symmetry

MDPI

Article

Understanding User Behavioral Intention to Adopt a Search Engine that Promotes Sustainable Water Management

Ana Reyes-Menendez [1], Jose Ramon Saura [1], Pedro R. Palos-Sanchez [2,3,*] and Jose Alvarez-Garcia [4]

[1] Department of Business Economics, Faculty of Social Sciences and Law, Rey Juan Carlos University, Paseo Artilleros s/n, 28032 Madrid, Spain; ana.reyes@urjc.es (A.R.-M.); joseramon.saura@urjc.es (J.R.S.)
[2] Department of Business Administration and Marketing, University of Sevilla, Av. de Ramón y Cajal, 1, 41018 Sevilla, Spain
[3] Department of Business Organization, Marketing and Market Research, International University of La Rioja, Av. de la Paz, 137, 26006 Logroño, Spain
[4] Department of Financial Economy and Accounting, Faculty of Business, Finance and Tourism, University of Extremadura, 10071 Cáceres, Spain; pepealvarez@unex.es
* Correspondence: ppalos@us.es; Tel.: +34-954-55-75-15

Received: 18 September 2018; Accepted: 22 October 2018; Published: 2 November 2018

check for updates

Abstract: An increase in users' online searches, the social concern for an efficient management of resources such as water, and the appearance of more and more digital platforms for sustainable purposes to conduct online searches lead us to reflect more on the users' behavioral intention with respect to search engines that support sustainable projects like water management projects. Another issue to consider is the factors that determine the adoption of such search engines. In the present study, we aim to identify the factors that determine the intention to adopt a search engine, such as Lilo, that favors sustainable water management. To this end, a model based on the Theory of Planned Behavior (TPB) is proposed. The methodology used is the Structural Equation Modeling (SEM) analysis with the Analysis of Moment Structures (AMOS). The results demonstrate that individuals who intend to use a search engine are influenced by hedonic motivations, which drive their feeling of contentment with the search. Similarly, the success of search engines is found to be closely related to the ability a search engine grants to its users to generate a social or environmental impact, rather than users' trust in what they do or in their results. However, according to our results, habit is also an important factor that has both a direct and an indirect impact on users' behavioral intention to adopt different search engines.

Keywords: internet; water; behavioral intention; TPB; social search engines; sustainable water management

1. Introduction

In recent years, the amount of information available on the Internet has dramatically increased [1]. The number of people who have access to the Internet has also grown, reaching 3.8 billion active users worldwide. Considering that online multimedia information is available in the form of images, text, video or audio [2], a classification system is necessary to be able to show this information to users according to the searches they perform. To this end, search engines have been created that show a series of Internet results that are indexed and that contain relevant information related to a search [3].

Several studies have studied the criteria followed by search engines to show the information and its optimization (e.g., [4]). Of all search engines that exist today, the one with the highest number of searches in the world continues to be Google, which accounts for 78.78% of the total number of searches [3].

Google is an information search engine that supports users' online searches. However, even though its main function is to support users in finding needed information, when a query is made in Google about the total number of searches carried out on the platform daily around the world, it is difficult to find such official data in figures. These data are not available even with Google Trends, a tool whose purpose is to show search trends in Google. Instead, Google Trends provides the data on the number of queries (in percentages), rather than figures [4]. Despite the difficulty of finding official data, it is estimated that, in 2018, around 2 trillion searches will have been conducted on Google around the world, although other pages limit that figure to several billion searches a day worldwide [5]. Overall, in 2017, about 88,000 employees worked full time for Google worldwide [6].

In recent years, natural resources have been used at an unprecedented rate, and the planet does not have time to replace what we spend. In 2015, for example, 1.5 times more resources than the planet can sustain were used [7]. In this context, sustainable management of natural resources becomes a priority [8], as we need to ensure that natural resources will also be available for future generations [9]. Water is one of such natural resources.

According to several estimates, in 2025, two-thirds of the population will experience water shortages [10]. Considering that Google is a company located in California, an area prone to droughts, various initiatives on the efficient use of water have been introduced. These include several projects in Google's data centers where they redesign and improve their cooling technologies and use non-potable water. Google.org has also founded the Climate Savers Computing Initiative that, since 2007, has pursued efficiency and sustainability standards. The company has also donated 45 million dollars for research on, among other things, relevant solutions to respond to the global challenges of water management.

The aim of the present study is to identify the factors that determine user intention to adopt a search engine that promotes sustainable water management. The search engine under study, Lilo.org, gives users a drop of water for each query made. With these drops of water, projects related to sustainable management can be supported and, therefore, the management of water resources can be improved. In order to comply with the proposed objective, a model based on TPB is proposed, which is contrasted using the statistical technique SEM with AMOS.

2. Theoretical Background

While it may seem, due to their being Internet-based, that search engines function in the most sustainable way, each individual search has externalities and thus can have an impact on the environment [7].

According to the official Google statement made in the blog of the multinational company [11], each search performed in the search engine is equivalent to 0.2 g of CO_2 and, for each query made, an average of 0.0003 kWh of energy (1 kJ) is consumed. This figure would be the equivalent to the energy consumed by the human body in 10 s. Translating these figures into everyday activities, the searches performed by each individual in a year would have the same impact on the environment as running a washing machine. These statements about the consumed energy were not by Google's own initiative, but were made in response to the research published by Wissner-Gross [12] who stated that each Google search produced 7 g of CO_2, half of the energy that a teapot consumes to warm up. After Google's rebuttal, the author had to correct the figures, stating that the impact on the environment was 0.2 g of CO_2.

Despite the efforts made by the search engine to minimize the impact of its activity on the environment, Google says that every search carried out with a laptop consumes more energy than Google consumes in facilitating the search—i.e., it consumes energy and produces CO_2 when search engines are used on personal computers, no matter how much Google tries to minimize its share [13].

Therefore, it is necessary to assess the use of alternative solutions to traditional search engines that, while fulfilling the function of providing information, also compensate for the generated externalities through social projects [7]. As can be seen in Table 1, among traditional online search engines, there are numerous alternatives; however, but not all of them offset the impact generated in the environment.

Among all the existing categories, we can differentiate the Social Search Engines, i.e., search engines based on creativity and innovation that calculate and compensate for externalities, since they pursue the sustainable management of companies while favoring the global sustainability of the Earth. Some examples of this type of Social Search Engine are Ecosia or Lilo [3,14].

Table 1. Types of Search Engines.

Search Engine Type	Description	Examples
Social Search Engines	These search engines have social purposes in which a percentage of the income is allocated to projects related to sustainability. They enable searching for images, video, music, and web pages.	Ecosia Lilo
Science Search Engines	These search engines allow access to scientific-technical materials through specific searches. The bibliographical production on the analyzed subject is gathered.	Google Scholar Scientific Commons Sci-Hub
General Search Engines	These search engines are the most widely used ones and contain files stored on web servers that, with each search, offer the results of general content that is most relevant to the user.	Google Yahoo Bing
Safe search Engines	These searchers allow safe searches for children. They do not show icon images to prevent display of inappropriate images.	Safe Search for kids
Local Search Engines	These local search engines help to find videos, news, blogs, web pages, radio, and images.	Rambler (Rusia) Goo (Japón) Baidu (China)
Social Media Search Engines	These search engines are created specifically to find content from social networks, including blogs, microblogs, comments, bookmarks, and videos. Some offer the possibility of creating alerts to track real-time topics of interest.	Social mention Social Search TagBoard

Source: Palos-Sánchez and Saura [3], An et al. (2017).

Social Search Engines are those search engines that support creativity and innovation to use an important part of their resources to improve the sustainability of the planet [15]. The social purposes of these search engines range from tree planting, sustainable water management, emission of CO_2 certifications or support to general projects. Table 2 shows some examples of search engines that develop actions on their own web pages to favor the efficient management of resources by supporting sustainable projects.

Table 2. Description of Social Search Engines that develop sustainable projects.

Social Search Engine	Description
Lilo	A search engine that finances sustainable projects related to water. Each time a user performs a search, s/he gets a drop of water; collecting the necessary amount of drops can finance a relevant project. This search engine is focused on innovation and creativity.
Ecosia	A search engine that allocates 80% of the benefits it obtains to finance sustainable projects; specifically, a portion of the profits goes to planting trees.
Good Search	A search engine that allocates a percentage of the purchases made through the platform to over 100,000 projects. It also offers discounts on products available for purchase.
Znout	A search engine that purchases CO_2 certificates to amplify its growth and sustainability in future projects. Revenue is obtained from the performed searches.
Benefind	A search engine that donates €0.5 to a social project supported by innovation and creativity every time a user performs a search. It has been active since 2010.

As can be seen in Table 2, as long as there is an approach to the sustainable management of resources and support for sustainable initiatives, business models used by search engines are diverse, and there are many ways to make projects focused on environmental sustainability viable in all senses [16].

2.1. Sustainable Water Management

Among all possible projects that can be supported via search engines, management of water resources is a particularly interesting domain. Water is not only essential for human survival, but is also the central element of sustainable development required for the development of economies and ecosystems [17,18]. Effective water management necessitates a union between human beings, the environment, and the climate system.

Of note, water is only a renewable resource if it is well managed. At present, 1700 million people live in places where the use of water exceeds the natural recharge rate and, according to several estimates, in 2025, about two-thirds of the population will experience water shortages.

