Central European Journal of Operations Research (2021) 29:201–225
https://doi.org/10.1007/s10100-020-00723-4

Supporting multi-criteria decision-making across websites: the Logikós approach

Alejandro Fernandez[1] · Pascale Zaraté[2] · Juan Cruz Gardey[1] · Gabriela Bosetti[1]

Accepted: 17 November 2020 / Published online: 5 January 2021

Abstract
Online customers frequently conduct activities that involve multi-criteria decision-making. They analyze and compare alternatives considering a set of shared characteristics. Websites present the information of products without special support for these activities. Moreover, the products of interest for the customer are frequently scattered across various shops, with no support to collect and compare them in a consistent and customized manner. We argue that multi-criteria decision-making methods (such as Analytic Hierarchy Process) can be effectively offered to online customers. In this article, we present an approach and supporting tools to enable multi-criteria decision-making on any website and across websites. They are based on web-augmentation to extract information items from websites, and the Analytic Hierarchy Process (AHP) to model multi-criteria decisions. The approach and tools were experimentally evaluated with end-users in two different countries. An illustrative scenario provides insight into the application of the approach and the role of the supporting tools. Evaluation showed that users appreciate creating AHP models specific to their needs, and trust the decisions they make using these models. Participants were reluctant to trust reusable decision profiles (i.e., AHP models created by other users). The numerous pairwise comparisons required by AHP in the presence of multiple criteria and alternatives, was reported as a drawback. However, participants indicated that the proposed smart-ranking functionality represented a good mechanism to cope with it.

Keywords Multi-criteria decision support · Analytic hierarchy process · E-commerce · Web augmentation

1 Introduction

Electronic commerce is nowadays growing fast; forecasting for the coming years indicates that the online retail market will still increase.

Extended author information available on the last page of the article

Buying online can be effortless and almost automatic in some situations, such as in online supermarket purchases, for customers that are well accustomed. In some cases, buying online can be challenging; some customers invest considerable time and effort when buying expensive products, specially if it involves multiple competing alternatives and shops.

E-shops offer tools to support customers' decision making. Recommender agents are a common feature of most online shops, helping customers identify items that might be of interest. Recommender agents frequently rely on collaborative filtering algorithms, that learn from the user's actions to identify items of interest. In addition, customers are encouraged to provide reviews on the products they purchase (either on the merchant's site or on specialized product review sites and communities). The level of detail in reviews may vary, from a numerical rating to a structured textual review covering various aspects. By providing reviews, customers support each other's decisions. Decisions based on reviews or the e-shop's recommender agent reflect what Pingle (1995) identifies as non-rationals decisions based on imitation . Moreover, concerns have been raised concerning trust and transparency issues with both these approaches (Choudhury and Srinivasan 2019; Afridi 2019). In this work we focus on customer decision support with an emphasis on rational decision making (i.e., support to compare alternatives and make the best choice). As pointed out by Pingle (1995) both approaches are complementary.

Buying online is a multi-criteria decision process because it usually involves comparing several items, considering not one but many properties. Akarte et al. (2001) defined 18 criteria for supplier assessment (as sample delivery time, maximum casting size or minimum section thickness). A problem with existing e-commerce platforms is that they do not support users to make rational decisions in a personalized and controllable way. Some of them have functionalities that let customers compare products, but these are usually limited to ranking and filtering. There are product review sites and blogs where organizations or persons, from a position of experts, offer advice for others. For the most part, these sites are used to find choices to imitate, or to learn about the many aspects to consider when making a rational decision.

Several approaches to support a decision maker in his/her decision process exist. One of them is called Multi-Criteria Decision Analysis (MCDA) in which several criteria are defined and used to compare multiple alternatives. Then, to find the suitable ranking for the end-user, several straightforward criteria aggregation operators such as the Weighted sum and even richer ones such as the "Ordered weighted sum", "Choquet Integral" are developed. Multi-Criteria Decision Analysis is not available in existing e-commerce platforms.

Additional issues arise when the items or alternatives that the customer wants to consider are not available in a single e-commerce website, or when the information describing a specific alternative is scattered across different sites. This is known as uncompleted information. Customers are not very well supported to collect and compare the alternatives available in various sites in a consistent way. Some websites propose a solution to this challenge like for example meta-search engines but only for some domains, like Trivago[1] for hotels and flights.

[1] http://www.trivago.com Last accessed December 2018.

In this work we propose an approach to empower decision makers with multi-criteria decision-making support on any website, and across different websites. A descriptive scenario of users shopping for smartphones is presented in order to illustrate our approach. We develop Logikós, a toolbox supporting such decision-making approach. We evaluate the developed system in a controlled experiment, involving participants from Argentina and France.

The "shared decision profile" is a central feature of Logikós. A shared decision profile is, at its core, a reusable analytic hierarchy process model (leaving out the alternatives). Logikós offers an editor of shared profiles that supports basic collaboration; profiles can be edited by several users working asynchronously and without any specific negotiation support. Profiles are normally created by a group of users that share decision criteria. The tools support users while creating, editing, testing and sharing the decision profiles. Logikós is not aimed at Group decision-making but at sharing criteria. The system is developed to support a single user even if, from a group of end-users, a generic profile can be created. The main objective of this shared profile is to make it rather general to fit it to several end-users. Logikós can be combined with existing collaborative work tools to enable discussion and agreement for shared profile generation.

Shared decision profiles are dependent on the expected properties of the alternatives, and not on the type, nor on the values that these properties take for specific alternatives. Shared profiles can be reused whenever the properties of the items under consideration match those used in the profile, and the decision maker considers that the profile represents her interests. Only if the decision maker does not find a shared profile that matches these requirements it becomes necessary to create and share a new one.

The article is organized as follows. Section 2 introduces key background concepts and related works regarding decision support systems and multi-criteria approach. Section 3 presents the developed system: Logikós. An illustrative scenario is presented in Sect. 4. Section 5 describes the controlled experiment, and presents the results. Lastly, a comparison to related works and the conclusions follow.

2 Background and related work

2.1 Informed decision-making

Even if the Web is full of information, it is not always easy to find the right information to make rational purchase decisions. Information is generally ill-structured and incomplete. Information is hard to find. The information retrieval and the tools we might have to support purchase decisions are generally disconnected. Making a decision based on information sometimes requires complex (e.g., multi-criteria) decision processes, which is challenging for many people.

Spreadsheets are frequently used by decision-makers to aggregate the information in one unique place (Quinn and Bederson 2014). A simple web-search for "spreadsheet car shopping" will return multiple hits referring to a variety of prepared spreadsheet templates to support buyers to compare and select cars. Such spreadsheets serve two purposes. On the one hand, they help users to identify key attributes to look for and

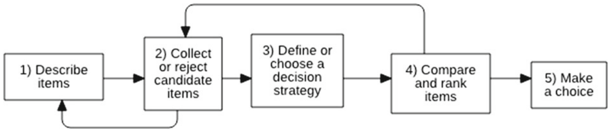


Fig. 1 A model of the spreadsheet strategy for rational purchasing

record them in a structured manner even if they still need to harvest the information manually. On the another hand, once attributes have been recorded for all alternatives, the spreadsheet could help to make a decision with calculations and comparisons that reflect the priorities and weights that the template's author gave to each criterion. This second option is not frequently used.

Customers who are proficient in the operation of spreadsheets sometimes use them to create similar templates to buy other kinds of products like for example smartphones, cameras or personal computers. However, in those cases, the use of the spreadsheet is limited to reproducing the comparison functionality commonly offered by e-commerce websites. That is: (a) select candidates, (b) have a general overview of the available properties of all candidates, (c) compare candidates attribute by attribute, (d) sort and filter candidates.

The effort that customers invest in making a decision is directly related to the outcome. There is a trade-off between effort invested and the perceived outcome. High stake decisions motivate users to make a more significant effort. When decision makers understand the stakes are not that high, they settle for a sub-optimal alternative, like the first option that meets some threshold criteria or a suggestion from a trusted colleague. This is the meaning of the term "satisficing" in the bounded rationality theory (Simon 1956).

