the explanatory power of R^2 values of 0.67, 0.33, and 0.19 to be substantial, moderate, and weak, respectively. In Table 4, we can see that PU ($R^2 = 0.416$), ATS ($R^2 = 0.335$), and USE ($R^2 = 0.417$) have a moderate explanatory power, while PEOU has a weak explanatory power ($R^2 = 0.133$).

7.3. Model and Hypothesis Testing. The model was then analysed using the bootstrapping technique. Using this technique, the standard deviation of the parameters and the Student t-values are found. From these, the simple regression coefficients for the components are calculated, and the results for the relationships between the latent variables of the hypotheses are found.

At this stage, the hypotheses were tested to see if the relationships established in the proposed model were confirmed [84]. Firstly, all the relationships between constructs had a significant impact on the behavioural intention to use the search engine (see Table 6). Therefore, the proposed TAM was supported together with the external Trust variable. All the hypotheses were supported with a 99.9% confidence level, except H3. The relationship between PEOU → PU was the least significant with a 95% confidence level ($\beta = 0.107$, $t = 2.628$).

The relationships that stood out most strongly were, in order, H7: TRUST → PU ($\beta = 0.598$; $t = 14.622$) and H2: PEOU → ATS ($\beta = 0.459$; $t = 10.675$).

7.4. Results for FIMIX-PLS: Study of Unobserved Heterogeneity. FIMIX-PLS calculates the probability of belonging to any given segment in which each observation is adjusted to the predetermined number of segments by estimating separate linear regression functions, which gives a group of possible segments. Each case is assigned to the segment with the greatest probability.

Table 5: HTMT and explanatory and predictive capacity of the model.

Constructs	ATS	USE	PEOU	PU	R^2 (with effect level)	Q^2
ATS					0.335 (moderate)	0.211
USE	0.716				0.417 (moderate)	0.293
PEOU	0.574	0.528			0.133 (weak)	0.070
PU	0.393	0.509	0.292		0.416 (moderate)	0.266
TRUST	0.479	0.570	0.378	0.692	—	—

Table 6: Statistical hypothesis test.

Hypotheses	Path	β path coefficients (t-values)	p value	Supported
H1	ATS USE	0.448 (8.877)***	0.001	Yes
H2	PEOU ATS	0.459 (10.675)***	0.001	Yes
H3	PEOU PU	0.107 (2.180)*	0.029	Yes
H4	PU ATS	0.234 (5.395)***	0.001	Yes
H5	PU USE	0.324 (6.851)***	0.001	Yes
H6	TRUST PEOU	0.364 (8.704)***	0.001	Yes
H7	TRUST PU	0.598 (14.622)***	0.001	Yes

Note: Bootstrapping with 5000 samples based on the Student t-distribution (499) in single queue: $^{*}p < 0.05$ ($t(0.05; 499) = 1.64791345$); $^{**}p < 0.01$ ($t(0.01; 499) = 2.333843952$); $^{***}p < 0.001$ ($t(0.001; 499) = 3.106644601$).

The test is done in four stages: firstly, the number of optimal segments is calculated with FIMIX. Then, the latent variables that justify these segments are found, in order to finally estimate the model and its segments.

FIMIX was used to divide the sample into different segments. The first problem encountered was the selection of the appropriate number of segments. It is typical to repeat the FIMIX-PLS procedure with consecutive numbers of latent classes. In our case, given the sample size $n = 445$, we calculated for $k = 5$, $k = 4$, $k = 3$, and $k = 2$. The results obtained were compared using different information criteria provided by the FIT indices. The following were compared, Akaike (AIC), the controlled AIC (CAIC), the Bayesian information criterion (BIC), and the standardized entropy statistic (EN). The results obtained for the FIT indices are shown in Table 7.

Firstly, the FIMIX test was used to find the number of segments into which the sample can be divided. The algorithm was configured for the size of the sample so that PLS-SEM could be applied with 10 repetitions. This configuration was done using the expectation maximization algorithm (EM). The EM algorithm alternates between performing an expectation step (E) and a maximization step (M) [47]. Step E evaluates and uses the current estimation of the parameters. Step M calculates the parameters maximizing the logarithmic registration probability found in step E. Steps E and M are applied successively until the results are

Table 7: Indices FIT. Criteria for model choice.

FIT indices	$k = 2$	$k = 3$	$k = 4$	$k = 5$
AIC (Akaike information criterion)	3984.504	3891.831	3689.352	3683.153
AIC3 (AIC modified with factor 3)	4007.504	3926.831	**3736.352**	3742.153
AIC4 (AIC modified with factor 4)	4030.504	3961.831	**3783.352**	3801.153
BIC (Bayesian information criterion)	4078.760	4035.264	**3881.961**	3924.940
CAIC (AIC controlled)	4101.760	4070.264	**3928.961**	3983.940
LnL (LogLikelihood)	−1969.252	−1910.916	−1797.676	−1782.577
MDL5 (minimum description length with factor 5)	**4639.783**	4888.994	5028.399	5364.085
EN (standardized entropy statistics)	**0.998**	0.819	0.787	0.766

stabilized. Stabilization is achieved when there is no substantial improvement in the values obtained.