Despite the importance of water for the survival of living beings, at present, the management of water resources is not sustainable from the environmental perspective [19,20]. Two of the indicators that demonstrate this are water withdrawal and water treatment [21].

First, water withdrawal refers to the extraction of water transported for its use, temporarily or permanently, to another place. Among the most common uses of water are the public water supply, irrigation, industrial processes, or cooling of power plants. Along with the river discharge and climate changes, water withdrawal is the main cause of water shortage and poses a great threat to the populations living in places where the water is extracted [22].

This indicator is measured per m^3 per capita. Owing to several recently implemented policies, this measure has been considerably reduced in most countries (see Table 3).

Table 3. Water withdrawals.

Location	2007	2008	2009	2010	2011	2012	2013	2014	2015
Mexico	78,949.6	79,752.3	80,587.0	80,213.4	81,588.1	82,733.7	81,651.2	84,928.8	85,664.2
Russia	74,633.0	74,354.0	69,915.0	72,685.0	68,652.0	66,296.0	65,104.0	64,807.0	62,163.0
Australia			14,613.0	13,842.0	13,702.0	16,351.0	20,133.0	19,364.0	18,222.0
Poland	12,027.0	11,365.0	11,517.0	11,645.0	11,911.0	11,478.0	11,242.0	11,308.5	11,093.5
Greece	9471.6				9934.6	9934.9	9924.5	9916.3	9907.7
Costa Rica		384.5	486.4	853.3	1066.2	1246.1	1347.4	1656.2	1990.3
Estonia	1834.3	1605.3	1388.0	1842.0	1873.9	1631.0	1747.8	1724.1	1615.3
Czech Republic	1970.0	1988.0	1948.0	1950.0	1886.0	1840.0	1650.0	1650.0	1603.1
Israel	1689.0	1595.0	1313.0	1340.0	1266.0	1318.0	1296.0	1271.0	1145.0
Slovenia	935.0	1040.0	943.0	925.0	851.0	781.1	892.5	977.4	895.1

Source: OECD [23].

The second major problem in sustainable water management is the treatment of wastewater [24]. By definition, waste water treatment should neutralize the negative impact of wastewater on the environment and favor the continuation of the water cycle.

In sum, we need be aware of the causes that can, according to available estimates, lead two-thirds of the population to suffer from water shortages in the future. In addition, efficient solutions should also be sought and implemented. In this context, support and financing of projects related to sustainable water management, such as social seekers, highly assist this purpose, as they support projects of efficient water management [25,26].

2.2. Lilo: Sustainable Water Management Through Donation of Drops

The Lilo search engine is a search engine that finances, through the searches made on the platform, social and environmental projects related to water. Each time a user performs a search, s/he user obtains drops of water that allow him/her to decide to which projects s/he will allocate the generated money.

Table 4 shows some key data about the Lilo search engine. Lilo was created by three young individuals in 2014. Its headquarters are in Paris, France. It currently has 136,279 monthly searches and 2750 users. The total income generated thus far amounts to €60,675.

Table 4. Overview of Lilo.

Lilo.org	Description
Foundation	2014
Headquarters	Paris/France
Industry	Internet, Social Business
Product and Services	Internet Search Services
Short Description	Independent Non-profit website
Partners	130 businesses with social projects
URL	www.lilo.org
Employees	3
Total Revenue (estimated)	€60,675
IT infrastructure	Bing, Yahoo, and Google

The technology used by Lilo incorporates the algorithms of major search engines such as Bing, Yahoo, or Google. When a user performs the search, Lilo relies on the algorithms of the search engines to show the results and, simultaneously with the display of the information searched for, commercial announcements are displayed. The last step consists of sending money through drops of water to the chosen projects.

When a user uses browsers from Chrome, Firefox, and Safari, Lilo requests "do not track" to avoid unwanted tracking of users. Lilo protects privacy by blocking advertising tracking by advertisers who offer their services in the search engine; in addition, Lilo neither collects personal data, nor sells them to third parties. For the analysis of the information, Lilo does not use Google Analytics, but a proprietary tool called Piwik. This tool ensures that users' IPs remain anonymous. The concerns of users about privacy are highlighted in Rieder research [27]. Rieder proposed the concept of "Symmetry of confidence" on the Internet. It reflects the symmetry of users' interest in using search engines, although they know that their personal data may be at risk, users are still using search engines because it is the easiest way to find information on the Internet. This "Symmetry of confidence" can make them modify their attitude and behavior to adopt a search engine.

Lilo collected money comes from the commercial links displayed during the searches carried out by the users. The income is distributed as follows: 50% goes to projects through water drops, 25% finances the activity of operation of the search engine, 20% is used to communicate the project, and the remaining 5% is used to offset carbon emissions (see Figure 1).

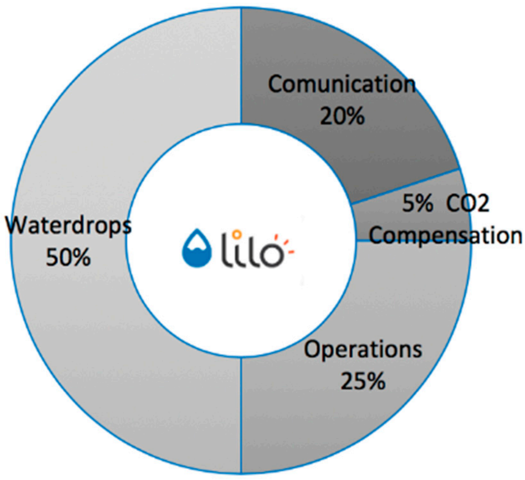

Figure 1. Distribution of income obtained by Lilo.org. Source: Lilo.org.

With respect to donations, each search results in a drop of water. Users can decide which project to donate their water drops to. All projects are characterized by being innovative and having a social or environmental character. The partners propose the projects to which the contributions of other partners can be allocated through drops of water. Table 5 shows the projects that have received the most drops of water from the Lilo user community.

Table 5. Projects with the most donations through drops of water (Lilo).

Name of the Project	Description	Waterdrop Donations
The Oasis project of Colibris	Building an environmentally friendly society	44.467€
Arutam Zero Deforestation	Combating deforestation and global warming	22.346€
Agrisud International	Creating very small-scale sustainable farms	14.669€
Ecological cookers	Stock-pilling CO_2 by encouraging the use of solar cookers	3.514€
GreenWave	Saving seas	1513€
Mazí Mas	Supporting women from migrant and refugee communities	840€

Source: Lilo.org.

2.3. Behavioral Intention to Adopt a Meta Search Engine that Favors Sustainable Water Management

Recent years have witnessed the development of numerous new technologies, resulting in the launch of many new products on the market [28]. However, of these new technological products, some have worked, but 90% have failed [29].

Although a social search engine may appear to be a good idea, since it is supported by big trends in consumer behavior such as the growing number of search engines, the increasing number of searches made daily by users and the concern that people show for the environment, it is necessary to understand if those users have behavioral intentions with respect to the adoption of this search engine and identify the key factors determining the success or failure of a search engine. To this end, in the present study, we have reviewed the most important works that address the behavioral intention of users with respect to new technologies—in particular, those related to the Internet, mobile devices and search engines on-line (Table 6).

In his work, Hsiu-Fen [30] analyzed user intentions to be part of online communities. This study was based on the TPB in its extended model and aimed to identify the key factors that will make users part of these online communities. Some of the variables taken into account were the perceived utility, ease of use, facilitating conditions, and trust. The analysis is done with SEM and AMOS.

Table 6. Previous studies: A review.

Author	Description	Aim	Object
Hsiu-Fen [30]	Explaining the behavioral intention by identifying the key factors that favor users' participation in virtual communities. The model is based on the Theory of Planned Behavior (TPB) and includes variables such as perceived utility, ease of use, facilitating conditions, trust. The analysis is done with SEM (Structural Equation Modeling).	Behavioral intention	Virtual communities
Lu, Yao, & Yu [31]	Studying the keys factors determine the adoption of mobile phones as devices to connect to the Internet and search it. The analysis is done with SEM and the AMOS (Analysis of Moment Structures) as a statistical model in which constructs such as Social Influence, Perceived ease of use, Perceived usefulness or Perceived innovativeness are included.	Behavioral intention	Wireless Internet services

Table 6. *Cont.*

Author	Description	Aim	Object
Sung, Jeong, Jeong & Shin [32]	Identifying the factors that determine the intention to adopt mobile technologies for learning. The analysis is carried out with modeling with structural equations (SEM) using the AMOS. Among the constructs are the social influence, the expectation of effort, and self-efficacy. The results show that those responsible for mobile learning had to focus on user self-efficacy to improve their behavioral intention.	Behavioral intention	Mobile devices for e-learning
Morgan-Thomas & Veloutsou [33]	Developing an on-line brand adoption model that integrates the Information Systems and marketing approach. SEM is used for the analysis. Among the studied factors are trust, perceived usefulness, and behavioral intention.	Technology acceptance/ Behavioral intention	On-line brands
Tai [34]	Analyzing factors such as habit, hedonic motivations, and utilitarian motivations that influence the behavioral intentions of users vis-à-vis search engines. The AMOS is used for data analysis.	Behavioral intention	Meta search engines

Furthermore, Francis et al. [35], Mathieson [36] and Ajzen [37] also used the TPB as a starting point to better understand the factors that affect user behavioral intention in Information Technologies.

