



A Framework for Informing Consumers on the Ecological Impact of Products at Point of Sale

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A Framework for Informing Consumers on the Ecological Impact of Products at Point of Sale

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The use of intelligent information technologies has the means to provide ecological information just-in-time, thus alleviating consumers' cognitive burden at the time of purchase. We propose a computational framework for supporting consumer awareness of the ecological impact of products they consider purchasing at point of sale. The proposed framework permits consulting multiple information sources through diverse access interfaces, combined with a recommendation engine to score product greenness. We evaluate our approach in terms of usability, performance, and user-influence tests through two conceptual prototypes: an online store and an augmented reality interface to use at physical stores. Our findings suggest that providing ecological information at the time of purchase is able to direct consumers' preference towards products that are ecological and away from products that are not; consumers also express willingness to pay slightly more for ecological products. The experimental results obtained with the interface prototypes are statistically significant.

Keywords: ecological impact; consumer decision; augmented reality; recommender systems

1. Introduction

There is a global need for higher awareness of the importance of nature and climate preservation (Coelho, de Castro, and Alcides Gobbo Jr. 2011). Even though this is a complex task with several stakeholders, simple consumer choices in everyday life can contribute (purchasing recyclable products, using renewable energy sources, etc.). However, cultural views and scientific literacy (i.e., the ability to interpret scientific results) affect the interpretation of information on ecological issues (Kahan et al. 2012). Selecting green products may seem simple at a first glance, but consumers in general are not necessarily aware the ecological impact of products they choose at the time of purchase; particularly novice consumers struggle identifying eco-labels (Thøgersen, Haugaard, and Olesen 2010).

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2 Gan et al. (2008) confirm in their study that ecologically conscious consumers are more likely to
3 make ecologically sound purchase decisions. Accurate knowledge about product ecological compat-
4 ibility is nevertheless necessary for ecologically-conscious consumers to make sound decisions at the
5 time of purchase (Roberts and Bacon 1997). The *cognitive burden* at the time of purchase (that is,
6 the strain to recall pertinent aspects and carrying out an evaluation of available products) is high,
7 especially when there is a considerable number of options to take into account (Miller 1956). It is
8 easier to simply buy “the same as usually” or “whatever is on sale” than making green choices as a
9 consumer. Providing abundant, detailed information at time of purchase actually hinders decision
10 making instead of easing the task (Chen, Shang, and Kao 2009). Customers are also usually rather
11 stressed and time-pressed, which further limits their cognitive efforts (Fram and Axelrod 1990;
12 Aylott and Mitchell 1998).

13
14 Some European countries report success stories regarding recycling and eco-labels for nature-
15 friendly products (Galarraga Gallastegui 2002). However, consumers have been found unlikely to
16 transform their behaviour in response to information they receive (regarding energy consumption),
17 explaining their lack of action as having forgotten or it being tiresome and highlights the impor-
18 tance of social context and explicitness in consumer information, as general-level recommendations
19 are ignored in practise by the consumers, even when understood and agreed with in principle (Bar-
20 tiaux 2008). The same applies in nutritional choices (Moorman 1990): upon purchase, the stimulus
21 available at the time outweighs previous nutritional information (only highly motivated consumers
22 would recall nutritional information and take in into account upon deciding a purchase), and con-
23 sumers with low level of education are particularly prone to ignore any information previously
24 provided.