The approach followed by decision makers, like the ones described above, can be characterized by the following process (see Fig. 1). We call it "The spreadsheet strategy for rational purchasing". First, the decision maker describes the items to be purchased (1). The description of the items includes the properties to look for when collecting information. Then, the harvesting starts. The decision maker browses various websites recording information about the items that are a good candidate for purchase (2). The URL of the collected candidates must be recorded so the decision maker can find them again. The decision maker must be able to identify a new and valuable property, not considered so far. He consequently updates the description of the items and starts collecting the new information from that moment on (1). Ideally, he goes back and updates the information of already collected items that did not include the new properties (2). When an interesting list of candidates is available, the decision maker attempts a decision. For that, he needs to define a decision strategy or use an existing one, like the one created by other users as a spreadsheet template (3), and apply it to rank the so far collected items (4). Applying the decision strategy on already collected items might trigger the need for collecting more items or removing some bad performing candidates (2). This iterative process of item modeling, harvesting, and evaluation continues until the optimal candidate is found or the "satisficing" threshold is met.

2.2 Multi-criteria decision analysis

Several schools of thought exist that study MCDA (Ishizaka and Nemery 2013). The output of the studied techniques is to obtain a ranked list of alternatives. There are two well-known schools of MCDA: the American school and the European school. The American school is based on an evaluation of the utility function of each alternative. A utility function is inspired by the Economy area for which the one global utility function is mathematically modeled to translate the utility of one decision. One of the most well-known MCDA methods in this school is called the Analytic Hierarchy Process (AHP) (Saaty 2004). AHP is a mature and widespread process to support decision makers to choose among various alternatives in a context where the decision involves comparing the alternatives according to multiple aspects, each of which contributes differently to the decision. . For AHP, the decision maker is asked to do a pairwise comparison of each alternative on each criterion and a pairwise comparison among the criteria. That means that the decision maker must fill in several matrices. On the other hand, the European school is not based on the evaluation of a set of matrices but the evaluation of thresholds for each criterion. For each criterion, a preference, indifference and veto thresholds are defined. These thresholds are used to compare alternatives two by two on each criterion and then on several criteria. The two main methodologies in this school are Promethee (Brans and Mareschal 2005) and Electre (Roy 1991). They are less time consuming to use than AHP, but the definitions of the thresholds are quite difficult. This work presented in this article follows the American school.

AHP helps to identify the properties to be considered (criteria), supports the exploration of relations among them and their use to choose an alternative. It relies on pairwise comparisons and the judgment of experts to obtain priority scales (Saaty 2008). AHP has been used for a wide variety of domains, as in education, healthcare, public administration, telecommunications, manufacturing, and various branches of the Industry (like airlines, defense, entertainment, manufacturing) (Russo and Camanho 2015).

At its core, AHP consists of three well-defined steps. First, the decision problem is decomposed into a hierarchy of sub-problems (commonly referred to as decision criteria). Then, decision makers compare the identified sub-problems to each other in order to obtain a model for their relative importance regarding solving the higher level problem. This pairwise comparison among elements in the decision hierarchy is used to obtain the weight or priority of each decision criterion. Such weights represent how much each of the decision criteria is important to the final decision. At this point, a consistency check can be performed. In any given level, if there are C criteria, $\sum_{n=1}^{C-1} n$ pair-wise comparisons are required.

Russo and Camanho conducted a literature review regarding how criteria are being defined and measured (Russo and Camanho 2015). In a few cases, criteria were obtained from literature on the domain. More cases involved experts in defining/selecting criteria. In this study, we involved decision-makers, and the proposed approach is designed for a single user or single decision maker. The decision makers preferences are modeled in matrices; if the number of used criteria is n, then the number of matrices to fill in is n + 1 depending on the decomposition structure.

Up to this step, the method does not require an analysis of the available alternatives (e.g. products that the customer considers buying). In fact, an interesting aspect of AHP is that it aims to force the decision maker to explicitly reflect on the decision criteria without focusing his attention on the concrete alternatives (thus reducing the preference bias). AHP is about focusing on the factors; it facilitates the decision-making by decomposing a decision-problem into factors and organizing them in order to exhibit the forces that influence a decision (Saaty 2008).

In a final step, the alternatives are compared to each other with respect to each criterion, which can be tangible (e.g. price) or intangible (e.g. aspirational appeal). If A is the number of available alternatives, and C is the number of criteria, the decision maker needs to make $C * \sum_{n=1}^{A-1} n$ pair-wise comparisons.

Although pairwise comparisons among criteria and among alternatives are not complex per se, the number of required comparisons rises fast. If 4 criteria are considered, and 5 alternatives are available, the number of pair-wise comparisons is computed as $(\sum_{n=1}^{3} n) + 4 * \sum_{n=1}^{4} n = 6 + 4 * 10 = 46$. Moreover, as the number of pairwise comparisons increases, so does the probability of introducing inconsistencies in the resulting model. This methodology is easy to use; however, without adequate support, it might be time-consuming in real-life situations.

2.3 Concerns regarding AHP

As mentioned by Vargas (1990) "the Analytic Hierarchy Process (AHP) is a theory of measurement for dealing with quantifiable and/or intangible criteria that has found rich applications in decision theory, conflict resolution and in models of the brain. It is based on the principle that, to make decisions, experience and knowledge of people is at least as valuable as the data they use".

Decision applications of the AHP are carried out in two phases: hierarchic design and evaluation. The design of decision hierarchies requires experience and knowledge of the problem area. Two decision makers would normally structure two different hierarchies of the same decision. Thus, a decision's hierarchy is not unique. On the other hand, even when two people design the same decision's hierarchy, their preferences may yield different courses of action. However, a group of people can work together to reach a consensus on both the hierarchy (design) and on the judgments and their synthesis (evaluation).

The evaluation phase is based on the concept of paired comparisons. The elements in a level of the hierarchy are compared in relative terms as to their importance or contribution to a given criterion that occupies the level immediately above the elements being compared. This process of comparison yields a relative scale of measurement of the priorities or weights of the elements. That is, the scale measures the relative standing of the elements concerning a criterion independently of any other criterion or element that may be considered for comparison. These relative weights sum to unity. The comparisons are performed for the elements in a level regarding all the elements in the level above. The final or global weights of the elements at the bottom level of the hierarchy are obtained by adding all the contributions of the elements at a level concerning all the elements in the level above. This is known as the principle of hierarchic composition. While there is an infinite number of ways of synthesizing the weights of the alternatives and the weights of the criteria, the additive aggregation rule of the AHP has the advantage of intuitive understanding of the apportionment of the whole into its parts.

A useful feature of the AHP is its applicability to the measurement of intangible criteria along with tangible ones through ratio scales. In addition, by breaking a problem down into its constituent parts and logically relating them from the large, descending in gradual steps, to the smaller and smaller, one is able to connect through simple paired comparison judgments the small to the large. The AHP is a tool that has found uses in a wide range of problem areas from simple personal to complex and capital intensive decisions".

Even if this theory had a great success thanks to its simplicity, it is uneasy for a Decision Maker to deal with several criteria and alternatives if the problem comprehends a large number of criteria and alternatives. However, it has been also proved that this theory is not correctly satisfying the following Axioms:

- Axiom 1: (Reciprocal Comparison). The decision maker must be able to make comparisons and state the strength of his preferences.
- Axiom 2: (Homogeneity). The preferences are represented by means of a bounded scale.
- Axiom 3: (Independence). When expressing preferences, criteria are assumed independent of the properties of the alternatives.
- Axiom 4: (Expectations). To make a decision, the hierarchic structure is assumed to be complete.