Finally, Sung, Jeong, Jeong & Shin [32], Morgan-Thomas & Veloutsou [33], and Lu, Yao, and Yu [31] used SEM and AMOS to identify the behavioral intention of mobile device users. Likewise, Tai [34] focused on identifying the key behavioral variables of online searchers. Among the factors analyzed in the latter study were habit, hedonic motivations, and utilitarian motivations. Structural equations and the AMOS were used to perform the analysis and hypothesis testing.

3. Hypothesis Development and Research Model

Following Hsiu-Fen [30], Mathieson [36], and Ajzen [37], in the present study, we have taken the Theory of Planned Behavior as a starting point to develop our model and formulate the hypotheses. The Theory of Planned Behavior has received much scholarly attention in the domain of Information Technologies (IT) [37,38]. All this body of work has highlighted the value of this theory, characterized by multidimensionality of its components, in terms of describing and predicting user behavior in digital environments [39,40]. The Theory of Planned Behavior is used in this research due to the fact that search engines have given rise to concepts such as "Symmetry of confidence", in which Reference [27] links data privacy on the Internet with the decisions taken by users with respect to the adoption of a search engine. Likewise, studies like Reference [41] also worked on the mathematical concept of symmetry in order to link a ranking relational search results list with the behavior of users when they use a search engine. In this research, facilitating conditions implies that the technical conditions of the user or the environment are sufficient to support innovations or the adoption of a new technology like search engines that supports data privacy or the "Symmetry of confidence" and sustainable purposes.

According to Venkatesh et al. [42], facilitating conditions affect both behavioral intention and use. Based on the above, the following prediction can be formulated:

Hypothesis 1 (H1). *Facilitating conditions would have a positive effect on user behavioral intention.*

Behavioral intention refers to the purpose of using a particular technology over time [37]. There have been several studies on how social influence impacts this behavior in the long term [43–45]. Other studies, such as Alaiad and Zhou [46], found that social influence was the most prominent predictor of user behavioral intention. Therefore, we expect the following:

Hypothesis 2 (H2). *Social influence would have a positive effect on user behavioral intention.*

On the other hand, the facilitating conditions—i.e., elements that allow a user to adopt a technology so that the greater the facilities available to the user, the less effort should be devoted to adopt this new technology—are an important element in the TPB, since they influence both user behavior and intention [37]. In this context, it can be predicted that the search engines can improve the sustainable water management [30,42]. Also, the more prepared the user is to use a certain technology, such as online search engines, the easier it will be to generate the habit of using that technology [27,47,48]. Based on the above, the following predictions can be formulated:

Hypothesis 3 (H3). *Facilitating conditions would have a positive effect on effort expectancy.*

Hypothesis 4 (H4). *Facilitating conditions would have a positive effect on habits.*

Social influence is the measure in which users understand that people in their environment have an influence on their decision making. Users might think that this environment wants them to use a technology, mobile device or an online search engine [49,50].

The influence of the social environment of the user occurs in various constructs [31]. On the one hand, there are habits. According to Sánchez [51], both the family and school environment of the children will condition the habits they develop. An example would be reading or the use of technologies. It is exactly the new information and communication technologies that are setting the pace of the users, and it is the families, the environment, and the social influences received from the outside that can help children generate healthy habits [52]. Based on the above, we can predict the following:

Hypothesis 5 (H5). *Social influence would have a positive effect on habits.*

Regarding the impact of social influence on trust, in a new technology, trust must be won over time and experience [53]. However, due to social influence, the time normally required to develop confidence in a new technology may be shortened [49].

Next, according to Durkheim [54] and Santos [55], happiness, fun, and hedonic motivation increase with an increase of the number of people in users' immediate environment and with the development of closer relationships between users and people in immediate environment. The same holds true regarding the adoption of new technologies, such as a search engine that supports the efficient management of water. That is, social influence can be expected to have an effect on user happiness and hedonic motivation [34]. Based on the above, the following predictions can be formulated:

Hypothesis 6 (H6). *Social influence would have a positive effect on trust.*

Hypothesis 7 (H7). *Social influence would have a positive effect on hedonic motivation.*

According to Venkatesh et al. [42], effort expectancy can be understood as the degree of ease related to the use of a certain technology. The more successful the effort that the user believes s/he should devote to adopting a technology, the greater the hedonic motivation that will be produced [44,45] and the greater the confidence that will be generated in that determined technology—in our case, a search engine [34]. Accordingly, we predict the following:

Hypothesis 8 (H8). *Effort expectancy would have a positive effect on Hedonic motivation.*

Hypothesis 9 (H9). *Effort expectancy would have a positive effect on Trust.*

The habit reflects the tendency to repeat a behavior that occurred in the past when the same circumstances occur again in the future [56]. Habit is guided by automatic cognitive processes, rather than by elaborate decision processes [57]. Mcknight, Choudhury, and Kacmar, [58] related the habits generated in the consumers of online stores with the trust, highlighting that this trust is not only in the first purchase, but also that it extends over time for repeated purchases. Therefore, the following prediction can be formulated:

Hypothesis 10 (H10). *Habits would have a positive effect on trust.*

In digital environments, i.e., where there is no direct contact between the provider of an on-line search service and the user, trust becomes a determining factor for the adoption of technologies [59–61]. Furthermore, the adoption of these products or technologies produces a psychological and emotional satisfaction in the users, coupled with the sense of entertainment, which is jointly known as hedonic motivation [62]. Gefen et al. [63] states that trust has an impact on perceived enjoyment and on hedonic motivation. Accordingly, we expect the following to be true:

Hypothesis 11 (H11). *Trust would have a positive effect on hedonic motivation.*

Among the factors that influence behavioral intention is Effort expectancy [64]. The decision to adopt a new technology—in this case, a search engine for sustainable purposes—will be determined by the effort that users believe they should devote to learning and adopting this new technology [34,65]. According, our prediction is as follows:

Hypothesis 12 (H12). *Effort expectancy would have a positive effect on behavioral intention.*

In addition, considering that having a habit implies that we continue to do the same thing for a long time without considering other options [47,48], habits can influence behavior. In this respect, Ling Tai [34] analyzed how habits influence the behavioral intention of online search users. Accordingly, following Ling Tai [34] who analyzed how habits influence behavioral intention of online search users, we predict the following:

Hypothesis 13 (H13). *Habits would have a positive effect on behavioral intention.*

Another factor within the framework of the Theory of Planned Behavior is trust [30,66]. While trust is also a barrier to electronic transactions [67], if a trust relationship is created, users will develop behavioral intention [68]. For instance, this relationship between trust and behavioral intention was demonstrated by Morgan-Thomas [33]. Based on the above, we expect the following:

Hypothesis 14 (H14). *Trust would have a positive effect on behavioral intention.*

In their work on online search engine adoption by users, Ling Tai [34] identified habit and hedonic motivations as two major factors that influence behavioral intention. Furthermore, Venkatesh, Thong, and Xu [50] analyzed the relationship between hedonic motivation and behavioral intention and found that, if the activity developed produces happiness to the user, this user will develop behavioral intention. Based on the above, our last hypothesis is as follows:

Hypothesis 15 (H15). *Hedonic motivation would have a positive effect on behavioral intention.*

Based on the 15 hypotheses formulated above, the research model has been constructed (see Figure 2).

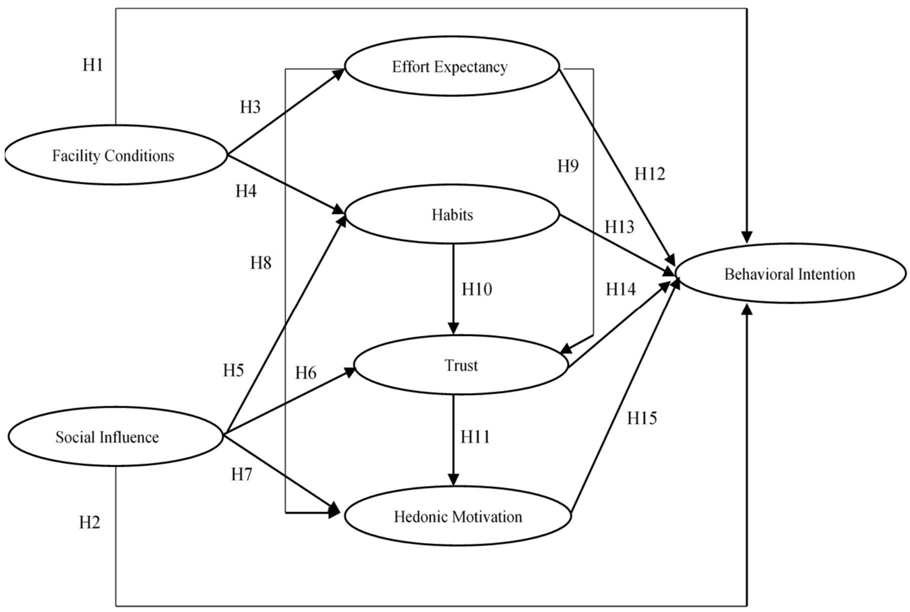

Figure 2. Research model.