Table 7 shows the results after running FIMIX with different numbers of k partitions. Since the number of segments was unknown a priori, the different segment numbers were compared in terms of suitability and statistical interpretation [85, 86].

A purely data-based approach was taken, which only provided an approximate guide to the number of segments that should be selected. Heuristics, such as the information criteria and the EN, are fallible because they are sensitive to the data and the characteristics of the model [47].

The different criteria obtained were then evaluated. Sarstedt et al. [51] evaluated the effectiveness of different information criteria in FIMIX-PLS for a wide range of data constellations and models. Their results showed that researchers should consider AIC 3 and CAIC. As long as these two criteria indicate the same number of segments, the results probably point to the appropriate number of segments. In Table 6, it can be seen that in our analysis these results do not point to the same number of segments. Therefore, AIC was used with factor 4 (AIC 4, [87]) and BIC. These indices usually work well and, in our case (see Table 6), they indicated the same number of segments, which was $k = 4$. Other criteria showed this as a pronounced overestimation, although MDL5 indicated the minimum number of segments $k + 1$, which in this case would indicate 3 [47].

Measurements of entropy, such as the standardized entropy statistic (EN), were also considered [88]. EN uses the probability that an observation belongs to a segment to indicate whether the partition is reliable or not. The higher the probability of belonging to a segment is for a measurement, the clearer segment affiliation is. The EN index oscillates between 0 and 1. The highest values indicate a better quality partition. Previous research provided evidence that EN values above 0.50 allow a clear classification of the data into the predetermined number of segments [89, 90]. In Table 6, it can be seen that all the partitions have values of EN > 0.50, although the highest value is reached in $k = 2$ with EN = 0.998; for $k = 3$ EN = 0.819, and EN = 0.717 for $k = 4$.

Therefore, from the proposed solutions, the number of optimal segments was between $k = 3$ and $k = 4$. $k = 3$ was taken as the number of segments indicated by FIMIX-PLS, given that the smallest size of the partitions in this case was 12.1%.

Table 8: Relative segment sizes.

k	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
2	0.637	0.363			
3	**0.582**	**0.296**	**0.121**		
4	0.561	0.285	0.105	0.049	
5	0.374	0.286	0.202	0.089	0.049

As can be seen in Table 8, for the $k = 3$ solution and a sample $n = 445$, the partitioning of the segments was 58.2% (259), 29.6% (131), and 12.1% [91, 92]. The segment sizes are not small despite the percentages. Therefore, the sample sizes are sufficient to use PLS. The sample size can be considerably smaller in PLS than in SEM due to covariance [47]. There can even be more variables than observations, and there may be a small amount of data that is completely missing [46, 93]. Different authors have shown that in PLS the sample can be very small [94] and that the minimum can even be 20 [64].

The segmentation structure of the obtained data is prepared in the third step of FIMIX. To do this, an ex post analysis was performed [50], which means, firstly, assigning each observation to a segment from the highest result for the probability of belonging to that segment. Secondly, the data are divided by means of an explanatory variable or a combination of several explanatory variables, resulting in data grouping that corresponds to that produced by FIMIX-PLS.

A post hoc analysis was carried out to determine the explanatory variables that justify this segmentation. Using the recommendations of several authors, CHAID decision or classification and regression trees were used to do this [48, 95].

A CHAID decision tree [96] is a graphical and analytical way of representing all the events that may arise from a decision. These trees allow the examination of the results and visually determine how the model flows. The visual results help to find specific subgroups and relationships that might not be found with more traditional statistics [97]. In this investigation, this method was used to make the "best" decision from a probabilistic point of view on a range of possible decisions. As seen in Figure 2, the obtained results show that the HABITAT variable is sufficiently explanatory for the choice of 4 segments.

Another technique that could be used in the post hoc analysis was to compare the classificatory explanatory

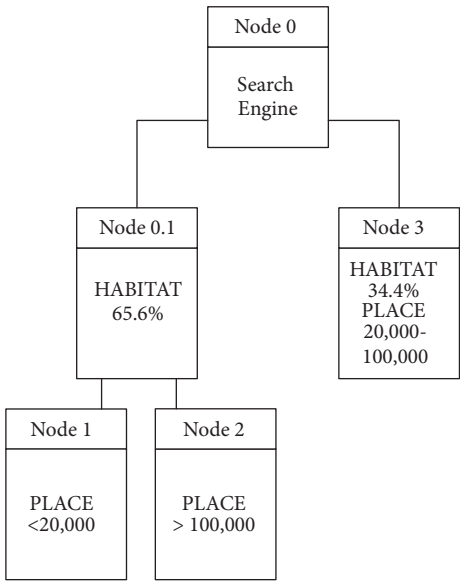

Figure 2: CHAID decision tree.

variables using the Analysis of Variance (ANOVA) for a factor applied to the segment assigned to each observation.