So, it appears that AHP is not theoretically the most suitable method, but it is easily understandable for anyone. A large number of applications of this theory shows how it is simple to use it in real situations. Using other methodologies, like for example Electre or Promethee, implies defining indifferent and preference thresholds that is quite difficult to understand and define. As mentioned early, AHP has been chosen to be embedded in Logikós for its simplicity of use. Nevertheless, we aim to implement other multicriteria methodologies embedded in Logikós and to recommend one methodology depending on the context of the problem to solve.

3 Approach

Using the spreadsheet approach as a reference, we created the Logikós platform. Logikós reduces the cognitive workload of decision-making by providing tools that support and simplify each step of the decision-making process. Figure 2 provides an overview of how the different tools in the platform support the tasks in the decision-making process. The decision makers use the *Template Editor* to model the items. The editor generates a template object that specifies how to extract an information object from any page matching a URL pattern. Templates are stored in a shared *Templates Repository*. The *Items Collector* is available for pages that match the URL pattern

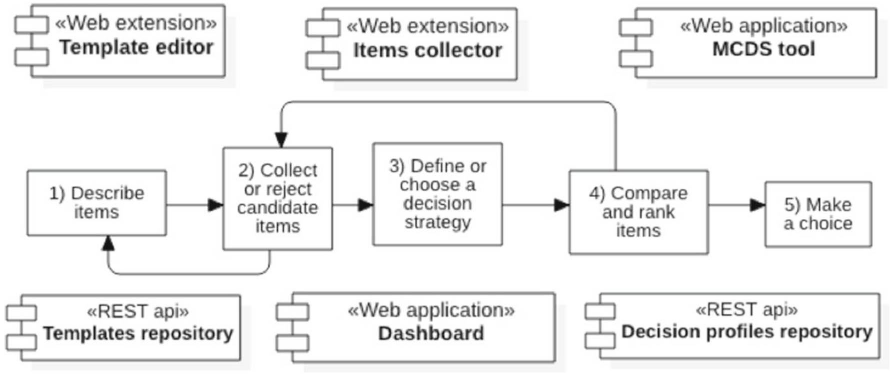


Fig. 2 Approach overview

of a template in the repository. Decision makers use the items collector to collect in a *Dashboard*, one by one, the items of interest. Dashboards can be shared among users. With items in a dashboard, the decision maker uses *Multi Criteria Decision-Making Tool* to explore the various applicable decision profiles; each decision profiles produces an alternative ranking of the collected items. Decision profiles are available in a shared *Decision Profile Repository*. They are created and shared by a community of like-minded users, using AHP modeling tools provided by the platform.

Logikós is based on three core concepts namely, *web information objects*, *shared decision profiles*, and *smart ranking strategies*. While web information objects are prominent in earlier tasks (i.e., item description and collection), shared decision profiles and smart ranking strategies become relevant in the later tasks (i.e., definition of the decision strategy, comparison and ranking, and final choice).

The following sections discuss each of these core elements in more detail.

3.1 Web information objects

Logikós was built on-top of WOA (Web Objects Ambient) (Firmenich et al. 2016; Bosetti et al. 2016), a web augmentation approach that support information extraction (i.e., semantic scrapping) on any website. With WOA, users define extraction templates and use them to collect and share information objects. They can do this without any need for programming.

WOA is designed as a set of related tools: the templates editor, the information objects collector, and two repositories; one repository for templates and one repository to store the collected information objects (the dashboard). Users define, with the template editor, templates that specify objects (with types and properties) that can be recognized and extracted in web pages. For each template, the users indicate the type/class of the information object (a Semantic Web type), a URL pattern to select pages for which the template works, and a dictionary of properties that make up the information object. There might be several templates for a given type and properties, each one targeting different URL patterns (as various websites might publish comparable information). For each property, a template specifies an XPath selector that must be navigated to obtain the value of the property.

The information object collector can be used in any web-page that matches the urlPattern of one of the templates in the templates repository. When many templates match the URL of a page, it is up to the user to decide which one to use. When the user visits a page where there is an object (item) of interest, he has to explicitly click the "Collect item" button. What WOA then does, is to automatically (transparently) obtain all pieces of information on the page and assemble the object. Extracted information objects (items) are stored in the user's dashboard. Dashboard access is protected with an access code; sharing the access code allows collaborative item collection.

WOA is deployed as a browser extension. It uses web augmentation strategies (Díaz 2012) to transparently attach itself to any website, and to enrich it with functionality to support information objects extraction. Web Augmentation can be implemented using different strategies (like DOM manipulation at a proxy, bookmarklets, and extensions at the client). WOA performs Document Object Model (DOM) manipulation through the API of web-extensions on the client side.

3.2 Shared decision profiles

A shared decision profile models how a given group of users decides among alternatives of certain type of items. It is used to rank items (alternatives) comparing and weighing properties. For example, a profile labeled "Money talks" might rank smartphones as customers with budget restrictions would do, considering features like price, processor and memory (in that order of importance). The "Gamer on a budget" profile might be an example of a shared profile that considers the same properties as "Money talks" but gives properties different weights. Although Logikós promotes sharing of decision profiles, users can also create private profiles.

Logikós can be combined with existing collaborative work tools to enable discussion and agreement for shared profile generation. Based on this shared profile, one multicriteria methodology can be recommended to the end-user depending on the context of use. A recommender system, called STROma, has been developed by Fomba (2018) in order to recommend a multicriteria aggregation operator depending on the context of the problem to solve, the type of problem. With this kind of recommendation it should be possible to adapt the type of shared profile to a type of problem.

3.3 Smart ranking strategies

The more criteria an AHP model has, the more pairwise comparisons are required. Without tool support, every user would have to make all required comparisons before moving on to consider the alternatives (or items). However, if the user finds a shared profile that matches her needs, comparisons among criteria won't be necessary. However, as it is impossible to foresee all items the user will consider as candidates, pairwise comparisons among alternatives still need to be performed. Logikós introduces the abstraction of "smart ranking strategy" (or SRS) to limit the need for performing pairwise comparisons at the level of alternatives. SRS specifies, for a given attribute and without the need for the user's intervention, how a pair of alternatives must be compared.

Logikós currently supports three strategies that can be used to automate comparison and ranking of alternatives in terms of a given attribute.

The *normalized numeric difference strategy* treats the value of an attribute as a number, and compares values taking the magnitude into consideration. This means that the weight of the difference among two values decreases as the individual values get larger.

There are cases when all possible values of an attribute can be known in advance, can be ordered on a scale from the worst to the best, and the preference among two consecutive values is equally important regardless of the position of the elements in the scale. In such a case, values can be compared by their positions and the distance among them in a scale of *equally spread values*.

For both, the normalized numeric differences, and distances between equally spread values in a scale, the obtained value is mapped onto Saaty's 1 to 9 scale (Saaty 2004).

The third strategy is used in cases where all possible values of an attribute can be known in advance but cannot be ordered in a scale of equally spread elements. Values are compared in a pairwise manner and the results are stored (all comparisons), so other decision-makers do not have to perform them. This strategy is only practical when the domain of the property has a manageable number of possible values. Moreover, it also depends on the available tools to aid pair-wise comparisons, thus reducing the effort and minimizing inconsistency. Users can conduct such pair-wise comparisons collaboratively using external tools such as GRUS (GRoUp Support) (Zaraté et al. 2016) or SuperDecisions (Mu and Pereyra-Rojas 2017).

Figure 3 presents a UML class diagram documenting the design of the shared profiles. The class Node is the principal abstraction; it represents a node in an AHP model. One instance of Node will act as the root of a decision tree (the goal model of a shared profile). Subsequent levels in the decision tree (criteria and sub-criteria) can be defined by adding children to an existing intermediate node. Criteria and sub-criteria can either be tangible (such as weight), or intangible (such as aspirational appeal). The leaves in the decision tree correspond to the properties of the alternatives. A SharedProfile object has only one goal model (one AHP decision tree). The expectedProperties() method queries the goal model to obtain the list of properties that items must have to be used with the profile. When a shared profile is used to make a decision, instances of class Alternative are added as children of each of the goalModel leaf nodes. The properties of the alternatives take their values from the items collected in the dashboard. Subclasses of class SmartRankingStrategy implement the smart ranking strategies previously mentioned.