4. Methodology

The research problem that requires the rigorous application of a quantitative methodology. According to Tamayo [69], the quantitative methodology consists in the contrast of hypotheses from a theoretical framework. It is necessary to obtain a sample, either in a random or discriminated form, but representative of a population or phenomenon of study. The quantitative method focuses on the facts or causes of the social phenomenon, with little interest in subjectivity [70].

In quantitative methods, fieldwork is carried out to collect data to test hypotheses. All of this occurs in line with numerical measurement and statistical analysis, to establish theories and patterns of behavior of the variables studied [71]. Thus, one of the enormous advantages of working with quantitative methods is the possibility of studying a small sample of the population under study and extrapolating the results.

The research technique chosen was the survey (n = 387). A questionnaire was elaborated based on the recommendations proposed by Francis et al. [35] in their manual and subsequently applied by Hadadgar et al. [72] in their research on the Theory of Planned Behavior in digital educational platforms in the medical sector. Next, aspects of the chosen methodology related to data collection and data analysis (measuring scales and Estimation of Structural Equation Modeling) will be presented.

4.1. Data Collection

The population sample consisted of professionals and postgraduate students who used an e-learning learning platform at three Spanish universities. As the only condition, it was established that they should use a search engine to carry out learning activities. The respondents used the search engine for tasks as case studies, text comments, information search work where the data sources or bibliographic reviews were cited. In this way, we made sure that they had used various applications in the use of the search engine.

The sample was established by selecting sample elements using the non-random sampling technique, also referred to as convenience sampling [73,74]. The questionnaire was anonymously responded to by 406 people, and 387 questionnaires were finally validated. A control question was included to avoid bias. 53.49% of the respondents were employed, while 46.51% were unemployed. As for gender distribution, 56.11% were female, while 43.89% were male. The age distribution was as follows: most participants were aged between 37–46 years old (34.63%), followed by those aged 28–36 years (36.36%), 47–56 years (22.48%), and 18–27 years old (16.54%).

4.2. Data Analysis

A two-step process was followed for data analysis. First, the scale of measurement was validated by applying the Exploratory Factor Analysis (EFA) and the Confirmatory Factor Analysis (CFA). Next, the proposed model was estimated using the SEM technique. The Statistical Package for the Social Sciences SPSS 19.0 (scale validation) and the AMOS 20.0—Analysis of Moment Structures program (scale validation and SEM model estimation) were used.

4.2.1. Measuring Scales

To validate the measurement models of the seven variables contained in the proposed model (facility conditions, social influence, effort expectancy, habits, trust, hedonic motivation, and behavioral intention), we followed the methodological recommendations of Anderson and Gerbing [74]. More specifically, the psychometric properties of the scales (reliability, unidimensionality, and validity) were analyzed, which delimited the number of items measured by each variable. Likert 5-point scale (1 = "totally disagree" and 5 = "totally agree") was used.

In terms of reliability, Pearson's item-total correlation coefficients and Cronbach's alpha were examined [75]. According to Nurosis [76], the correlation between the items should exceed 0.3 and a Cronbach's must be above 0.7 [77] or 0.8 for confirmatory studies [78]. To confirm the one-dimensionality of the scales, an EFA with Varimax rotation was performed [79]. The indicators used were the explained variance that must be above 50% and loadings factorial; following Hair et al. [80], significant loads below 0.3 were considered.

To finish the analysis of the scale, the quality of the adjustment of the structural measurement models was evaluated through the CFA; thereafter, reliability, validity, and one-dimensionality were analyzed again [81,82]. To analyze to what extent the structural measurement model of each variable was adjusted, the significance of the coefficients estimated according to the following parameters was considered: (i) the critical coefficient (t-value) of each standardized indicator must exceed $\pm$ 1.96; (ii) standard regression weight might approach 0.7; some authors place the minimum level at 0.5 [81,82]; (iii) the parameter R^2 should take the value 0.5 recommended by Sharma [83]. The internal validity of the measurement model was evaluated by calculating the compound reliability (CR), which value might be greater than 0.7 [77,84] and, through the extracted average variance (AVE), that should be greater or equal to 0.5 [80,85].

4.2.2. Estimation of Structural Equation Modeling

In order to test the model that includes the proposed hypotheses, SEM is used. This statistical technique enables testing the structure of causal relationships and the importance of the impact that each of the variables proposed have in behavioral intention. To examine the overall fit of the model, the significance of standard regression weight (β) is taken into account; the critical coefficient must exceed $\pm$ 1.96 and the goodness indices of the model [82]. The following indices were considered: chi-square (χ^2), goodness fit index (GFI), adjusted goodness fit index (AGFI), comparative fit index (CFI), robustness of mean squared error approximation (RMSEA), and χ^2Normalized. According to Hair et al. [80] and Bentler and Bonett [86], the recommended values of CFI, GFI, and AGFI are above 0.9, while for RMSEA, the recommended values below 0.08 and 0.06 would be optimal [87–89] and (χ^2) Normalized values are between 2 and 3 and get up to 5 [82], being 1 the minimum [80]. The measure of R^2 refers to the amount of variance of the construct explained by the model.

5. Results

5.1. Measurement Model

The mean value, standard deviation, item-total correlation, and factor loadings for each item are summarized in Table 7. The results of the reliability analysis showed that all items, except for the social influence scale, have an item-total correlation above the recommended minimum of 0.3. Specifically, the items IS4 (0.131) and habits, H2 (0.238) were eliminated by improving Cronbach's alpha, higher than the recommended minimum of 0.7 [77], indicating an adequate internal consistency of the scales. The results of the EFA, analysis of the unidimensionality, showed that in all cases, the factorial loads were superior to 0.5 [80], and the cumulative percentage of variance explained was superior to 50% in all scales.

Table 7. Descriptive results and exploratory factor analysis (reliability and validity of scales).

Constructs Included SEM	Scale Items [A]	Mean	(s.d.) [B]	Item-Total Correlation	Loadings	Exploratory Factor Analysis Bartlett's Test of Sphericity [1] Kaiser-Meyer_Oklin Index
Effort Expectancy (α = 0.843)	EE1	4.45	0.717	0.667	0.816	χ^2 (sig.): 711.226 (0.000)
	EE2	4.29	0.759	0.707	0.847	KMO: 0.811
	EE3	4.47	0.699	0.716	0.851	Measure of simple adequacy: (0.832–0.848)
	EE4	4.32	0.742	0.628	0.787	% Variance: 68.18
Influence Social (α = 0.944)	IS1	2.93	1.139	0.859	0.937	χ^2 (sig.): 1254.283 (0.000)
	IS2	2.90	1.148	0.907	0.960	KMO: 0.762
	IS3	2.94	1.156	0.881	0.948	Measure of simple adequacy: (0.819–0.763)
	IS4	4.16	0.996	**0.131**	deleted	% Variance: 89.88
Facilitating Conditions (α = 0.827)	CF1	4.40	0.795	0.713	0.860	χ^2 (sig.): 728.369 (0.000)
	CF2	4.26	0.847	0.692	0.848	KMO: 7.99
	CF3	4.42	0.766	0.738	0.874	Measure of simple adequacy: (0.788–0.896)
	CF4	4.06	0.883	0.497	0.675	% Variance: 67.01
Habits (α = 0.753)	H1	4.16	0.896	0.618	0.843	χ^2 (sig.): 323.361 (0.000)
	H2	3.25	1.071	**0.238**	deleted	KMO: 0.688
	H3	4.09	0.876	0.583	0.821	Measure of simple adequacy: (0.661–0.724)
	H4	4.15	1.003	0.552	0.795	% Variance: 67.26
Behavioural Intention (α = 0.820)	B1	4.16	0.930	0.665	0.830	χ^2 (sig.): 656.727 (0.000)
	B2	3.90	1.015	0.676	0.833	KMO: 0.798
	B3	4.22	0.910	0.713	0.860	Measure of simple adequacy: (0.788–0.870)
	B4	3.67	1.104	0.538	0.717	% Variance: 65.90
Trust (α = 0.861)	T1	3.48	0.992	0.751	0.893	χ^2 (sig.): 622.871 (0.000) KMO: 0.733
	T2	3.61	0.968	0.750	0.893	Measure of simple adequacy: (0.717–0.770)
	T3	3.50	1.037	0.711	0.870	% Variance: 78.38
Hedonics Motivation (α Cronbach: 0.853)	HM1	3.69	0.958	0.706	0.870	χ^2 (sig.): 603.720 (0.000) KMO: 0.715
	HM2	3.53	1.010	0.779	0.909	Measure of simple adequacy: (0.735–0.757)
	HM3	3.86	1.019	0.692	0.860	% Variance: 77.40

[A] The items listed in this table are summarized for ease of presentation and comprehension. [B] s.d.: Standard deviation. [1] Tests that show that the data obtained through the questionnaire are adequate to perform the factor analysis (requirements: Bartlett's Sphericity Test χ^2 (sig. < 0.05), Kaiser Meyer Oklin Index (KMO) >0.7 median and >0.8 good, Measurement of Simple Adequacy (MSA) unacceptable for values below 0.5).

The next step in the process of debugging the scales of measurement was to apply the Confirmatory Factor Analysis in order to examine the measurement model and the structural model of the scale of measurement, guaranteeing its validity and reliability (see Table 8).