25
26 Information technologies can provide tools to overcome these obstacles; while being pervasive,
27 they can provide relevant knowledge at the moment it is needed, taking into account the user
28 context (Kalnikaitė and Whittaker 2008, 2011). In this work, we propose a framework for gen-
29 erating just-in-time visualisations of relevant ecological information for the products under the
30 consumer’s consideration at the time of purchase. The information is displayed through user inter-
31 faces for different shopping scenarios (we implemented as conceptual prototypes a browser plugin
32 for e-commerce and an augmented-reality interface for in-store purchases) and integrates various
33 *information sources* for calculating a *score* related to the product’s greenness; this score, as well as
34 an explanation for it, can be visualised through the user interface. The information sources for the
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2 framework range from official sites to social networks such as Twitter; consumers show greater in-
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4 terest towards information obtained through internet discussion boards than towards that provided
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6 by the manufacturer through marketing (Bickart and Schindler 2001). The main contributions of
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8 this work are:

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10 • The design of a computational framework that assesses product greenness by invoking a se-
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12 ries of scoring modules, such as general opinion in social networks, identified eco-labels (i.e.,
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14 national or international certifications regarding the ecological impact of the product, if appli-
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16 cable), identified ecological boycotts, and manufacturing distance; information is received and
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18 transmitted through different user interfaces, such as a Web browser and augmented-reality
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20 glasses.
- 21 • Two conceptual prototypes that implement the user interfaces mentioned above.
- 22 • Evidence to demonstrate that the implemented prototypes influence shopper decisions to-
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24 wards greener choices.

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26 The rest of this paper is organised as follows: Section 2 introduces necessary background on
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28 recommendation systems and computer vision; Section 3 reviews related work, after which Section 4
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30 describes the framework for product automatic green assessment. Section 5 presents the conceptual
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32 prototypes used to validate our approach. Finally, Section 6 discusses conclusions and future work.

33 34 35 **2. Background**

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38 In this section, we review some of the background information necessary for the remainder of this
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40 work, specifically terminology and conceptual definitions.

41 42 43 **2.1. *Eco-friendly consumer behaviour***

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45 Ecologically responsible consumers prefer organic products, avoid aerosols, choose locally produced
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47 goods, and bring reusable bags to the supermarket; the degree of fulfilment with these activities
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49 classifies consumers into four categories: committed environmentalists, mainstream environmental-
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51 ists, occasional environmentalists, and non-environmentalists (Gilg, Barr, and Ford 2005). Factors
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53 that may drive a consumer towards the purchase of environmentally friendly products are nu-
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55 merous and not fully understood, although published literature on consumer behaviour as such
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57 is abundant — a survey of literature regarding numerous empirically observed factors is given by

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Joski and Rahman (2015).

The following four factors are empirically found to have an influence in green marketing: *eco labels* that seek to ease understanding of ecological information, including the capability of building an emotional relationship with customers, product value and attractiveness, and green advertisement components (Azad et al. 2013).

Consumers are reported to struggle to understand eco labels and to assess the credibility of ecological information on product packaging; only those consumers who express the high interest in ecology are unhindered (Carrero Bosch and Valor 2012). An analysis of factors affecting green consumption in Australia found that consumers are generally sceptic about companies risking their profitability in exchange for a greener production and that aspects such as labels, packaging, and ingredients do not affect consumer perception on green products. (D'Souza et al. 2006) In that study, consumers reported to experience difficulty understanding eco labels and the only factor found to make a positive impact on green product perception was consumers' past experience with the product. A European study reports that only a small fraction of consumers prefer to purchase eco-labelled products (TNS Political & Social 2013); similarly, consumer awareness appears to diminish at product level and that eco-labels do not play an important part in consumer food choices (Grunert, Hieke, and Wills 2014).

A positive correlation has been reported between environmental opinions and green purchasing behaviour, as well as perceived quality of green products and green purchasing behaviour (Hossein Khorshidi, Gholizadeh, and Naghash 2013), along with a positive correlation between effective green marketing strategies and customers' purchasing patterns for green products (Juwaheer and Pudaruth 2001). Curiously, positive feedback that acknowledges green behaviour is reported to have a negative impact on green choices in the future, whereas consumers who receive negative feedback are more prone to become green (Longoni, Gollwitzer, and Oettingen 2014). However, *positive cues* for common ecological behaviours (e.g. avoidance of littering) results in a more frequent selection of eco-friendly products (Cornelissen et al. 2008).