4 Illustrative scenario: shopping for smartphones

The following detailed scenario provides further insight into the application of the approach and the role of the supporting tools.

John Sito is a 24 years old, (wannabe) IT influencer. He spends most of the time reviewing IT gadgets and apps, and talking to people on social media about them.

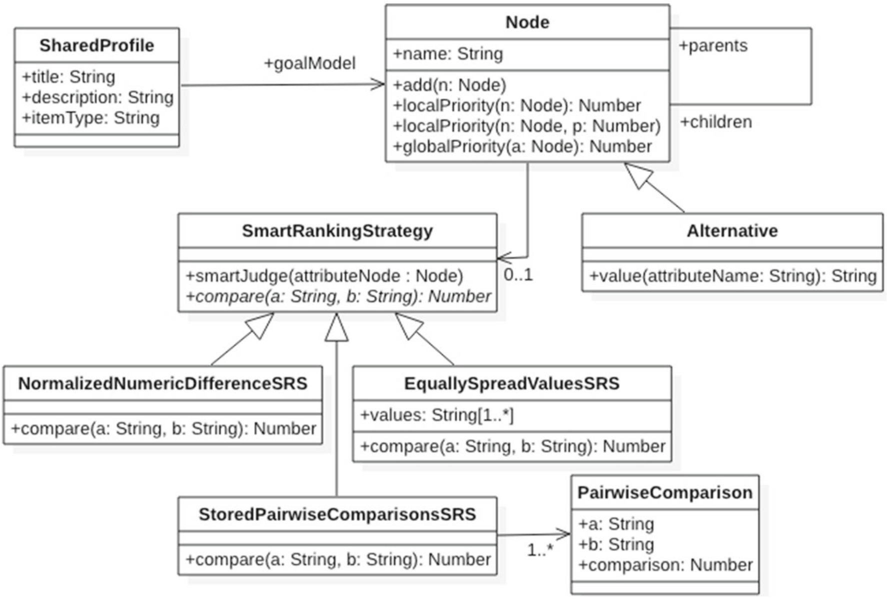


Fig. 3 UML Class model of a shared profile

He has decided to buy a new smartphone. His biggest challenges are saving money while buying technology, and never running out of phone memory to install apps and save videos. After reading many reviews (from other, more popular influencers) he felt they were trying to convince him without any solid, rational arguments. Last time he bought something expensive (a bicycle), he used an excel spreadsheet that a colleague suggested. When he looked online for a similar spreadsheet but for smartphones, his stumbled across the Logikós website. These are the steps he followed to finally make a purchase he felt certain with.

Getting started:

With some help from the video-tutorials in the "Installing the toolset" section, he was able to install the browser extension and learn how to use it. He first installed the web-extensions and created a new, private, list of alternatives. He didn't install a server for the templates, he used the default shared public repository. This took about the same time as installing the spreadsheet tool. Next time, the tools will be already available.

Collecting items:

After a web search, he identified a couple of websites that sold smartphones. He started by visiting the Good-Phones.com store. He realized that another user had already defined a template for smartphones in that site (by following the steps 1 to 5 in Fig. 5), therefore, the Items Collector was already prepared to extract items from the site. The existing template extracts the phone's name, camera, memory, price, and processor. John browsed the site looking for phones. He extracted five phones from this site that he considered within his budget. He did it as shown in steps 1 to 3 in Fig. 4. At this point, he realized the difference of this approach. There was no need to copy

Fig. 4 Extracting items: (1) activate the extractor from a toolbar button; (2) use the check marks to select the properties to include/exclude; (3) click the "Collect item(s)" button to collect the item in your dashboard

and paste all attributes and the URL of the page. He did not make any of the common copy&paste mistakes he did last time (e.g., pasting to a wrong row or column). He felt like he would collect as many candidates as he wanted.

Defining a template:

Then, he visited the technology e-commerce site Cheap-Gadgets.com. He found a phone he liked, but he was not able to collect it. Logikós was not prepared to collect items on this website. Following the steps mentioned in Fig. 5, John defined an extraction template and pushed it to the public repository for other users to use. The template extracted the same attributes as the template he used for Good-Phones.com. He collected other five more phones from Cheap-Gadgets.com. He had already collected two of those (the same name and specs) from the first website he visited. However, they were cheaper in Cheap-Gadgets. Defining a template was something really new. It did not take much time, but he had to learn it. When he finished, he realized why the previous step was so simple; someone had already prepared a template. He also realized he was now helping others. A new template for this site will not be needed as long as the structure of the site did not change.

Exploring dashboard:

Figure 6 shows what John found when he accessed the Logikós dashboard using his access code. He realized he had collected, with support from Logikós, 10 candidates (for 8 phones) from 2 different online stores. This part felt exactly as if it were a spreadsheet. He could sort, filter, and browse. Moreover, he realized that the automatic extraction did not deal with different forms of expressing the same value in various sites (e.g., Octa Core 1.8 vs Octa Core 1.8GHz). He activated the fast column edit function for the processor attribute. Then he standardized the values Quad Core and Octa Core (as he knew, it would be useful later on). At any time, he could click the "open in new window" icon (on the right side of each row) to navigate to the web-page where the item was collected from.

Making a decision:

John turned on to the "Decisions" tab of Logikós. He had heard about multi-criteria decision-making (and AHP), and he was ready to make lots of pairwise comparisons; but he also knew that Logikós could help. He started a new decision by giving it a name and some notes. He also had to select a decision profile to rank the items he had collected. Figure 7 shows the three profiles that were available to John. Judging by the name, notes, and weights, he chose "Gamer on a budget"; processor and memory were

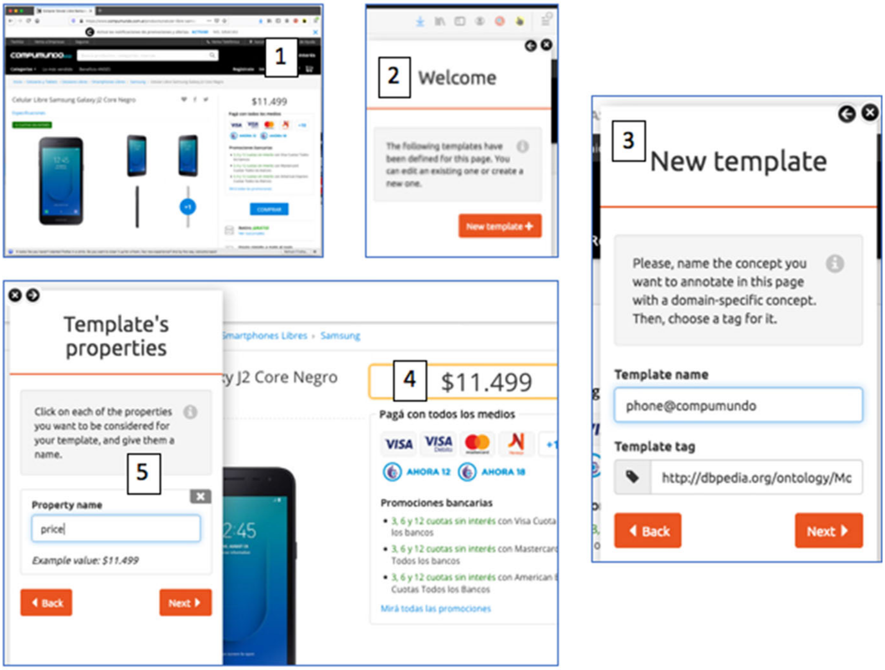


Fig. 5 Creating a template to extract phones: (1) Activate the templates browser from a toolbar button; (2) browse the list of available templates and click "'new template"; (3) provide the name and semantic type for the template; (4) click on elements in the page to indicate they are property values; (5) provide a name for the property