According to the criteria proposed by Jöreskog and Söbom [82] and Chin [90] (see Table 8), it was observed that standard regression weight (β) was significant, critical coefficient superior to $\pm$1.96 (p-value < 0.001), and minimum level for its acceptance as part of the construct was higher than 0.5 or 0.6; all values exceeded this minimum load. With respect to the goodness of fit indexes of the optimal measurement model, all the indicators had the values within the generally accepted limits; CFI = 0.947, GFI = 0.907 and AGFI = 0.879, RMSEA = 0.057, and χ^2Normalized = 2.418.

Finally, the reliability and validity of the scales were re-analyzed. With regard to reliability, the composite reliability coefficient (CR) was calculated for each of the variables (minimum value 0.7), recommended by Bagozzi and Yi [84] and the variance extracted (AVE); acceptable values were greater than 0.5 [80,85]. It was observed that, in all cases, CR and AVE exceeded the recommended values; therefore, it can be said that the scale is reliable. The validity of the content was supported by a literature review and the validity of the concept was measured through the convergent and discriminant validity. Convergent validity was confirmed (see Table 2); all weight standard regression weight (β) coefficients were higher than 0.5 minimum required [82] and significant (optimal values critical coefficient >±1.96).

Table 8. Reliability and confirmatory factor analysis.

Scales [a]	**β**	**CR**	**AVE**
Effort Expectancy (α = 0.843)			
EE1 Learning to use my Internet search engine is easy for me EE2 My interaction with the Internet search engine is clear EE3 I find my Internet search engine easy to use EE4 It is easy for me to be proficient in using my favourite Internet search engine	0.726 0.777 0.804 0.732	0.91	0.72
Influence Social (α = 0.944)			
IS1 The people that are important to me think that I should use my Internet search engine more IS2 The people that influence my behavior think that I should use my Internet search engine more IS3 People whose opinions I value think that I should use my Internet search engine more	0.888 0.958 0.917	0.93	0.81
Facilitating Conditions (α = 0.827)			
CF1 I have necessary resources to use an Internet search engine CF2 I have necessary knowledge to use an Internet search engine CF3 My Internet search engine is compatible with other technologies I use (Browser, Operating, System, etc.) CF4 I can get help from other users when I have difficulty using my search engine on the Internet	0.819 0.782 0.840 0.558	0.88	0.66
Habit (α = 0.753)			
H1 Using my Internet search engine could become a habit for me H3 Using my Internet search engine could become natural for me H4 Using my Internet search engine could become something I do without thinking	0.788 0.688 0.665	0.78	0.55
Behavioral Intention (α = 0.820)			
BI1 I intend to use my Internet search engine in the future BI2 I will always try to use my Internet search engine in mu day to day life BI3 I plan to use my Internet search engine soon BI4 I intend to recommend the use of my Internet research engine to other users	0.763 0.780 0.816 0.598	0.83	0.55
Trust (α = 0.861)			
T1 My Internet search engine is honest T2 My Internet search engine understands the users T3 My Internet search engine has good intentions	0.825 0.841 0.802	0.86	0.68
Hedonics Motivation (α = 0.853)			
HM1 I enjoy using my Internet search engine HM2 When I use my search engine on the Internet, I have fun HM3 Using my search engine on the Internet, in my free time, entertains me	0.831 0.856 0.754	0.86	0.67

[a] β: weight standard regression (*p*-value < 0.001); α = Cronbach's (reability); CR: composite reliability; AVE: average variance extracted. The scales used have been adapted from the literature; Effort Expectancy: Rayburn and Arkalgud [65], Ling Tai [34]; Social Influence: Arman and Hartati [43], Chang et al. [44], Phichitchaisopa and Naenna [45], Alaiad and Zhou [46]; Facilitating Conditions: Venkatesh et al. [41], Hsiu-Fen [30]; Habit: Ling Tai [34], Garber [47], Drolet et al. [48]; Behavioral Intention/Use Behavior: Venkatesh et al. [41], Arman y Hartati [43], Chang et al., [44], Phichitchaisopa and Naenna [45]; Trust: Gefen et al. [60], Cheng-ling [59], Gefen et al. [63], Pavlou [61]; Hedonics Motivation: Chang et al. [44], Phichitchaisopa and Naenna [45]. Composite reliability test: χ^2 = 558.565 (p = 0.000), GFI = 0.907, AGFI = 0.879, CFI = 0.947, RMSEA = 0.057, χ^2Normalized(χ^2/df) = 2.418.

Discriminant validity was analyzed examining if the Cronbach's alpha of each scale was greater than any of the correlations between that scale and the rest [91], if the correlations between factors were less than the square root of the average variance extracted [85], and if the confidence interval for the estimated correlations ± twice the standard error did not include the value 1. As can be seen in Table 9, the results of all these tests were satisfactory [74]. The correlation matrix also showed that most variables were highly correlated. We also verified that the root of the Average Variance Extracted (AVE) was greater than the relation between the construction and the rest of the constructs of the model.

Table 9. Correlation matrix and discriminant validity.

	Square Root AVE	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Effort Expectancy (1)	0.88	**0.843** [a]	0.001 [d]	0.546	0.326	0.282	0.141	0.142
Influence Social (2)	0.9	0.043 [b] (0.079–0.033) [c]	**0.944**	0.003	0.028	0.027	0.078	0.081
Facilitating Conditions (3)	0.81	0.739 ** (0.302–0.198)	0.061 (0.108–0.028)	**0.827**	0.495	0.310	0.145	0.123
Habit (4)	0.74	0.571 ** (0.261–0.157)	0.169 ** (0.200–0.040)	0.704 ** (0.391–0.255)	**0.753**	0.490	0.225	0.276
Behavioral Intention (5)	0.74	0.534 ** (0.247–0.147)	0.167 ** (0.198–0.042)	0.557 ** (0.319–0.195)	0.700 ** (0.426–0.274)	**0.820**	0.282	0.378
Trust (6)	0.82	0.376 ** (0.212–0.108)	0.280 ** (0.321–0.141)	0.381 ** (0.267–0.139)	0.475 ** (0.350–0.198)	0.531 ** (0.384–0.232)	**0.861**	0.488
Hedonics Motivation (7)	0.82	0.378 ** (0.208–0.104)	0.286 ** (0.318–0.142)	0.351 ** (0.243–0.119)	0.526 ** (0.371–0.219)	0.615 ** (0.429–0.268)	0.699 ** (0.546–0.362)	**0.853**

[a] Shown in bold on the main diagonal are the Cronbach's alpha for each scale, which should be higher than the correlation between that scale and the rest. [b] Inter-scale correlation; significant at ** *p*-value < 0.01. [c] Corresponding confidence intervals for each pair of factors are presented under the diagonal (±twice the standard error, does not include the value 1). [d] Squared correlations are presented over the diagonal.

5.2. Hypothesis Testing

Figure 2 shows the results of hypothesis testing. Weight standard regression (β) that appears next to the hypotheses indicates the weights of the direct effects of one variable on another and the direction. All effects were significant at $p < 0.05$, $p < 0.01$, or $p < 0.001$. Furthermore, the analyzed indexes showed a good fit of the model (χ^2 (df) = 576,844 (p = 0.000), GFI = 0.904, AGFI = 0.880, CFI = 0.946, RMSEA = 0.056, χ^2Normalized (χ^2/df) = 2.404). The measure R^2 that appears next to the constructs shows the amount of variance explained by the model. As can be seen in Figure 2, the model demonstrated a high level of predictive power (R^2), which explains 58.8% of the variance in behavioral intention, which is considered acceptable.

Finally, following Edwards and Lambert [91], in addition to the direct effects of each variable on behavioral intention, the indirect and total effects were examined. The results show that three variables had a significant total effect on behavioral Intention; these include facility conditions (value 0.558) through an indirect effect, as well as habits (value 0.531) and hedonics (value 0.349), both through a direct effect. As concerns trust, the total effect was of lesser importance, but it should be noted that it was through an indirect effect (value 0.219) (see Table 10).

Table 10. Direct, indirect, and total effects of variables on behavioral intention.

	Variables	Effects	3	4	5	6	7
1	**Facility Conditions**	Direct effects	0.747 ***	0.710 ***			
		Indirect effects			0.383	0.344	0.558
		Total effects	0.747	0.710	0.383	0.344	**0.558**
2	**Social Influence**	Direct effects		0.130 **	0.213 ***	0.105 ***	
		Indirect effects			0.049	0.164	0.152
		Total effects		0.130	0.261	0.269	**0.152**
3	**Effort Expectancy**	Direct effects			0.158 *	0.140 *	0.160 ***
		Indirect effects				0.099	0.083
		Total effects			0.158	0.239	**0.243**
4	**Habits**	Direct effects			0.373 ***		0.449 ***
		Indirect effects				0.234	0.082
		Total effects			0.373	0.234	**0.531**

Table 10. *Cont.*

	Variables	Effects	3	4	5	6	7
5	**Trust**	Direct effects				0.627 ***	
		Indirect effects					0.219
		Total effects				0.627	**0.219**
6	**Hedonic Motivation**	Direct effects					0.349 ***
		Indirect effects					
		Total effects					**0.349**

Effects Direct * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

6. Discussion

As can be seen in Table 10 and Figure 2, our results support the explanatory capacity of the proposed model (R^2 = 58.8%). When analyzing the predictive power of the model in terms of variance, Hu and Bentler [88] proposed to consider values for R^2 of 0.67, 0.33, and 0.19 to be strong, moderate, and weak, respectively. The basic measure to determine the predictability of endogenous variables is R^2, which can be defined as the amount of variance of the construct explained by the model. This data supports the research carried out and gives it a moderate capacity, close to weak. Therefore, the research model proposed in the present study is accepted and has a high moderate explanatory capacity.