The relationship between *price* and perceived quality in consumer decision making appears to be reactionary instead of derived from experience (Tellis and Gaeth 1990); this finding highlights the importance of presenting any relevant information at the time of purchase instead of expecting the consumer to remember and learn. Similarly, a study of the effect of information regarding climate change in the decision making of tourists found consumers improperly informed of such

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2 ecological concerns (Gössling et al. 2012). Also consumer *lifestyle* has been reported to affect
3 purchase decisions in Taiwan: a tailored marketing strategy is needed for each lifestyle to promote
4 green consumption (Wang 2012b,a).
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7 Several recent studies have focused on consumer behaviour in developing countries, specially
8 those with a high population (e.g. India). A positive relationship between social perception (green
9 self-identity, for instance) and eco-friendly consumer behaviour has been reported (Barbarossa
10 and De Pelsmacker 2016); other positive factors include values such as biospheric values (Nguyen,
11 Lobo, and Greenland 2016, 2017), a positive attitude, and moral. The more committed consumers,
12 including youngsters (Prakash and Pathak 2017), are even willing to pay more for eco-friendly
13 products and accept their shortcomings. In general, a greater eco-friendliness is observed when
14 there is a greater knowledge about environmental issues (Biswas and Roy 2015; Yadav and Pathak
15 2016). However, it has also been reported that, in some contexts, eco-friendly consumers have
16 different motives (other than care for the environment) for their choices; this has been the case for
17 eco-city dwelling in Singapore (Flynn et al. 2016). Other recent studies have surveyed the types of
18 most popular green products, revealing that preference is given to those with a relative comparative
19 advantage (Fraccascia, Giannoccaro, and Albino 2018).
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32 **2.2. Recommender systems**

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34 The purpose of a *recommender system* is to detect items of interest for a target user. Recommen-
35 dations can be *non-personalised* or *personalised*: while the former are centred on suggesting “hot”
36 items (e.g. top-ten songs), the latter collect particular user preferences (either implicitly or explic-
37 itly) and recommend items based on these preferences. The two classical approaches for making
38 recommendations are *content-based systems* and *collaborative filtering*. Content-based systems take
39 into account items that were given high ratings by the user and search for other items similar to
40 these, whereas collaborative filtering searches for items that were given high ratings by users that
41 are similar to the target user. Other approaches include demographic, knowledge-based, social-
42 based, context-aware, and hybrid (Ricci, Rokach, and Shapira 2011; Adomavicius and Tuzhilin
43 2011; Bobadilla et al. 2013). Recommender systems normally produce a sorted list of items, where
44 order determines the items’ likelihood to be highly rated by the target user.
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53 Currently, recommender systems have focused on user profiling (Al-Shamri 2016), as well as
54 social and trust-centric recommenders, which take advantage of friendship networks to provide
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2 recommendations with a higher level of reliability or trust (Moradi and Ahmadian 2015). Further-
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4 more, advances in machine learning (deep learning, for example) have improved the state-of-the-art
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6 by approaching the cold-start problem (Elahi, Ricci, and Rubens 2016) and increasing product ac-
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8 quisitions (Cheng et al. 2016). Moreover, it has been stated that recommender agents influence
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10 consumer behaviour (Huseynov, Huseynov, and Özkan 2016). However, there is still work to do,
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12 for instance, in the area of interactive recommender systems (He, Parra, and Verbert 2016) — i.e.,
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14 systems that combine recommendations with visualisation. Another interesting direction, which
15
16 can also impact product recommendations, is the incorporation of open linked data (Musto et al.
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18 2016).