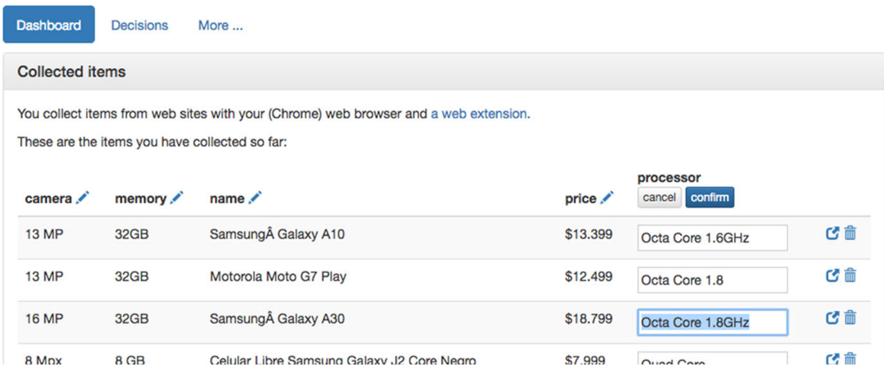


Fig. 6 Browsing, sorting, filtering, and curating collected items

much more important than price, but price was still relevant. The thunderbolt sign next to memory and price indicates that he will have to do no pairwise comparisons for these. However, he will have to do some for processor.

After he clicked proceed, he was presented with the screen shown in Fig. 8, with one important difference. Instead of phone names, the ranking presented question marks.

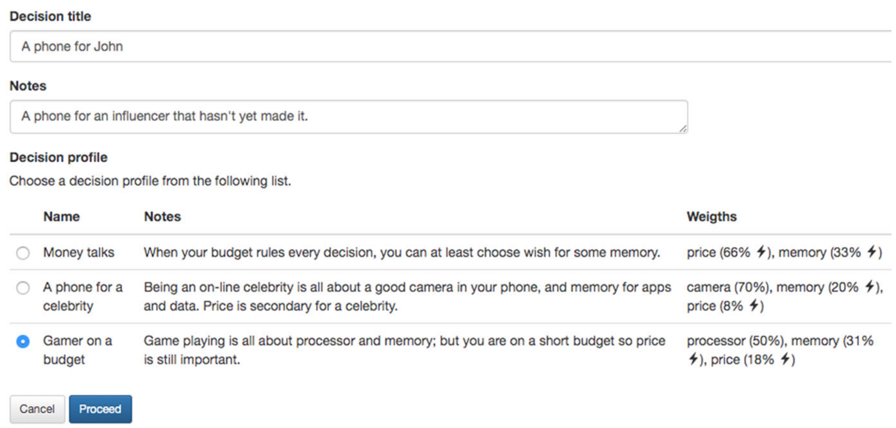


Fig. 7 Starting a decision: give it a name, notes, and choose a base decision profile

There was also a question mark in the tab labeled “Processor (Tangible)”. This was an indicator that Logikós needed John to compare (pair-wise) the observed values for the processor property. Luckily, there where only two possible values. After John compared them, the tab’s question mark went away, and the final ranking of phones was presented (at the top part of the screen). He was satisfied with the phone at the top of the ranking.

Decision profiles:

When John used Logikós there were three different decision profiles available for smartphones. These profiles were created by groups of users that wanted to help others make informed decisions. As shown in Fig. 9, each profile includes a graphical description (a pie chart) of the relative weights given to the item properties. Changing the pairwise importance comparisons between the criteria, updates the weights. A profile also includes a textual description to help users decide on its applicability for them (or their needs). As the profile has been authored by a group of volunteer users, access to the group’s discussion forum is available. John felt like he could be part of such a community, helping them better understand what the needs of an influencer like him.

5 Experimental evaluation

We conducted a controlled laboratory experiment with 10 subjects from two different institutions, in Europe and South America. The general goal of the experiment was to learn how “Logikós approach to augment the web with multi-criteria decision” helps users deal with frequent burdens to decision making while purchasing items online. It concentrates on purchases that, from the perspective of the customer, require thoughtful analysis. It particularly targets a scenario that exhibits opportunities for cross-store purchasing, variability in availability of information, and perceivable difficulty in item comparison and ranking. A key goal of the experiment was to learn if online customers trust decisions based on simple multi-criteria decision analysis support. Moreover, as

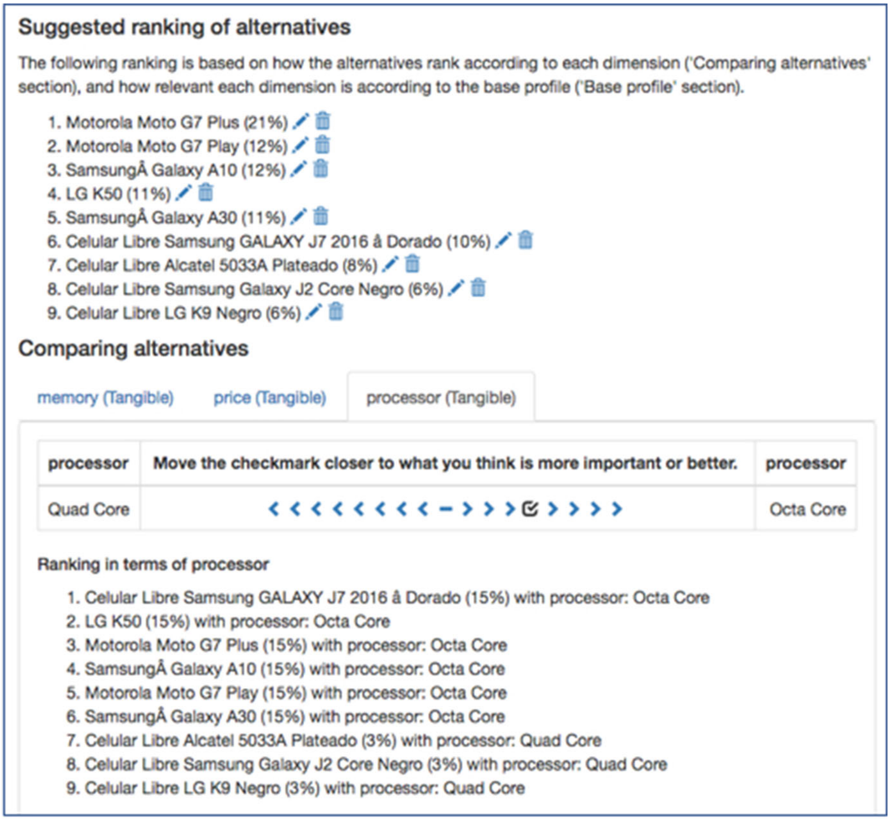


Fig. 8 Pairwise comparisons are only required for properties that were not configured with a smart ranking strategy

Logikós uses AHP, the evaluation also explored the impact of smart ranking strategies to reduce the number of pairwise comparisons.

5.1 Selection of participants

Participants were selected from a population of computer science students and faculty (undergraduate, graduate) in Argentina and France. All participants were proficient web users. Three participants had expert training in multi-criteria decision-making (or tools to support it). All participants had previous experience in buying a mobile phone (that is, they had the intuition of what it means to compare and select phone alternatives taking multiple features into account).