Regarding the hypotheses, our results support the existence of 12 causal relationships, three of which are not significant. First, Hypothesis 1 was not supported by our results, meaning that there is no significant relationship between facilitating conditions and behavioral intention. Facilitating conditions are those elements that allow a user to adopt a technology, so that the greater the facilities available to the user, the less effort should be devoted to adopt this new technology—in our case, the search engines that improve the management sustainable water [30]. This result is not consistent with the basic theoretical model based on the Theory of Planned Behavior (TPB) according to which facilitating conditions influence behavioral intention. and that therefore contradicts Ajzen [37] if we apply this adoption theory to this search engine. This fact could be explained by the ease of use of the search engine.

Furthermore, Hypothesis 2 was not supported either, as our results demonstrated a social influence of the user's family or friends on the user's use of a particular search engine. This result is line with previous research [3].

Finally, the last unsupported hypothesis was the causal relationship between trust and behavioral intention. The lack of this relationship highlights the enormous credibility given to the information displayed by a search engine, without playing any role of trust in all this. This result contradicts other authors who discovered this relationship in the adoption of other technologies, such as in electronic transactions [67] or in other technologies where trust has been proven to be essential [33,68]. However, our results agree with several other studies [3], particularly those focused on the ethics of search engines and their results for online reputation [90].

In relation to the accepted hypotheses, we should emphasize that the construct that we found to have the largest impact on the model is facilitating conditions. This factor was found to be strongly related to effort expectancy (β = 0.747, t = 12.585) and habits (β = 0.710, t = 12.406). Likewise, habits were found to have a positive impact on behavioral intention (b = 0.449, t = 6.979), confirming previous studies [3,34]; however, this factor was found to have a positive impact also on hedonic motivation (β = 0.627, t = 11.027) and trust (β = 0.373, t = 5.443). Therefore, while there is a direct influence of habit on behavioral intention, habit also has an indirect on behavioral intention through hedonic motivation or the relationship of trust with this last construct. This underscores the importance of habit that turns out to be a dependent construct with a strong importance in its explanatory capacity of the model (R^2 = 52.1%).

Therefore, it appears that, in the educational environment, the use of this type of search engine is strongly influenced by habit, which suggests that users do not consider using another search engine.

Moreover, the results show that users are happy about their use of a search engine that contributes to a more fair and equitable distribution of water resources. This result confirms previous studies [34,50] and demonstrates the influence of this emotion of happiness on the behavioral intention. The effect of social influence on habits (β = 0.130, t = 2.931), trust (β = 0.213, t = 4.429), and hedonic motivation (β = 0.105, t = 2.437) increases, suggesting that the users of Lilo, in their use of this search engine, experience more happiness and confidence, as well as have a tendency to rely on habit.

Finally, the effort expectancy construct was found to have a positive influence on hedonic motivation (β = 0.140, t = 2.919), trust (β = 0.158, t = 2.490), and behavioral intention (β = 0.160, t = 2.878). The final explanatory capacity of effort expectancy was moderate and close to weak, similarly to that of behavioral intention (R^2 = 55.8%).

Taking into account the results obtained and collected in Figure 3, as well as the discussion made in this section, by way of summary in Table 11 the hypotheses and the results obtained are presented.

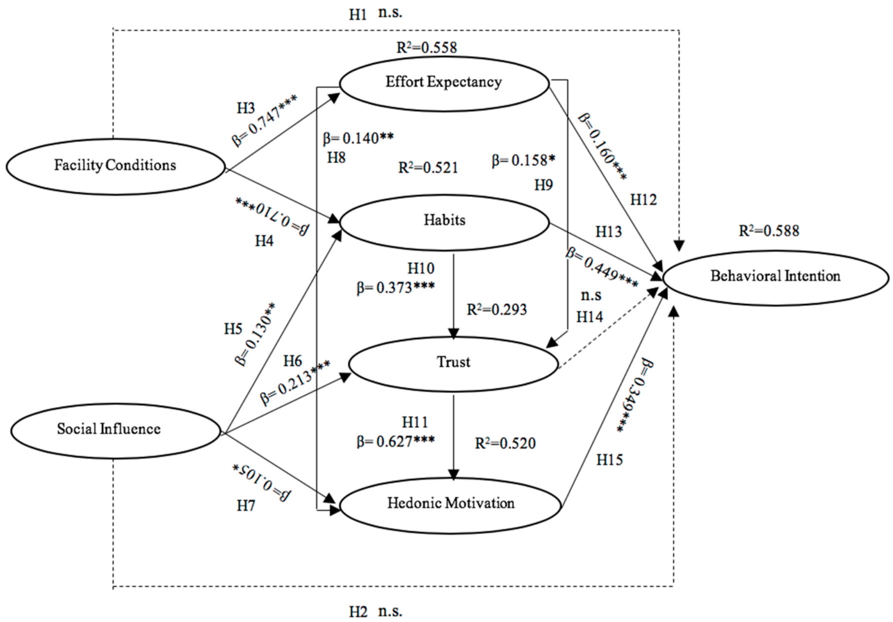

Figure 3. Result of Structural Equation Model. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; n.s. insignificant at the 0.05 level. χ^2(df) = 576.844 (p = 0.000), GFI = 0.904, AGFI = 0.880, CFI = 0.946, RMSEA = 0.056, χ^2Normalizada (χ^2/df) = 2.404.

Table 11. Summary of the results on hypotheses testing.

Hypothesis	Relations	Result
H1	Facility Condition → Behavioral Intention	Not supported
H2	Social Influence → Behavioral Intention	Not supported
H3	Facility Condition → Effort Expectancy	Supported
H4	Facility Condition → Habits	Supported
H5	Social Influence → Habits	Supported
H6	Social Influence → Trust	Supported
H7	Social Influence → Hedonic Motivation	Supported
H8	Effort Expectancy → Hedonic Motivation	Supported
H9	Effort Expectancy → Trust	Supported
H10	Habits → Trust	Supported
H11	Trust → Hedonic	Supported
H12	Effort Expectancy → Behavioral Intention	Supported
H13	Habits → Behavioral Intention	Supported
H14	Trust → Behavioral Intention	Not supported
H15	Hedonic Motivation → Behavioral Intention	Supported

7. Implications and Conclusions

Given that the sustainable management of water resources involves different actors, it is necessary to take into account their points of view and their interests so that the adoption of measures is effective, as in this case the use of a social search engine that supports the projects related to water and sustainable projects that can help sustain responsible policies [92,93].

Since, according to recent estimates, by 2025, around two-thirds of the population will experience water shortages, it is necessary to look for alternatives. One option is to support those initiatives that present proven solutions to improve sustainable management of water resources based on new social and technological developments. For example, the introduction of social search engines that improve the management of water resources and promote social projects that actively support a more effective water management.

The number of queries made in search engines is growing every day. Therefore, considering that, by 2030, each inhabitant of the planet is expected to have on average 6 devices connected to the Internet, it is important to consider the externalities generated by the activity of those search engines and compensate for these adverse effects by concrete actions for the efficient management of water around the world.

The innovation driven by the development of new technologies has led to the emergence of new sustainable business models that can help improve the water management models of today. The sustainable search engine presented in the present study proposes the improvement of water management achieved through its own use. The results obtained in the present study demonstrate that an Internet search engine that contributes to the effective management of water makes individuals who intend to use it develop hedonic motivations and, therefore, feel happy because they think that they are developing a responsible and sustainable approach to water management. Similarly, the success of this technological product is closely related to the ability it grants to its users to exert a social impact on the environment, rather than to its ability to gain users' trust in what they do or in their results. This is so mainly because the search engine model is beneficial to society and its sustainable development, as well as to the maintenance of the natural resources. However, habit will definitely be the main factor determining the improvement of the product, since, as our results demonstrate, habit has both direct and indirect influences on behavioral intention. The developers and designers of this and similar products should take into consideration that users have low expectations of effort since, otherwise, they will not show the behavioral intention to use this type of product.

A limitation of the present study is that our sample of respondents, who were users of the Lilo search engine, was limited to professionals and postgraduate students. Therefore, future research should also focus on contexts other than education and be conducted in countries where effective management of water resources is of vital importance for the country itself.