In this way, the CHAID tree was constructed, and the characteristics of the segments were found using FIMIX-PLS. The results obtained for the Analysis of Variance (ANOVA) defined the category variables with explanatory capacity. Table 9 shows that not only the HABITAT variable has explanatory capacity but also AGE and FAVORITE SEARCH ENGINE.

In a more detailed analysis in Table 10, AGE was not found to be significant when studying the differences of means for the 3 segments. However, HABITAT and FAVORITE SEARCH ENGINE were significant.

Table 10 indicates the differences in segments 1 and 2 between towns of <20,000 inhabitants, from 20,000 to 100,000 inhabitants, and >100,000 inhabitants. There are significant differences between Google and https://www.ecosia.org/ search engines in these same segments.

The last step of the FIMIX analysis was to estimate segment-specific models. Once the HABITAT and FAVORITE SEARCH ENGINE variables were found to be the main explanatory variables that justify the FIMIX-PLS partitions, only the final step remained. In this step, the specific models for the indicated segments were found.

In order to do this, a multigroup analysis was carried out for HABITAT, as the results of the CHAID decision tree suggested. The 3 groups corresponding to living in a place <20,000 inhabitants, 20,000–100,000 inhabitants, and > 100,000 inhabitants were used. An analysis of variance found significant differences for HABITAT between segments 1 and 2 and also for the FAVORITE SEARCH ENGINE: Google or Ecosia. After applying bootstrapping again, the results in Table 11 were found.

These analyses complete the basic steps of the FIMIX-PLS method. However, other research suggests testing whether the numerical differences between the specific path coefficients of the segment are also significantly different

Table 9: ANOVA results.

ANOVA	F	Sig.
What is your genre?	1.091	0.337
Where is your current house?	3.858	0.022
What is your current situation?	1.558	0.212
What is your education level?	1.649	0.193
How old are you?	3.211	0.041
What is your favorite search engine?	5.415	0.005

using multigroup analysis. Document research found several approaches for multigroup analysis, which Sarstedt et al. [98] and Hair et al. [47] discuss in more detail. Hair et al. [47] recommend using the permutation approach (Chin & Dibbern, 2010; Dibbern & Chin, 2005), which has also been implemented in the SmartPLS 3 software.

However, before interpreting the results of a multigroup analysis, the researchers must make sure that the measurement models are invariable in all the groups. Once the measurement invariance (MICOM) described by Henseler et al. [99] had been checked, an analysis was carried out to find if there were any significant differences between the segments using multigroup analysis (MGA). The results can be seen in the three columns on the right of Table 12.

As can be verified from the results obtained by the nonparametric testing, the multigroup PLS-MGA analysis confirmed the parametric tests and also found significant differences between segments 2 and 3.

There are differences between the first and second segments but only $k = 2$ and $k = 3$ in H1 ATS → USE ($\beta = 0.642^{***}$) and $k = 1$ and $k = 3$ in H1 ($\beta = 0.521^{***}$) and H7 ($\beta = 0.316^{***}$) show a significant difference.

The validity of the segment measurement model and its explanatory capacity using R^2 is shown in Table 11 with the main results classified by segment. It can be seen that $k = 2$ has values for CR and AVE below the limits ($k = 2$, CR PU = 0.293, AVE PU = 0.497). The explanatory capacity of each segment (R^2) was shown to improve in the general model in all the partitions with the main dependent variable USE.

7.4.1. Assessment of the Predictive Validity. PLS can be used for both explanatory and predictive research as it can predict both existing and future observations [100] Predictive validity indicates that a given set of measurements for any construct can predict a dependent construct [101], as is, in our case, intention to use (IU).

Predictive validity (prediction outside the sample) was evaluated by cross-validation with retained samples. The approach suggested by Shmueli et al. (2016) was used in this investigation.

Using the research by other authors [102, 103], the current PLS Predict algorithm in the SmartPLS software version 3.2.7 was used [65]. This software gave results for the k-fold cross prediction errors and the summaries of prediction errors, such as the root mean square error (RMSE) and the mean absolute error (MAE). The predictive performance

Table 10: ANOVA differences of means for segments.