5.2 Evaluation protocol

The evaluation was conducted by one participant at a time, with the support of a moderator. To make sure the experiment was conducted in the same condition for all

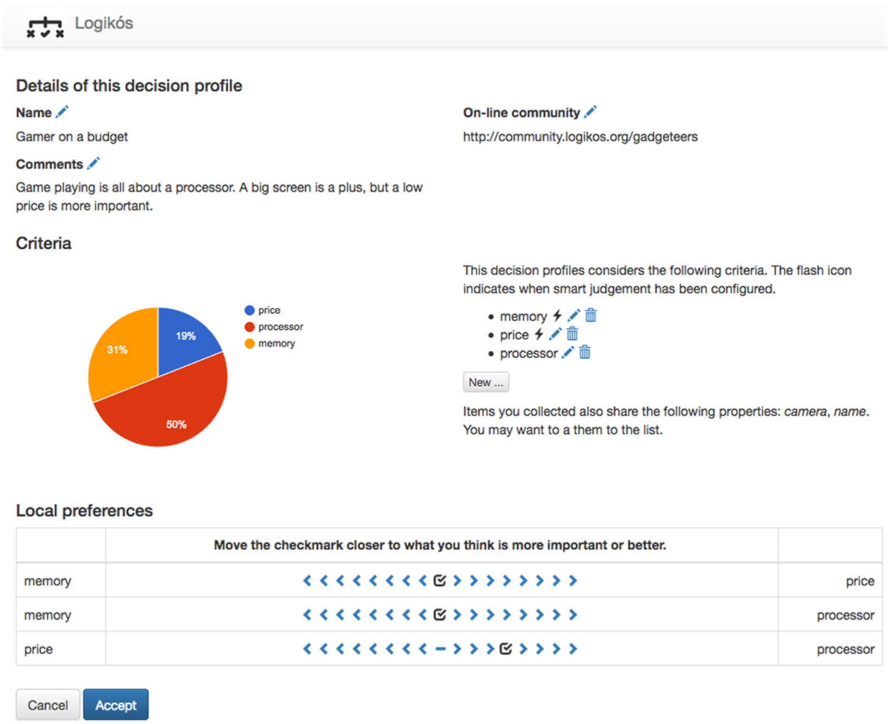


Fig. 9 Pairwise comparisons are only required for properties that were not configured with a smart ranking strategy

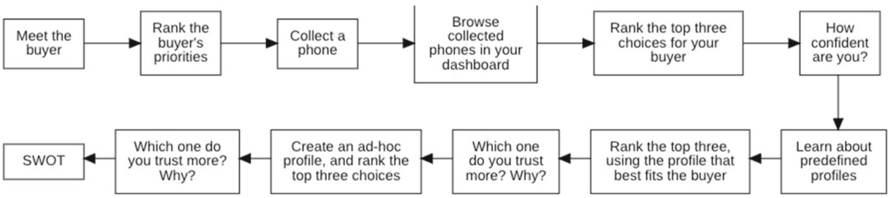


Fig. 10 Workflow for the evaluation: make criteria explicit, collect, rank by intuition, rank with predefined decision profiles, rank with an ad-hoc profile, and identify strengths, weaknesses, opportunities, and threats

participants, a Dashboard was pre-populated with the data of phones collected from various online stores, and the experiment protocol was documented and followed with care. Figure 10 provides an overview of the evaluation protocol.

The experiment starts after a model of the alternatives (a template) was created by the researchers, and enough phones were collected. The model of a mobile phone included the following properties: camera, memory, name, price, and processor.

Meet the buyer, and rank his priorities

Participants were told that they had to help a person choose a mobile phone. Following the UX design strategy of Personas (Adlin and Pruitt 2010), participants were introduced to a fictitious buyer, John Sito. The description of the buyer included enough information to then ask the participant to make, and write down, a simple ranking of the properties (name, price, processor, memory) from the perspective of the buyer.

Select top alternatives with no support

Using the available “Items collector” web-extension, participants collected one phone from an online store. In this way, they experience items collection on the web. Then, they accessed the dashboard and browsed the list of collected items. The phone they had just collected was available along with the phones previously collected by the researchers.

Having in mind the ranking they created for the properties of the phones, participants were asked to select and rank what they considered to be the top three choices. After they recorded (in paper) the ranking they proposed, they were asked the following questions to reflect on their confidence in their choices.

– How confident are you regarding your choices? (not much / ok / very confident)
– Some people made different recommendations; does it make you doubt your decision? (very much / maybe / not at all)

Select top alternatives using shared decision profiles

The moderator explained the shared (predefined) decision profiles to the participants. Then the moderator asked the participants to choose the one that they considered best matched the profile of the fictitious buyer, and use it to select the top three alternatives. Three decision profiles were available. These profiles were described as follows.

– Money talks: When your budget rules every decision but you can at least wish for some memory. Weight/importance for the properties: price (66%), memory (33%).
– A phone for a celebrity: Being an online celebrity is all about a good camera in your phone, and memory for apps and data. Price is secondary for a celebrity. Weight/importance for the properties: camera (70%), memory (20%), price (8%).
– Gamer on a budget: Game playing is all about processor and memory; but you are on a short budget so price is still important. Weight/importance for the properties: processor (50%), memory (31%), price (18%).

In all cases, price and memory were configured with the NormalizedNumericDifereceSRS smart ranking strategy discussed in Sect. 3.3, which was explained to the participants as “the property value will be smartly transformed into a number; numbers will be automatically compared”. In the case of camera, if required, participants had to perform the pairwise comparisons among the available values.

After the users produced a top three ranking of alternatives using an existing decision profile, they were asked:

– Comparing these choices to the one you first provided …Which one do you trust more? Why?

Select top alternatives using an ad-hoc decision profile

The moderator showed how to create new decision profiles, with and without smart ranking strategies. Participants were asked to create a new decision profile that best matched the priorities of John Sito, the buyer. After creating the new profile, participants had to use it to rank the items in the dashboard, and to select the top three. Then, they were asked again:

Fig. 11 How confident are you regarding your choices?

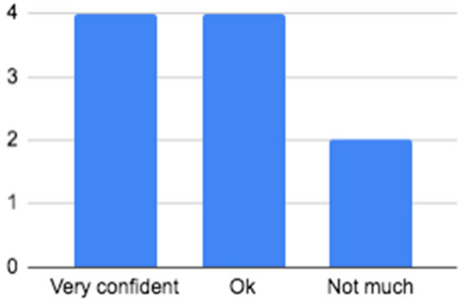
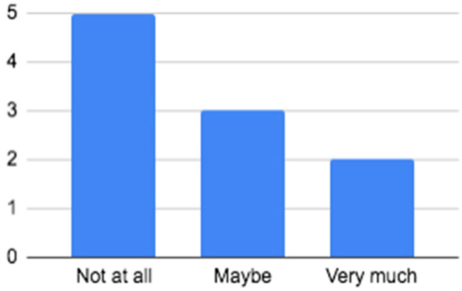


Fig. 12 Some people made different choices; does it make you doubt your decision?



– Comparing these choices to the previous two …Which one do you trust more? Why?

To finalize the test session, participants were asked to write down what they considered to be the principal strengths, weaknesses, opportunities, and threats of the approach and supporting tools they used.

5.3 Results

Participants provided three top rankings of alternatives for the buyer. They produced the first one by intuition, without tool support. They produced the second ranking with the support of one of the predefined profiles. And they produced the third one, using a decision profile they created. The following graphs provided an overview of how they responded to the questions they were asked after each task.

Immediately after producing the first ranking, 8 out of 10 were confident in their choices, 4 of them felt very confident (Fig. 11). However, when they were faced with the fact that others make different choices, half of them doubted their decisions (Fig. 12).

After producing the second ranking, 8 of them preferred their intuition based choices to those obtained using one of the predefined profiles (Fig. 13). These are the reasons they provided:

– "I trust more in the manual recommendation because the decision-maker profile didn't exactly [correspond] to my preferences. (4 subjects)"
– "I'm sure that Logikós can make a recommendation from large amounts of available items observing all the details involved. That gives me confidence for a first

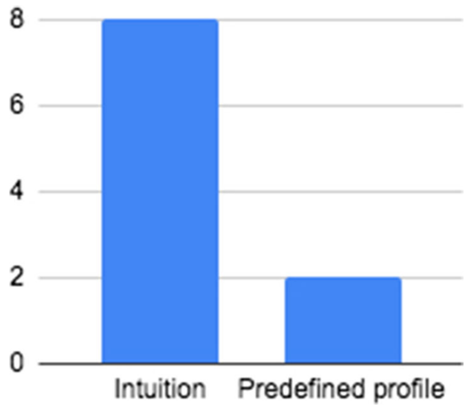


Fig. 13 Intuition or predefined profiles, which one do you trust more?