Author Contributions: All authors contributed equally to this work. All authors wrote, reviewed, and commented on the manuscript. All authors have read and approved the final version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Saura, J.R.; Palos-Sánchez, P.; Cerdá Suárez, L.M. Understanding the Digital Marketing Environment with KPIs and Web Analytics. *Future Internet* **2017**, *9*, 76. [CrossRef]
2. Lyman, P.; Varian, H.R. Reprint: How Much Information? *J. Electron. Publ.* **2000**, *6*. [CrossRef]
3. Palos-Sanchez, P.; Saura, J.R. The Effect of Internet Searches on Afforestation: The Case of a Green Search Engine. *Forests* **2018**, *9*, 51. [CrossRef]
4. Browman, H.I.; Stergiou, K.I. Perspectives on ecosystem-based approaches to the management of marine resources. *Mar. Ecol. Prog. Ser.* **2004**, *274*, 269–303. [CrossRef]
5. Choi, H.; Varian, H. Predicting the Present with Google Trends. *Econ. Rec.* **2012**, *88*, 2–9. [CrossRef]

6. Hannak, A.; Sapiezynski, P.; Kakhki, A.M.; Krishnamurthy, B.; Lazer, D.; Mislove, A.; Wilson, C. Measuring personalization of web search. In Proceedings of the 22nd International Conference on World Wide Web—WWW 13, Rio de Janeiro, Brazil, 13–17 May 2013. [CrossRef]
7. Saura, J.R.; Palos-Sánchez, P.; Reyes-Menendez, A. Marketing a través de Aplicaciones Móviles de Turismo (M-Tourism). Un estudio exploratorio. *Int. J. World Tour.* **2017**, *4*, 45–56.
8. Saura, J.R.; Reyes-Menendez, A.; Alvarez-Alonso, C. Do online comments affect environmental management? Identifying factors related to environmental management and sustainability of hotels. *Sustainability* **2018**, *10*, 3016. [CrossRef]
9. Bennett, D.; Yábar, D.P.B.; Saura, J.R. University Incubators May Be Socially Valuable, but How Effective Are They? A Case Study on Business Incubators at Universities 2017. In *Entrepreneurial Universities. Innovation, Technology, and Knowledge Management*; Peris-Ortiz, M., Gómez, J., Merigó-Lindahl, J., Rueda-Armengot, C., Eds.; Springer: Cham, Switzerland, 2017. [CrossRef]
10. Guarnascheli, A.B.; Garau, A.M.; Lemcoff, J.H. Water Stress and Afforestation: A Contribution to Ameliorate Forest Seedling Performance During the Establishment. In *Water Stress*; Intech: London, UK, 2012. [CrossRef]
11. Google Blog. 2009. Available online: https://googleblog.blogspot.com/2009/01/powering-google-search.html (accessed on 1 February 2018).
12. Chin, W.W.; Newsted, P.R. Structural Equation Modeling Analysis with Small Samples Using Partial Least Squares. In *Statistical Strategies for Small Sample Research*; Hoyle, R., Ed.; Sage Publications: Thousand Oaks, CA, USA, 1999; pp. 307–341.
13. Palos-Sanchez, P.; Martin-Velicia, F.; Saura, J.R. Complexity in the Acceptance of Sustainable Search Engines on the Internet: An Analysis of Unobserved Heterogeneity with FIMIX-PLS. *Complexity* **2018**, *2018*, 6561417. [CrossRef]
14. Palos-Sanchez, P.R.; Saura, J.R.; Reyes-Menendez, A.; Esquivel, I.V. Users Acceptance of Location-Based Marketing Apps in Tourism Sector: An Exploratory Analysis. *J. Spat. Organ. Dyn.* **2018**, *6*, 258–270.
15. Wang, Y.Y.; Luse, A.; Townsend, A.M.; Mennecke, B.E. Understanding the moderating roles of types of recommender systems and products on customer behavioral intention to use recommender systems. *Inf. Syst. e-Bus. Manag.* **2015**, *13*, 769–799. [CrossRef]
16. Hsieh, H.L.; Kuo, Y.M.; Wang, S.R.; Chuang, B.K.; Tsai, C.H. A Study of Personal Health Record User's Behavioral Model Based on the PMT and UTAUT Integrative Perspective. *Int. J. Environ. Res. Public Health* **2016**, *14*, 8. [CrossRef] [PubMed]
17. Zalewski, M. Ecohydrology—The scientific background to use ecosystem properties as management tools toward sustainability of water resources. *Ecol. Eng.* **2000**, *16*, 1–8. [CrossRef]
18. Somlyody, L.; Yates, D.; Varis, O. Challenges to freshwater management. *Int. J. Ecohydrol. Hydrobiol.* **2001**, *1*, 65–96.
19. Wagner, W.; Gawel, J.; Furumai, H.; Pereira de Souza, M.; Texeira, D.; Rios, L.; Ohgaki, S.; Zehnder, A.; Hemond, H.F. Sustainable watershed management: An international multi-watershed case study. *Ambio* **2002**, *31*, 2–13. [CrossRef] [PubMed]
20. Dare, L.; Evans, M. Understanding water governance: The case of Australia's Murray-darling basin. *Policy Stud.* **2017**, *38*, 411–417. [CrossRef]
21. Lee, J.; Kim, Y. Selection of representative GCM scenarios preserving uncertainties. *J. Water Clim. Chang.* **2017**, *8*, 641–651. [CrossRef]
22. Xenopoulos, M.; Lodge, D.; Alcamo, J.; Marker, M.; Schulze, K.; Van Vuuren, D. Scenarios of freshwater fish extinctions from climate change and water withdrawal. *Glob. Chang. Biol.* **2005**, *11*, 1557–1564. [CrossRef]
23. OECD. Water Withdrawals [Indicator]. 2018. Available online: https://www.oecd-ilibrary.org/environment/water-withdrawals/indicator/english_17729979-en (accessed on 15 May 2018).
24. OECD. Waste Water Treatment [Indicator]. 2018. Available online: https://www.oecd-ilibrary.org/environment/waste-water-treatment/indicator/english_ef27a39d-en (accessed on 15 May 2018).
25. Larsen, T.; Gujer, W. The concept of sustainable urban water management. *Water Sci. Technol.* **1997**, *35*, 3–10. [CrossRef]
26. Russo, T.; Alfredo, K.; Fisher, J. Sustainable Water Management in Urban, Agricultural, and Natural Systems. *Water* **2014**, *6*, 3934–3956. [CrossRef]
27. Rieder, B. Networked control: Search engines and the symmetry of confidence. *Int. Rev. Inf. Ethics* **2005**, *3*, 26–32.

28. Bayus, B.L. *Understanding Customer Needs in Handbook of Technology and Innovation Management*; Shane, S., Ed.; Wiley: Chichester, UK; Hoboken, NJ, USA, 2008.
29. Stevens, G.; Burley, J. 3000 raw ideas = 1 commercial success! *Res. Technol. Manag.* **1997**, *40*, 16–27. [CrossRef]
30. Lin, H.F. Understanding Behavioral Intention to Participate in Virtual Communities. *CyberPsychology Behav.* **2006**, *9*, 540–547. [CrossRef] [PubMed]
31. Lu, J.; Yao, J.; Yu, C. Personal innovativeness, social influences and adoption of wireless Internet services via mobile technology. *J. Strateg. Inf. Syst.* **2005**, *14*, 245–268. [CrossRef]
32. Sung, H.; Jeong, D.; Jeong, Y.; Shin, J. The Relationship among Self-Efficacy, Social Influence, Performance Expectancy, Effort Expectancy, and Behavioral Intention in Mobile Learning Service. *Int. J. e-Serv. Sci. Technol.* **2015**, *8*, 197–206. [CrossRef]
33. Morgan-Thomas, A.; Veloutsou, C. Beyond technology acceptance: Brand relationships and online brand experience. *J. Bus. Res.* **2013**, *66*, 21–27. [CrossRef]
34. Tai, C.L. The Impacts of Utilitarian and Hedonic Motivations on Habit and Online Browsers' Behaviors. *Int. J. Adv. Comput. Sci. Appl. IJCSIA* **2014**, *4*, 126–130.
35. Francis, A.J.J.; Eccles, M.P.M.; Johnston, M.; Walker, A.; Grimshaw, J.; Foy, R.; Kaner, E.F.S.; Smith, L.; Bonetti, D.; Francis, J. *Constructing Questionnaires Based on the Theory of Planned Behaviour a Manual for Health Services Researchers*; Centre for Health Services Research: Newcastle Upon Tyne, UK, 2004; pp. 1–42.
36. Mathieson, K. Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior. *Inf. Syst. Res.* **1991**, *2*, 173–191. [CrossRef]
37. Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **1991**, *50*, 179–211. [CrossRef]
38. Ajzen, I. *Attitudes, Personality and Behavior*; Open University Press: Milton Keynes, UK, 1988.
39. Armitage, C.J.; Conner, M.; Loach, J.; Willetts, D. Different perceptions of control: Applying an ex- tended theory of planned behavior to legal and illegal drug. *Basic Appl. Soc. Psychol.* **1999**, *21*, 301–316. [CrossRef]
40. O'Connor, R.C.; Armitage, C.J. Theory of planned behaviour and parasuicide: An exploratory study. *Curr. Psychol.* **2003**, *22*, 196–205. [CrossRef]
41. Goto, T.; Duc, N.T.; Bollegala, D.; Ishizuka, M. Exploiting symmetry in relational similarity for ranking relational search results. In *Pacific Rim International Conference on Artificial Intelligence*; Springer: Berlin/Heidelberg, Germany, 2010; pp. 595–600.
42. Venkatesh, V.; Thong, J.Y.; Xu, X. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Q.* **2012**, *36*, 157–178. [CrossRef]
43. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
44. Chang, I.; Hwang, H.; Hung, W.; Li, Y. Physicians' acceptance of pharmacokinetics-based clinical decision support systems. *Expert Syst. Appl.* **2007**, *33*, 296–303. [CrossRef]
45. Jang, Y.T.; Chang, S.E.; Tsai, Y. Smartphone security: Understanding smartphone users' trust in information security management. *Secur. Commun. Netw.* **2014**, *7*, 1313–1321. [CrossRef]
46. Phichitchaisopa, N.; Naenna, T. Factors affecting the adoption of healthcare information technology. *EXCLI J.* **2013**, *12*, 413–436. [PubMed]
47. Alaiad, A.; Zhou, L. The determinants of home healthcare robots adoption: An empirical investigation. *Int. J. Med. Inform.* **2014**, *83*, 825–840. [CrossRef] [PubMed]
48. Garber, D. *Thinking Historically/Thinking Analytically*; Oxford Scholarship Online; Oxford University Press: Oxford, UK, 2017. [CrossRef]
49. Drolet, A.; Bodapati, A.V.; Suppes, P.; Rossi, B.; Hochwarter, H. Habits and Free Associations: Free Your Mind but Mind Your Habits. *J. Assoc. Consum. Res.* **2017**, *2*, 293–305. [CrossRef]
50. Graf-Vlachy, L.; Buhtz, K.; König, A. Social influence in technology adoption: Taking stock and moving forward. *Manag. Rev. Q.* **2018**, *68*, 37–76. [CrossRef]
51. Brown, S.A.; Venkatesh, V. Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. *MIS Q.* **2005**, *29*, 399–426. [CrossRef]
52. Sánchez, E.M. Análisis de la influencia de la familia en los hábitos lectores de sus hijas e hijos: Un estudio etnográfico. Contextos Educativos. *Revista De Educación* **2001**, *4*, 177–196. [CrossRef]
53. Martínez-Ávila, D.; Segundo, R.S.; Zurian, F.A. Retos y oportunidades en organización del conocimiento en la intersección con las tecnologías de la información. *Revista Española De Documentación Científica* **2014**, *37*. [CrossRef]