19 20 **2.3. Image processing**

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22 Computer-vision techniques enable extracting information from product packaging with a digital
23
24 camera. There are several different approaches that can be used individually or complimentary
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26 to one another for processing images of product packaging. *Optical character recognition (OCR)*
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28 identifies text in the input images and attempts to recreate a digital textual version of the fragments
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30 of text found in an image (Jung, Kim, and Jain 2004). The extracted text can then be processed
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32 to identify information regarding the ingredients, the manufacturer, the geographical location in
33
34 which the product was manufactured, and so forth. *Feature detection* seeks to match graphical
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36 entities present in an image to a pre-processed database of images (logotypes of manufacturers or
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38 brands, eco-labels, etc.) (Tuytelaars and Mikolajczyk 2008). Thirdly, decoding bar codes and their
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40 two-dimensional variants QR codes (Ohbuchi, Hanaizumi, and Hock 2004) recovers the information
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42 embedded in the code — in the case of bar-codes, this is usually a series of digits (which then needs
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44 to be consulted in a product database, some of which are available online), whereas for the QR
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46 codes the information contained is commonly a URL pointing to a website related to the product,
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48 but could also contain any other textual or numeric data.

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50 The potential sources of the images to process are diverse: in the case of e-commerce, there
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52 are often product photographs on the seller’s website, whereas a person shopping in a store can
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54 use a smart-phone with a camera to “scan” products of interest and then visualise the obtained
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56 information on the screen of the smart-phone (von Reischach et al. 2009). Commercial wearable
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58 *augmented reality (AR)* headsets are increasingly available and make it possible not only to capture
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60 in images the objects that a person is presently viewing but also allows for a graphical overlay of

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2 computer-created information on top of the user's view of the world directly (Azuma et al. 2001).
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4 This allows a person simply hold a product in their hand to view the information regarding the
5
6 product. The incorporation of AR technology into traditional supermarkets may help to bring
7
8 the decision-making process of the consumer closer to what it is when shopping online; consumer
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10 choices differ between online and in-situ shopping (Degeratu, Rangaswamy, and Wu 2000).

11 A relatively recent application for augmented reality concerns the retailing context. In this
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13 context, augmented reality has mainly been used for cloth or makeup buying, especially for an
14
15 enhanced consumer experience. However, one of the main open issues consists of making the use of
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17 AR to be profitable for retailing stores (Bonetti, Warnaby, and Quinn 2018). Furthermore, there
18
19 is an apparent rivalry (and almost controversy) between the utilitarian use (for convenience) and
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21 the hedonistic use (for fun) of AR in the retailing context, since the utilitarian use — as opposed
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23 to the hedonistic use — has been reported to influence usage intention (M. Kang 2014) but the
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25 hedonistic use has been reported to influence impulsive buying (Javornik 2016). Another issue for
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27 AR in this context consists of maximising consumer engagement (Scholz and Smith 2016).
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29 **3. Related work**

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31 Our present work aims at making ecological information more readily available and easier to inter-
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33 pret for consumers that are not motivated enough to inform themselves beforehand. Our main goals
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35 are providing access to information on a level of detail that the consumer may easily control at
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37 the time of purchase to lower the cognitive burden of remembering and understanding the factors
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39 involved in determining whether purchasing a specific product is an ecologically friendly choice
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41 and providing visual feedback on the eco-friendliness of the choices made at the time of purchase.
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43 Our proposal is effectively a shopping assistant that recommends eco-friendly products, with an
44
45 optional augmented-reality interface for in-situ purchases.

46 The use of AR in ecological content is scarce at present. Kamarainen et al. (2013) use of AR
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48 for ecological awareness of students during field trips, whereas Tarng and Ou (2012) apply AR for
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50 teaching ecology to students. Lu and Smith (2007) use AR to visualise three-dimensional models
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52 of products, for example to determine which couch would look good in the user's living room. We
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54 have not encountered any literature applying AR for informing consumers at time of purchase over
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56 ecological aspects of the products. Our proposed system differs from the aforementioned works by
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58 recognising images from the product on the user's field of vision and providing information related
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2 to the ecological impact of this product.