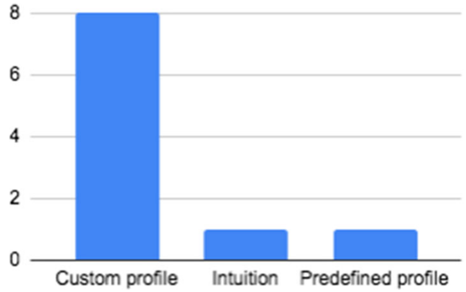


Fig. 14 Intuition, predefined, or ad-hoc profiles, which one do you trust more?

recommendation, but if I have to recommend between a few items, I would trust more in the manual decision".

– "I trust more in my decision because there are subjective aspects that are not represented in the criteria."
– "I trust more in manual decision-making. (this participant struggled to understand how weights of properties came into play when ranking items)."
– "Recommendation of Logikós is better, but in general not much."
– "I trust more in Logikós, it makes me doubt about my initial decision."

However, after producing the third ranking, preferences shifted strongly towards the Logikós supported answers (Fig. 14). Out of 10 participants, 8 indicated that they trusted more the choices they made using the decision profile they created. These are the arguments they provided for their responses.

– "Although I prefer my manual decision, I obtained good results defining my custom profile in Logikós."
– "I'm more confident using Logikós with my own decision profile. However, I would also consider a manual decision if I have to decide between a few items."
– "I get better results using a predefined profile."
– "I think that Logikós with a custom profile is more objective and useful."
– "In general the decision with Logikós is good, the results of the two strategies are similar compared with my manual choice."

– “The decision of Logikós with a custom profile is more confident because of good criteria and good weight of criteria.”
– “Custom profile is the most relevant since the user adjusts his preferences manually.”

5.4 SWOT analysis

Among the strengths of the approach and supporting tool, participants highlighted the use of smart ranking strategies (automatic comparisons), and the tool’s flexibility to define custom decision profiles (with visualization of the resulting ranking of properties).

Weaknesses were mainly related to usability, both in connection to the tool implementation and to intrinsic elements of AHP. In particular, participants complained about the need of doing pair-wise comparisons. Although smart ranking strategies considerably reduce the number of comparisons that are required, participants (specially those not used to AHP) marked it as a cumbersome and boring task.

Being domain-independent was a characteristic that many participants identified as an opportunity. So was the fact that many decision-makers find it heavy to perform all comparisons required by AHP.

The main threats that participants identified, are also valid for AHP in general, namely dealing with a large number of criteria, a need for training and expertise in multi criteria decision. Moreover, one participant stated that some decisions are not rational but more emotional.

6 Comparison to related work

The AskSheet tool (Quinn and Bederson 2014) explores the challenges of data collection on the web, aiming at decision makers that are proficient in the use of spreadsheets. First, the decision maker creates a spreadsheet with the data model and formulas needed to make a decision. Then, using a specific spreadsheet function, the decision makers turn data cells into requests for other online users to look for the data (using Amazon’s Mechanical Turk), and to submit it to the spreadsheet. Asksheet’s key concern is finding information on the web, minimizing the effort by prioritizing information requests, and maximizing coverage via crowdsourcing. It does not provide any specific support for information collectors to extract information from web-pages; information collectors are not considered stakeholders in the decision process. In this regard, Logikós differs from AskSheet in that it considers the data collector a stakeholder, deciding what items on the web are suitable candidates. In addition, Logikós simplifies data collection with templates at the expense of being useful only in websites with a stable structure. Asksheet does not provide any specific support for the later phases of the decision-making process (besides that offered by the spreadsheet formulae); the tool’s focus is data collection. In this regard, Logikós improves upon Asksheet in that it facilitates decision-making using AHP with information collected from the web.

The data collection facilities offered by Logikós (templates, the template editor, the item collector, and the dashboard) can be seen as tools for web scraping. Web scrapping tools and libraries have been available for a long time, many of them aimed at software developers. There are also tools (such as the Outwit Hub and the Web Scraper Chrome Extension) that help end users create extraction templates directly in the web-browser, and collect information in JSON format. These tools are, in principle, similar to those offered by for Logikós (and could be in fact used as a replacement for parts WOA). Logikós builds upon them by smoothing the transition from data collection to the later decision-making steps.

Frequent changes on websites break scrapping templates, making them hard to maintain. Scrapping wouldn't be necessary at all if websites adhere to the recommendations of the semantic web (Antoniou and Harmelen 2004), at least for the pieces of information that users and agents are likely to extract. Tools like the items collector can easily identify and extract information objects from web-pages that provide structured data using JSON-LD or other semantic web serialization approaches. Logikós has been prepared with this scenario in mind; types and properties in Logikós are linked to semantic web classes and properties. Unfortunately, adoption of the semantic web recommendations in websites is still low.

Logikós promotes sharing of items (by sharing dashboard access codes), extraction templates, and decision profiles. In a sense, it promotes collaboration towards decision-making. However, the decision is individual (one online customer making a decision for himself/herself). In this approach, it would be possible to extend Logikós to group decision making process in a collaborative way. The literature on collaborative decision-making (group decision support) studies collaboration at a deeper level. Collaborative or group decision-making involves a decision with multiple stakeholders/perspectives. GRUS (GRoUp Support) (Zaraté et al. 2016) is a Web-based Group Decision Support System (GDSS) supporting collective decision processes that take into account the individual preferences of different actors from the same or different organizations. It's based on a multi-criteria approach for solving a concrete problem, in which decision makers must agree on a concrete alternative, i.e. a solution of the decision to make, thanks to their individual preferences. SuperDecisions (Mu and Pereyra-Rojas 2017) is the reference tool for AHP and ANP. It provides extensive support for the application of these methods both to individual and group decisions. Logikós does not attempt to replace these tools but to explore, firstly how to simplify data modeling and data collection on the web, and secondly, how to bring MCDA to the wider audience of web users. The data simplification is a real problem for a single user, so we pretend that for a group of end-users it is more difficult to bring the accurate data for all the group members.

Decision makers adopt decision methods that economize the use of decision-making resources (Pingle 1992). Pingle and Day (1996) argued that imitation is one such method and therefore plays an important role in decision making. Rationality (i.e. comparing all alternatives and making the best choice) and imitation can be complementary. Conlisk (1980) demonstrated that when rationality is more expensive than imitation, imitators and rationalizers would always coexist. The coexistence of these types of decision makers can increase satisfaction in both groups. Decision makers can imitate choice (i.e. as in buying the most popular product) or beliefs (i.e., the information they use to make a decision). Support for the imitations of other's choice is frequent in e-commerce websites. If every decision maker acts as a strict imitator improvement in choice cannot occur (Pingle 1995) . Imitation of other's beliefs was the focus of the research conducted by Offerman and Sonnemans (1998). They argue that information of other people judgments has a predictable effect on the decision maker's judgments and that imitation improves the quality of the decision maker's beliefs. This later conception of imitation underlies the sharing of decision profiles in Logikós; users can learn by looking at shared decision profiles, and can also customize them to fit specific needs thus increasing the confidence in the support provided by the system.