Dependent variable	(*I*) segment	(*J*) segment	Differences of means (*I* − *J*)	Sig.
Where is your current house?	**1**	**2**	−0.246*	**0.016**
		3	−0.082	0.830
	2	**1**	0.246*	**0.016**
		3	0.164	0.527
	3	1	0.082	0.830
		2	−0.164	0.527
How old are you?	1	2	0.160	0.068
		3	−0.090	0.709
	2	1	−0.160	0.068
		3	−0.250	0.107
	3	1	0.090	0.709
		2	0.250	0.107
What is your favorite search engine?	**1**	**2**	−2.511*	**0.005**
		3	0.447	0.934
	2	**1**	2.511*	**0.005**
		3	2.957	0.079
	3	1	−0.447	0.934
		2	−2.957	0.079

Table 11: Disaggregate results for direct effects between latent variables.

Hypotheses	Global model	FIMIX segmentation					
		$k = 1$ $n = 292$	$k = 2$ $n = 116$	$k = 3$ $n = 37$	MGAk1 vs k2	MGAk1 vs k3	MGAk2 vs k3
ATS ➔ USE	0.448***	0.516**	0.637***	0.005 n.s.	0.121 n.s.	0.521***	0.642***
PEOU ➔ ATS	0.459***	0.501***	0.166 n.s.	0.597***	0.335**	0.096 n.s.	0.431 n.s.
PEOU ➔ PU	0.107*	0.089*	0.008 n.s.	0.068 n.s.	0.097 n.s.	0.157 n.s.	0.060 n.s.
PU ➔ ATS	0.234***	0.294***	0.340*	0.115 n.s.	0.634*	0.178 n.s.	0.455 n.s.
PU ➔ USE	0.324***	0.309***	0.196*	0.690***	0.505**	0.382 n.s.	0.887 n.s.
TRUST ➔ PEOU	0.364***	0.393***	0.408***	0.336 n.s.	0.015 n.s.	0.057 n.s.	0.071 n.s.
TRUST ➔ PU	0.598***	0.834***	0.300*	0.518**	1.134***	0.316*** n.s.	0.818 n.s.

Note: n.s. (not supported); $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 12: Reliability measurements for the general model and for the three segments.

	Global model			$k = 1$ (58.2%)			$k = 2$ (29.6%)			$k = 3$ (12.1%)		
	CR	AVE	R^2	CR	AVE	R^2	CR	AVE	R^2	CR	AVE	R^2
ATS	0.860	0.672	0.335	0.849	0.651	0.456	0.861	0.674	0.158	0.858	0.679	0.385
USE	0.898	0.746	0.417	0.878	0.705	0.519	0.828	0.618	0.535	0.919	0.791	0.475
PEOU	0.828	0.616	0.133	0.837	0.632	0.151	0.766	0.525	0.166	0.812	0.592	0.113
PU	0.860	0.673	0.413	0.912	0.776	—	0.293	0.497	0.092	0.828	0.616	0.249
TRUST	0.916	0.784	—	0.933	0.824	0.761	0.878	0.708	—	0.885	0.721	—

of the PLS route model for indicators and constructs could then be evaluated. The following benchmarks given by the SmartPLS team were used to evaluate the predictive performance of the model [102–104]:

(1) The Q^2 value in PLS predict: the prediction errors of the PLS model were compared with the simple mean predictions. If the value of Q^2 is positive, the prediction error of the PLS-SEM results is less

than the prediction error of simply using the mean values. Consequently, the PLS-SEM model offered appropriate predictive performance. This is the case here in the two subsamples of segments 1 and 3 (see Table 13) in the dependent construct IU (Table 14). This indicates that we obtained good prediction results

(2) The linear regression model (LM) approach: a regression of all the exogenous indicators in each endogenous indicator was made. When this comparison is made, an estimate is obtained of where better prediction errors could be obtained. This is shown when the value of RMSE and MAE are lower than those of the LM model. If this is found, predictions can be made. This technique can only be applied for indicators. As can be seen in Table 14, the values of RMSE and MAE were mostly negative, which indicated good predictive power

Following Felipe et al. [102], the predictions within the sample and outside the sample were compared to the real composite scores. In order to do this, the research by [105] was used:

Using this procedure, the following metrics were found for the IU construct: RMSE for the complete sample (see Table 8) was 0.374 and had a higher value in segment 1 (0.485, difference = 0.111) and lower values in segment 2 (0.205, difference = −0.169) and segment 3 (0.337, difference = −0.037). As the composite values are normalized and have a mean of 0 and variance 1, RMSE can be considered as a measure of standard deviation. The difference between RMSE within the sample and outside the sample had a maximum of 0.205, which is less than 25% of standard deviation [102]. Since the difference in RMSE is not substantial, excess capacity is not a problem for this study.

The density diagrams of the residues within the sample and outside the sample are provided in Figure 3.

As a result of the different analyses, this research found sufficient evidence to support the predictive validity (out-of-sample prediction) of our research model, in order to predict values for new cases of IU. Therefore, the model can predict the intention to use in additional samples that are different from the data set which was used to test the theoretical research model [106].

The predictive validity gives additional support for the research model tested in this paper.