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4 In the remainder of this section, we review related work on *shopping assistants* on (green) product
5 *recommenders*.

6 7 8 9 **3.1. Shopping assistants**

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11 The process of consumer decision making in an interactive online setting is studied by Häubl and
12 Trifts (2000), finding that recommendation systems have a substantial impact in consumer choices.
13 Also Park, Lee, and Han (2007) report that online consumer reviews effect consumer behaviour: a
14 purchase is more likely in the presence of positive reviews. Laros and Steenkamp (2005) document
15 the power of emotions over purchase decisions.

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21 Already in 2002, Menczer, Street, and Vishwakarma (2002) proposed a web-based agent that can
22 learn shopping preferences, search for items that match them, and guarantee user privacy. More
23 recently, Bhattacharya et al. (2012) implemented a mobile shopping assistant that can be accessed
24 using a Web or mobile-phone interface features that were determined with shopper questionnaires
25 and include a natural language processing module for extracting products from shopping lists,
26 predictive text input for making such lists, an engine for retrieving products given their name
27 or description, a product and promotion recommender, and an indoor positioning to help locate
28 products in the store — the system's inception in a supermarket helped increase sales.

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34 Kourouthanassis, Giaglis, and Vrechopoulos (2007) discuss the potential of ubiquitous systems
35 in affecting the shopping experience of users and conclude that it is possible to positively influence
36 emotions at time of purchase by creating an entertaining experience. Their work differs from the
37 one proposed in this paper as their chosen technology is a tablet device and the products are
38 recognised by RFID instead of computer vision and product recognition. Also, their goal differs
39 as they seek to help the user to be more economical, whereas our aim is influencing the ecological
40 behaviour of the user.

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46 There are also several patents related to shopping assistants. The patent by Burke, Lalwani,
47 and Thong (2003) provides product location and reviews by using a mobile device with a bar-code
48 reader connected to a database for product identification. Another patent by Kern and Abbass
49 (2008) describes a system that emits purchasing recommendations based on a correlation between
50 user profiles and products. The patent of Bravo (2014) introduces a shopping assistant based on
51 AR; this assistant guides its user *within* the store to the location of a specified product. Likewise,
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2 the patent by Martin (2012) permits to search for products, either on a mobile or augmented-
3 reality device, and receive the locations (stores) that have these products in inventory. Neither of
4 these patents attend aspects of product recognition via computer vision (as we do) nor ecological
5 concerns.
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9 The shopping assistants reported in the literature differ from our proposed framework mainly in
10 terms of the ecological orientation of the framework and the use of scoring modules to produce a
11 recommendation. Furthermore, our system — at this point — **is not designed to automatically infer**
12 **user preferences from the queries and the interactions, although** future work includes registering
13 user actions with the intent of producing recommendations.
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20 **3.2. Product recommenders**

21 Existing product-recommendation systems include *PromotionRank* (Nurmi et al. 2014) that ranks
22 and recommends grocery product promotions according to a personal shopping list. The process
23 initiates with the creation of a candidate product pool, which is then expanded with related prod-
24 ucts, and then category rank scores are calculated for the pool, after which the) promotion ranking
25 takes place. With focus on environmental recommendations, Lee, Huang, and Hwang (2009) pro-
26 pose a system that gradually suggests products with a higher greenness, based on eco-labels and
27 sentiment words, but — in contrast to our framework — it only considers an online shopping
28 interface. Fang and Sun (2016) propose and evaluate three user interfaces to stimulate household
29 water saving, focusing on emotional response.
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38 Liangxing and Aihua (2010) provide a hybrid recommender system for apparel retailing cus-
39 tomers that uses RFID technology to detect member cards and generate recommendations based
40 on products that are similar to past purchases and products that other clients have bought. Aciar
41 et al. (2007) score the quality of a product in terms of consumer reviews, using text-mining tech-
42 niques to extract reviews that are then mapped into an ontology with rule-based classification
43 techniques. A ranking, considering the reviewer's level of expertise, is computed for each product.
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48 Recommendation systems reported in the literature rarely apply computer-vision techniques;
49 furthermore, our proposed work is aimed at multiple interfaces and permits combining multiple
50 scoring modules to produce the recommendation.
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2 Figure 1. Principal components of the proposed ecological product-recommendation framework.
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5 **4. Proposed framework**