7 Conclusions and outlook

Literature (Simon 1955) identifies four key steps in the cognitive decision-making process: (1) Intelligence—collecting information; (2) Conception—creating a model for the decision; (3) Choice—using the model to select the best alternatives; and (4) Review—coming back to the intelligence step to have more information, redesign the model, and to choose again. It is an iterative process and non-linear. We argue that this process and more particularly in the first step: the intelligence step, is poorly supported on the web, especially in the context of e-commerce. In this article, we presented Logikós, an approach to augment any website using a MCDA approach for the data aggregation. Logikós supports the decision maker during the intelligence, conception, choice, and review phases. For the intelligence step, Logikós is able to automatically collect the suitable data for the problem to deal with. For the conception step, it supports users to make decisions in a personalized way by choosing the decision profile that best matches their needs. It gives users that are proficient with MCDA the chance to create and share reusable decision profiles. Less-experienced users can then apply such profiles, completing the cognitive decision-making cycle. For the choice step, Logikós supports the end-users by displaying a ranking of the selected alternatives. For the review step, the end-users can choose another profile or modify the chosen profile or add some new data (alternatives). The complete cognitive decision-making process is fully supported by Logikós.

One perspective of this work can be to combine our approach with other Multi-Attribute Decision Making methods like SWING, SMART etc. It would allow the decision makers to use several aggregation techniques. Some MCDA methods are more suitable for some particular problems. As an example it is well known that the Sugeno integral aggregation operator (Sugeno 1974) is more appropriate for qualitative problems.

This article focuses on decision support in the context of Business to Consumer (B2C) purchases. This choice is intentional as we consider the introduction of rational decision support, and multi-criteria decision support to be particularly challenging when dealing with end customers. However, the approach and tool can as well apply in the context of Business to Business (B2B) purchases where the decision maker acts on behalf of the organization, or representing the interests of individuals within the organization. Shared decision profiles can help make explicit the needs of the various internal customers. Moreover, as B2B purchases normally involve higher investments, decision makers might be more willing to invest time in rational decision making. The evaluation of Logikós in B2B scenarios is the focus of future work.

Logikós currently aims at the individual decision maker. Shared decision profiles are introduced as a means to foster learning by imitation, and to reduce the effort of profile creation. When the decision is made on behalf of a group of customers (as might be the case in certain B2B situations), collaboration during the creation or customization of the decision profiles is needed. For such scenarios we foresee the integration with other systems (for example GRUS) that support the structuring of decision models that can be later imported into Logikś. Logikś could also be used as an add-on to shopping forums where customers exchange questions, answers, and opinions. A shared profile could serve as an artifact to document someone's decision criteria, and focus the discussion.

Acknowledgements The authors acknowledge the contribution of RUC- APS: (www.ruc-aps.eu), funded by the European Union under their funding scheme H2020-MSCA-RISE-2015.

Funding The design and development of the methods and tools reported in this article were funded by Universidad National de La Plata (La Plata, Argentina). The experiments and reporting activities were jointly funded by Universidad Nacional de La Plata (Argentina), Toulouse 1 University Capitole (Toulouse, France), and the European Union [RUC-APS Project, Grant 691249, funding scheme H2020-MSCA-RISE-2015].

Availability of data and material Not applicable.

Compliance with ethical standards

Conflict of interest There are no relevant financial or non-financial competing interests to report.

Code availability Logikós source code is available under MIT license at: https://bitbucket.org/logikos-web/.

References

Adlin T, Pruitt J (2010) The essential persona lifecycle: your guide to building and using personas. Morgan Kaufmann

Afridi AH (2019) Transparency for beyond-accuracy experiences: a novel user interface for recommender systems. Proc Comput Sci 151:335–344. In: The 10th international conference on ambient systems, networks and technologies (ANT 2019)/the 2nd international conference on emerging data and industry 4.0 (EDI40 2019)/affiliated workshops

Akarte M, Surendra N, Ravi B, Rangaraj N (2001) Web based casting supplier evaluation using analytical hierarchy process. J Oper Res Soc 52(5):511–522

Antoniou G, Harmelen FV (2004) A semantic web primer, volume 57 of cooperative information systems. The MIT Press

Bosetti G, Firmenich S, Rossi G, Winckler M, Barbieri T (2016) Web objects ambient: an integrated platform supporting new kinds of personal web experiences. In: International conference on web engineering, pp 563–566. Springer

Brans J-P, Mareschal B (2005) Promethee methods, chapter 5. Springer, New York, pp 163–186

Choudhury M, Srinivasan K (2019) An overview into the aspects of fake product reviews, its manipulation, and its effects and monitoring. In: 2019 IEEE international conference on consumer electronics—Taiwan, ICCE-TW 2019

Conlisk J (1980) Costly optimizers versus cheap imitators. J Econ Behav Organ 1(3):275–293

Díaz O (2012) Understanding web augmentation. In: International conference on web engineering, pp 79–80. Springer
Firmenich S, Bosetti G, Rossi G, Winckler M, Barbieri T (2016) Abstracting and structuring web contents for supporting personal web experiences. In: International conference on web engineering, pp 77–95. Springer
Fomba S (2018) Décision multicritère : un système de recommandation pour le choix de l'opérateur d'agrégation. PhD thesis, University of Toulouse
Ishizaka A, Nemery P (2013) Multi-criteria decision analysis: methods and software. Wiley, Hoboken
Mu E, Pereyra-Rojas M (2017) Practical decision making. An introduction to the analytic hierarchy process (AHP) using super decision v2. Springer International Publishing, Berlin
Offerman T, Sonnemans J (1998) Learning by experience and learning by imitating successful others. J Econ Behav Organ 34(4):559–575
Pingle M (1992) Costly optimization: an experiment. J Econ Behav Organ 17(1):3–30
Pingle M (1995) Imitation versus rationality: an experimental perspective on decision making. J Soc Econ 24(2):281–315
Pingle M, Day RH (1996) Modes of economizing behavior: experimental evidence. J Econ Behav Organ 29(2):191–209
Quinn AJ, Bederson BB (2014) Asksheet: efficient human computation for decision making with spreadsheets. In: Proceedings of the 17th ACM conference on computer supported cooperative work and social computing - CSCW '14, pp 1456–1466
Roy B (1991) The outranking approach and the foundations of electre methods. Theor Decis 31(1):49–73
Russo RFSM, Camanho R (2015) Criteria in AHP: a systematic review of literature. Proc Comput Sci 55:1123–1132
Saaty TL (2004) Decision making—the analytic hierarchy and network processes (AHP/ANP). J Syst Sci Syst Eng 13(1):1–35
Saaty TL (2008) Decision making with the analytic hierarchy process. Int J Serv Sci
Simon HA (1955) A behavioral model of rational choice. Quart J Econ
Simon HA (1956) Rational choice and the structure of the environment. Psychol Rev
Sugeno M (1974) Theory of fuzzy integrals and its applications. PhD thesis, Tokyo Institute of Technology
Vargas LG (1990) An overview of the analytic hierarchy process and its applications. Eur J Oper Res 48(1):2–8 Desicion making by the analytic hierarchy process: Theory and applications
Zaraté P, Kilgour DM, Hipel K (2016) Private or common criteria in a multi-criteria group decision support system: an experiment. In: Yuizono T, Ogata H, Hoppe U, Vassileva J (eds) Collaboration and technology. Springer International Publishing, Cham, pp 1–12

Affiliations

Alejandro Fernandez[1] · Pascale Zaraté[2] · Juan Cruz Gardey[1] · Gabriela Bosetti[1]

✉ Pascale Zaraté
Pascale.Zarate@irit.fr

Alejandro Fernandez
alejandro.fernandez@lifia.info.unlp.edu.ar

Juan Cruz Gardey
juancruz.gardey@lifia.info.unlp.edu.ar

Gabriela Bosetti
gabriela.bosetti@lifia.info.unlp.edu.ar

[1] LIFIA, Facultad de Informática, UNLP, Comisión de Investigaciones Científicas de la Provincia de Buenos Aires, Calle 50 y 120, 1900 La Plata, Argentina

[2] IRIT, Toulouse 1 University Capitole, 2 rue du Doyen Gabriel Marty, 31042 Toulouse Cedex 9, France