7.5. Considerations for the Management of Internet Search Engines (IPMA). In line with research that studied data heterogeneity [59], the IPMA-PLS technique was used to find more precise recommendations for the marketing of search engines on the Internet. IPMA is a grid analysis using matrices that allows combining the total effects of the PLS-SEM estimation "importance" with the average value score for "performance" [59, 107]. The results are presented in an importance-performance graph of four fields. In this way, marketing actions can be prioritized by taking into account the average lines of importance and performance for each latent construct [108].

Table 13: Summary of dependent variable prediction.

Construct IU	RMSE	MAE	Q^2
Complete sample	0.374	0.286	−0.101
Segment 1	0.485	0.376	0.131
Segment 2	0.205	0.161	−0.311
Segment 3	0.337	0.235	0.291

The results for the different types of search engine users on the Internet are displayed in Figure 4. As proposed by other authors with different applications, four different recommendations can be made for more efficient search engine marketing actions on the Internet ([109] [59, 110, 111]).

For Groß [59], the interpretation of the four quadrants into which the graph is divided is as follows:

Quadrant I shows attributes of acceptance that are highly valued for performance and importance, competitive stress, and factors which gain or maintain the acceptance of search engines on the Internet at a high level. Therefore, companies that are developing search engines should take these attributes into account.

Quadrant II shows acceptance attributes of great importance but low performance, which need to be improved. In this case, Internet search engine developers should focus on these factors first.

Quadrant III shows acceptance attributes that are low in importance and performance. Due to their low priority, it is not advisable to focus the efforts of additional improvements in search engines on these attributes, as long as the strength of their influence does not change.

Quadrant IV shows acceptance attributes with little objective importance but a high performance index. This possible excess of positive acceptance of search engines must be taken into account so that resources and efforts can be assigned to other attributes that are not in this quadrant.

The results obtained give unequal results for each segment. For users belonging to $k = 1$, all constructs are important and offer reasonable performance and show lower importance and performance of PU but with similar results to those obtained for Trust and to a lesser extent to PEOU, which is more important.

Therefore, the individual results for the types of Internet search engine users can be interpreted in four different recommendations for carrying out more efficient marketing actions for search engines on the Internet.

For users belonging to $k = 2$, the results are the same for ATS but with slightly less performance in PEOU and TRUST. These show a very low PU performance, so developers should focus on marketing campaigns that show the enormous utility of the product in daily life, without highlighting the importance but rather the results that can be achieved with product use.

Finally, the results obtained for $k = 3$ show a different situation. These users valued importance >40 and <70, stating that PU is the least valued and obtained a score of 0.85. Therefore, in this segment, improvements should be made

Table 14: PLS predict assessment.

Items	PLS			LM			PLS-LM		
	RMSE	MAE	Q^2	RMSE	MAE	Q^2	RMSE	MAE	Q^2
Complete sample model									
IU1	0.877	0.665	0.114	0.88	0.665	0.107	−0.003	0	0.007
IU2	0.933	0.745	0.158	0.934	0.742	0.156	−0.001	0.003	0.002
IU3	0.861	0.661	0.107	0.863	0.659	0.102	−0.002	0.002	0.005
Segment 1									
IU1	0.68	0.534	0.178	0.682	0.535	0.173	−0.002	−0.001	0.005
IU2	0.772	0.625	0.264	0.777	0.621	0.255	−0.005	0.004	0.009
IU3	0.659	0.534	0.135	0.665	0.546	0.118	−0.006	−0.012	0.017
Segment 2									
IU1	0.857	0.688	0.031	0.886	0.682	−0.036	−0.029	0.006	0.067
IU2	0.908	0.724	0.025	0.936	0.745	−0.036	−0.028	−0.021	0.061
IU3	0.821	0.674	0.047	0.823	0.657	0.041	−0.002	0.017	0.006
Segment 3									
IU1	1.355	1.108	0.117	1.501	1.178	−0.083	−0.146	−0.07	0.2
IU2	1.201	0.952	0.193	1.146	0.928	0.265	0.055	0.024	−0.072
IU3	1.301	1.066	0.137	1.352	1.098	0.068	−0.051	−0.032	0.069

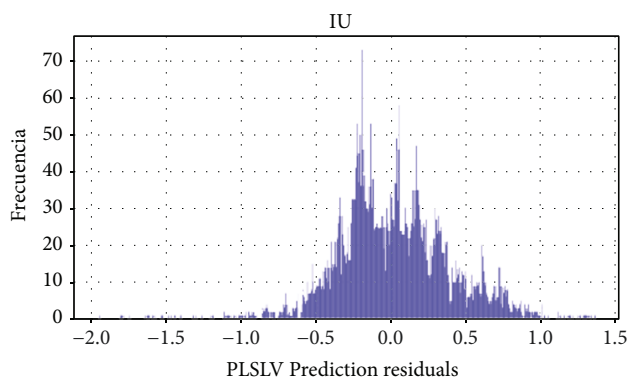

Figure 3: Residue density within the sample and outside the sample.

in the performance of PEOU and ATS, improving the users' perception of search engines. Most marketing actions should be taken in this segment, emphasising the ease of use, and working on actions that improve attitudes to Internet search engines.