54. Rashid, F.; Edmondson, A.C. Risky TrustHow Multi-Entity Teams Build Trust despite High Risk. In *Restoring Trust in Organizations and Leaders: Enduring Challenges and Emerging Answers*; Oxford University Press: Oxford, UK, 2012; pp. 129–150. [CrossRef]
55. Durkheim, E. *El Suicidio*; Akal: Madrid, Spain, 1989.
56. Santos, F.R. Redes de amistad, felicidad y familia. *Reis* **1994**, *1*, 73–89. [CrossRef]
57. Limayem, M.; Hirt, S.G. Force of habit and information systems usage: Theory and initial validation. *J. Assoc. Inf. Syst.* **2003**, *4*, 6597. [CrossRef]
58. Mcknight, D.H.; Choudhury, V.; Kacmar, C. The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *J. Strateg. Inf. Syst.* **2002**, *11*, 297–323. [CrossRef]
59. Lai, I.K.W.; Guicheng, S. The impact of privacy concerns on the intention for continued use of an integrated mobile instant messaging and social network platform. *Int. J. Mob. Commun.* **2015**, *13*, 641–669. [CrossRef]
60. Gefen, D.; Straub, D.; Boudreau, M.C. Structural equation modeling and regression: Guidelines for research practice. *Commun. Assoc. Inf. Syst.* **2000**, *4*, 1–77.
61. Pavlou, P.A. Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *Int. J. Electron. Commer.* **2003**, *7*, 101–134.
62. Babin, B.J.; Babin, L. Seeking Something Different? A Model of Schema Typicality, Consumer Affect, Purchase Intentions and Perceived Shopping Value. *J. Bus. Res.* **2001**, *54*, 89–96. [CrossRef]
63. Gefen, D.; Karahanna, E.; Straub, D.W. Trust and TAM in online shopping: An integrated model. *MIS Q.* **2003**, *27*, 51–90. [CrossRef]
64. Liaw, S. The theory of planned behaviour applied to search engines as a learning tool. *J. Comput. Assist. Learn.* **2004**, *20*, 283–291. [CrossRef]
65. Nillos, B.E. Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions are Factors that Influence Rural Health Workers in the Use of Wireless Access for Health and Perception of Behavior of their Pregnant Patients. *JPAIR Multidiscip. Res.* **2016**, *24*. [CrossRef]
66. Rayburn, W.E.; Ramaprasad, A. Three Strategies for the Use of Distance Learning Technology in Higher Education. *Web-Based Instruct. Learn.* **2012**, 27–42. [CrossRef]
67. Antoniou, D.; Plegas, Y.; Tsakalidis, A.; Tzimas, G.; Viennas, E. Dynamic refinement of search engines results utilizing the user intervention. *J. Syst. Softw.* **2012**, *85*, 1577–1587. [CrossRef]
68. Chang, S.E.; Shen, W.C.; Liu, A.Y. Why mobile users trust smartphone social networking services? A PLS-SEM approach. *J. Bus. Res.* **2016**, *69*, 4890–4895. [CrossRef]
69. Tamayo, M. *El Proyecto de la Investigación Científica*; Editorial Limusa Noriega Editores: Ciudad de México, Mexico, 2007.
70. Rodriguez Peñuelas, M.A. *Métodos de Investigación: Diseño de Proyectos y Desarrollo de Tesis en Ciencias Administrativas, Organizacionales y Sociales*; Nº 69; Universidad Autónoma de Sinaloa: Culiacán, Mexico, 2010.
71. Hernández, C.R.; Fernández, C.; Baptista, P. *Metodología de la Investigación*; Mc-Graw Hill: México City, Mexico, 2007.
72. Hadadgar, A.; Changiz, T.; Masiello, I.; Dehghani, Z.; Mirshahzadeh, N.; Zary, N. Applicability of the theory of planned behavior in explaining the general practitioners eLearning use in continuing medical education. *BMC Med. Educ.* **2016**, *16*, 215. [CrossRef] [PubMed]
73. Trespalacios, J.A.; Vázquez, R.; Bello, L. *Investigación de Mercados. Métodos de Recogida de Información para la Toma de Decisiones en Marketing*; Thomson-Paraninfo: Madrid, Spain, 2005.
74. Anderson, J.C.; Gerbing, D.W. Structural equation modeling in practice: A review and recommended two-step approach. *Psychol. Bull.* **1988**, *103*, 411–423. [CrossRef]
75. Cronbach, L.J. Coefficient alpha and the internal structure of tests. *Psychometrika* **1951**, *16*, 297–334. [CrossRef]
76. Nurosis, M.J. *SPSS. Statistical Data Análisis*; SPSS Inc.: Chicago, IL, USA, 1993.
77. Nunnally, J.C. *Psychometric Theory*; McGraw-Hill: New York, NY, USA, 1978.
78. Luque, T. *Técnicas de Análisis de Datos en Investigación de Mercados*; Ediciones Pirámide: Madrid, Spain, 2000.
79. Bagozzi, R.Y.B.; Baumgartner, P.J.H. The evaluation of structural equation models and hypothesis testing. *Princ. Mark. Res.* **1994**, 386–419.
80. Hair, J.F.; Anderson, R.E.; Tatham, R.L.; Black, W.C. *Análisis Multivariante*; Prentice Hall: Madrid, Spain, 1999; Volume 491.
81. Hildebrandt, L. Consumer retail satisfaction in rural areas: A reanalysis of survey data. *J. Econ. Psychol.* **1987**, *8*, 19–42. [CrossRef]

82. Joreskog, K.G.; Sorbom, D. *LISREL VII: A Guide to the Program and Applications*; SPSS: Chicago, IL, USA, 1988.
83. Sharma, S. *Applied Multivariate Techniques*; John Wiley& Sons: Hoboken, NJ, USA, 1996.
84. Bagozzi, R.P.; Yi, Y. On the evaluation of structural equation models. *J. Acad. Mark Sci.* **1988**, *16*, 74–94. [CrossRef]
85. Fornell, C.; Larcker, D.F. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
86. Bentler, P.M.; Bonett, D.G. Significance tests and goodness of fit in the analysis of covariance structures. *Psychol. Bull.* **1980**, *88*, 588–606. [CrossRef]
87. Steiger, J.H. Structural model evaluation and modification: An interval estimation approach. *Multivar. Behav. Res.* **1990**, *25*, 173–180. [CrossRef] [PubMed]
88. Hu, L.T.; Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Model. Multidiscip. J.* **1999**, *6*, 1–55. [CrossRef]
89. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E. *Multivariate Data Analysis*, 7th ed.; Prentice Hall: Upper Saddle River, NJ, USA, 2010.
90. Chin, W.W. The partial least squares approach to structural equation modeling. *Mod. Methods Bus. Res.* **1998**, *295*, 295–336.
91. Edwards, J.R.; Lambert, L.S. Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. *Psychol. Methods* **2007**, *12*, 1–22. [CrossRef] [PubMed]
92. Saura, J.R.; Palos-Sanchez, P.R.; Rios Martin, M.A. Attitudes to environmental factors in the tourism sector expressed in online comments: An exploratory study. *Int. J. Environ. Res. Public Health* **2018**, *15*, 553. [CrossRef] [PubMed]
93. Palos-Sanchez, P.R.; Robina Ramirez, R.; Cerda Suarez, L.M. Ethics of online reputation, personal brand and privacy in cloud computing: Protection of users against the right to forget. *Biblios-Rev. Bibliotecol. Cienc. Inf.* **2018**, *11*, 17–31.