8. Discussion

Firstly, a discussion is made of the results of an extended theoretical TAM with the external variable Trust, which analyses the intention to use socially and environmentally responsible search engines. The PLS method was used to analyse the measurement models and test the hypothesis. The results showed that the scales used were valid and reliable in all models. The result also indicated that all the variables were supported and even Trust influenced PU and PEOU. Other authors also confirmed this statement [37, 42, 44].

The FIMIX-PLS analysis divided the sample into three groups. The analysis of the FIT indices, the size of the segments, and the values of R^2 recommended segmentation into three sample groups. The multigroup analysis found significant differences for the relationships in different groups.

The post hoc analysis was made using a decision or classification CHAID tree [96] which resulted in the best classification variables for the sample groups. The results indicated that the HABITAT variable was the best variable for group classification. This meant that the three segments should be made with the size of the locality where the users of the search engines live. That is, users living in places with <20,000 inhabitants, between 20,000–100,000 inhabitants, and >100,000 inhabitants. FAVORITE SEARCH ENGINE (Google vs. https://www.ecosia.org/) is an additional classification variable.

The result of the bootstrapping analysis showed that some relationships were not valid in some of the segments, even though they were valid for the complete sample. All the hypotheses were supported in the largest segment (58.2%), which means that this group had the standard Google search engine user profile.

Google is a world leader in the search engine market, leading the ranking in all countries except China. In Spain, it has 95.79% of the market share, followed by Bing (2.61%) and Yahoo (1.34%) according to data from May 2018 [112]. Therefore, this segment represents the majority of users in Spain where it is the favorite search engine. It is clear that computers are not the only devices on which search engines are used, and many searches are also made with mobile devices. Taking into account that in Spain Android has 90% of the market share and that the search engine comes preinstalled in Google's mobile operating system, it is not surprising that the Google search engine usage statistics are so favorable.

However, this majority behaviour was not evident in the second segment (29.6%), where PEOU did not have significant relationships with PU and ATS. Of these two

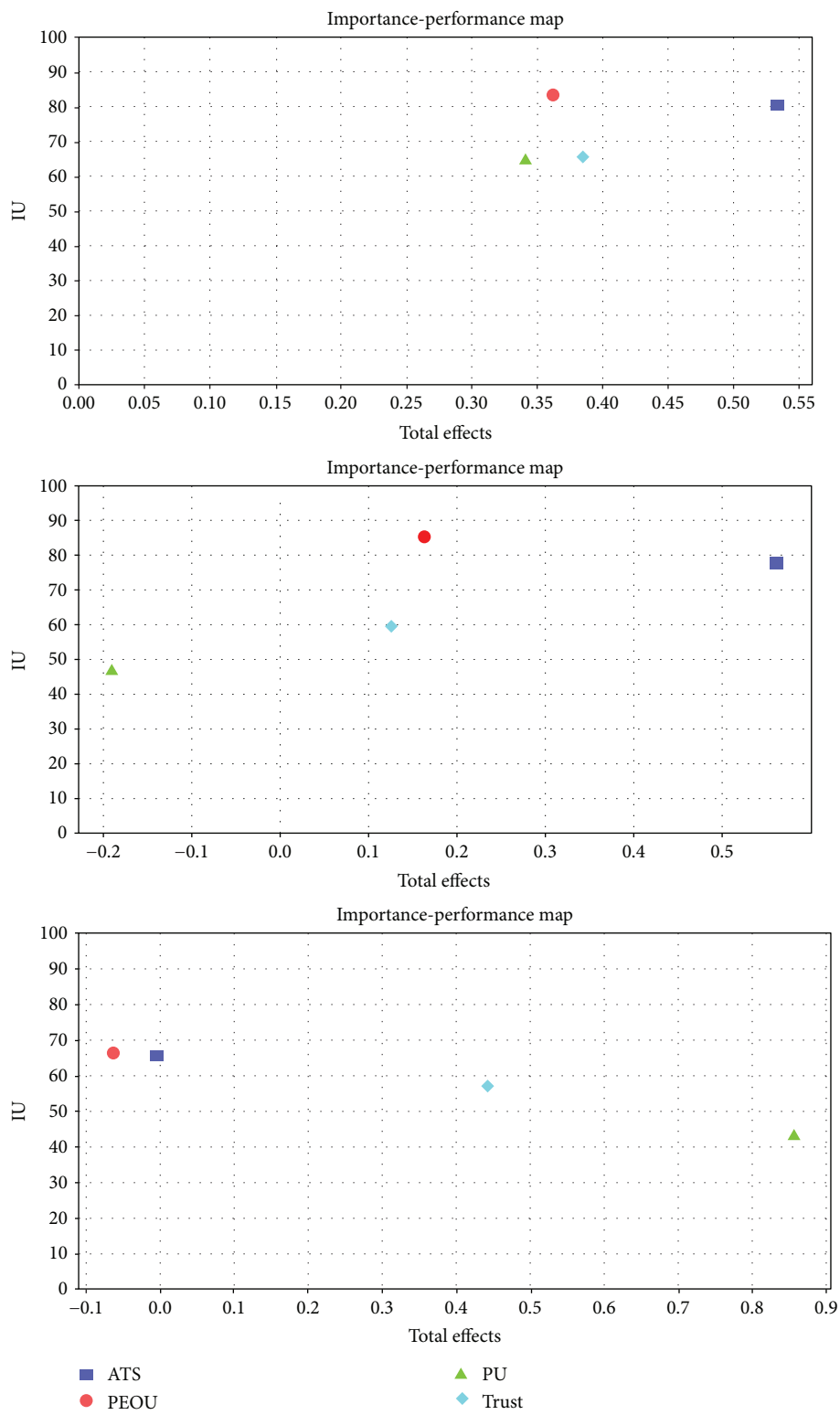

Figure 4: Importance-performance maps for $k = 1$, $k = 2$, and $k = 3$.

relationships, the multigroup analysis showed significant differences (confidence level = 99.9%) in PEOU → ATS in the first two segments. Therefore, it seems that the users in the second segment do not take into consideration that the search engines are easy to use, and this fact does not influence their attitude towards them.

Similarly, segment 2 showed a decrease in the path coefficients and the significance of the relationships. As

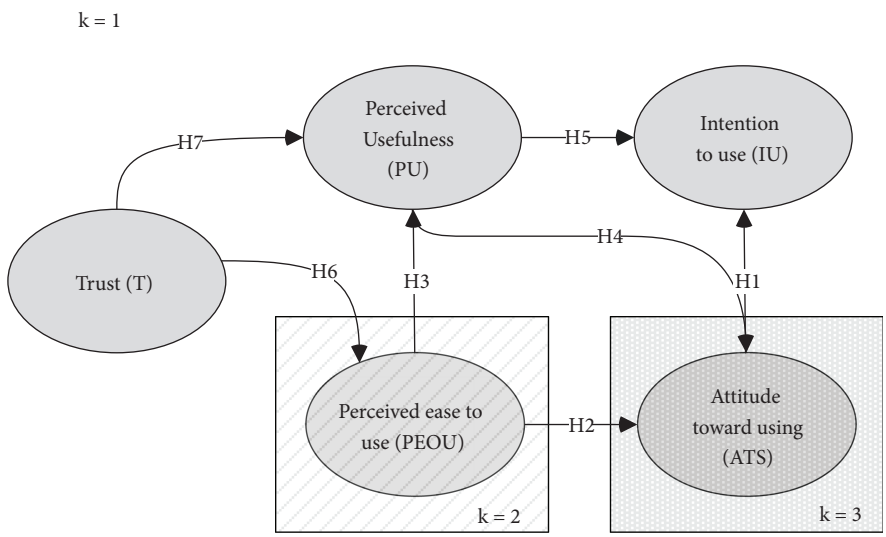

Figure 5: Segmentation results.

can be seen in Figure 5, the relationships that changed in this segment were PU → ATS and TRUST → PU. Other relationships increased, such as TRUST → PEOU and ATS → USE. These users are the ones for whom learning how to use the search engine is not a problem and who do not take into account its ease of use. The decision to use a search engine is taken based on the perceptions of its utility and the confidence generated. This user could therefore be a potential user of socially and environmentally sustainable search engines.

For segment 3 (12.1%), it can be seen that the four hypotheses were not confirmed (ATS → USE, PEOU → PU, PU → ATS, TRUST → PEOU), so users in this segment prefer simple search engines and only consider their usefulness. However, PU is not influenced by PEOU, which means that useful search engines are only influenced by trust. This type of user prefers alternative search engines that contribute socially and environmentally and that have additional search engine utilities, such as being sustainable. This group, therefore, consists of possible users of sustainable search engine.

The explanatory capacity of the segments was higher in the three analysed partitions (moderate) than in the general model, with segment 2 having a moderately higher value.

8.1. Segmentation Using Habitat and Favorite Search Engine. Like other recent studies [60], this study found that segmentation using PLS is a valid and adequate technique for studying unobserved heterogeneity and can help to improve understanding of marketing in complex systems. In our case, the place where the user lives (Habitat) and the user's favorite search engine (Favorite Search Engine) provided the sample segmentation and also moderate the relationships in the accepted model.

Existing scientific literature recognizes the importance of the moderating effects in relationships and most studies consider this influence in classic TAM [32], TRA (Theory of Reasoned Action) [61], UTAUT (Unified Theory of Acceptance and Use of Technology) [113], and in derived adaptations.

However, literature that uses Habitat as a segmentation variable or that moderates technology adoption is quite scarce. Recent studies confirm that adoption of Internet standards are moderated by national culture [114], and therefore, the place where one lives conditions perception of the Internet.

Some authors [5] point out that the second proposed segmentation variable, favorite search engine preference, conditions the relationships in the adoption model.

In contrast with other studies into the influence of habitat, a priori variables were not used. This study used unobserved segmentation to divide the sample into groups so that the heterogeneity could be found and homogenous groups created in the population. Later, CHAID analysis showed that the habitat variable was the best predictive variable for segmentation of the available information. Later, the unobserved heterogeneity was used as observed heterogeneity for a later analysis with ANOVA.

These results show that the habitat variable has a moderating effect on the intention to use certain search engines. In the group analysis, the MGA test found differences in the PEOU → ATS relationship in the k1 and k2 segments. At the same time, the ATS → USE relationship was not supported in the third segment, and significant differences were detected with respect to k1 and k2. The rest of the differences are in the intensity of the relationship. In the first segment, Trust → PU has greater significance than in the second segment, which implies that the search engine effectiveness is more important than other aspects. This confirms that segment 2 contains potential users of sustainable search engines.

9. Conclusion

9.1. Implications for Business Management. In the current market, technology companies have to deal with complex problems. Two of the most important are the increasing variety of products and the changes in consumer demands. These have forced market research to stop recommending

undifferentiated marketing strategies and to adopt processes using segmentation based on causal relationships.

The use of technological products which are designed to be environmentally friendly and therefore sustainable from a social point of view is a recent area of interest in the IT sector. There is still little research in this area, and only a few companies consider the results of these attributes for their products. However, users are increasingly interested in these attributes. This research studied Internet search engines, where there are still only a few which are socially and environmentally sustainable. In order for a search engine to work all over the world, many computer resources that consume electricity are needed. Search engine use generates high temperatures that are mitigated with air conditioned rooms, and these also consume electricity. In fact, Google states that each query which is made requires around 1 kJ or 0.0003 kWh of energy [10]. A small part of this energy is generated by renewable energies, 16.5% in the case of Spain (Eurostat, 2016). This means that the company must compensate for all the pollution generated by the production of energy for the servers, network devices, and storage units needed for search engines to work, by improving the search engine sustainability and environmental awareness. This study found the best relationship model for the variables that condition the users' preference and acceptance of search engines as well as the profile of sustainable search engine users.

This research makes two important contributions to the scientific literature. The first contribution is methodological, with the use of nonparametric heterogeneous unobserved segmentation as a technique that helps to understand complex systems. As was seen in the literature review, this methodology has been used by authors for business, marketing, and management, but it has not been applied to technological products in the IT sector. Consequently, the behaviour of different Internet search engine user groups was explored, with special consideration given to environmental sustainability attributes.

All the constructs of the proposed hypotheses in the general model were accepted. Trust was an important consideration in the acceptance of search engines on the Internet [5, 37, 38, 42, 44, 45], as it indirectly influences PU and PEOU.

The following actions were proposed after studying the segmentation variables and user behaviour in each group. Users in towns with less than 20,000 inhabitants showed a utilitarian behaviour, so strategies aimed at increasing performance, productivity, and efficiency are suggested along with highlighting the advantages of using the search engine.

For users belonging to the second segment, the results are the same for ATS but with slightly less importance of PEOU and TRUST. These users give importance to PU, so the search engine companies should have marketing campaigns that show the enormous utility of their product in daily life, and the results that can be achieved by using it.

Finally, the results obtained for the users in the third segment reflect a different scenario. These users state that PU is the least important variable for them. Therefore, in this case, PEOU and ATS should be considered by improving the users' perception of the search engine. The most important marketing actions should be taken in this area, promoting the attributes of ease of use and actions that improve the users' attitude towards using Internet search engines. Sustainability and respect for the environment are important aspects which should be included in marketing actions.

9.2. Limitations and Future Lines of Research. The research that was carried out has limitations because it is an exploratory study in the very recent area of research into sustainable IT products. In the future, larger population sizes should be used to compare and contrast the results found in this study. Also, marketing is a complex system where cause and effect can only be seen in retrospect. The complexity of these systems must be understood and strategies developed to face these challenges. Another important point is that the speed of innovation development is often not the same as that of market research. In addition, users were still not very familiar with the use of these applications and needed to watch a video and interact with the sustainable search engine to see how it worked, but perhaps, more time should be spent on this for a complete understanding of the application and its wider ranging effects.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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