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7 With the intent of helping consumers to make greener choices *at the time of purchase* (while
8 at the same time alleviating the burden of keeping in mind every aspect related to a product's
9 greenness), we propose the *design* of a *computational framework* that produces both global and
10 specific scores for the greenness of a given product. Our proposed framework, consequently, takes a
11 product as input (e.g. as an image or unique identifier) from a *user interface*, breaks down the input
12 information into a set of usable keywords (which we shall refer to as *query*), evaluates the product's
13 greenness using different *scoring modules* that take the query as input, and returns the score (as
14 well as an explanation that consists of an individual score per module) as a smart *visualisation* by
15 means of the same user interface. Figure 1 visualises this structure, and the principal operational
16 entities are discussed in this section.
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25 As in all human-computer interaction, the possibility of incorrect input due to distractions or
26 misunderstandings is omnipresent. Hence the output needs to clearly identify how the input was
27 interpreted (for example, if a query was assumed to refer to a specific product, an image of the
28 product can be included in the response so as to identify the product that the results refer to)
29 and, ideally, a confidence score (on a numeric scale, an icon-based scale or a background colour,
30 for example) on how precise and exhaustive the results are also needs to be presented to the user,
31 together with an option to refine the query in case the result was not the desired one. When
32 multiple potential matches are found to a user's query, the list of the possible results needs to be
33 ordered by relevance (similar to a search engine's results) for the user to select from.
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43 **4.1. User interfaces**

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45 Providing in-situ information can be efficient if delivered right (Bird, Kalnikaité, and Rogers 2011),
46 although existing works have mainly been limited to overall recommendations. *Ecological consid-*
47 *erations, which are the main focus of the present work, often rely on multiple factors (Gan et al.*
48 *2008), many of which require a more elaborate presentation. As reported by Pancer, McShane, and*
49 *Noseworthy (2017), isolated visual cues do not work well, while Lee, Bhatt, and Suri (2018) find*
50 *that limiting to a small subset of aspects results in a negative consumer attitude. Relevant factors*
51 *include but are not limited to the following:*
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4 **Origin:** Can the product be considered locally produced? How far away the product was produced
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6 and how has it been transported to the point of sale; also, for online retail, from where it will
7
8 be delivered to the customer and by which means of transport?
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10 **Raw materials:** What are the ingredients the product is made of or grown with? What is the
11
12 packaging made of? (The effect on how green the packaging appears to be on how green the
13
14 product is perceived to be has been studied by Magnier, Schoormans, and Mugge (2016) for
15
16 food products.) How sustainable are these raw materials? From where are the raw materials
17
18 obtained and what are the ecological impacts of their recollection? If the raw materials are
19
20 renewable, how rapid is this renewal?

21 **Manufacturing:** How sustainable is the process used to manufacture the product (or cultivate
22
23 the produce)? What energy sources are used? What type of waste is created by the process?
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25 Does the process contaminate the environment at the site of production?

26 **Useful life and reuse:** How long will the product be useful? Will some parts of the product or
27
28 its packaging be reusable after the useful life of the product itself ends?

29 **Recycling:** Will the product or its packaging result in waste? How much and what type of waste?
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31 How much of it can be recycled, where, and how? If and how recycling is to be carried out
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33 at the place of residence of the consumer: is there a drop-off spot, a collection service, is the
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35 waste biodegradable, etc.

36 **Certifications:** Which organisations, if any, have verified the eco-friendliness of some of these
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38 aspects of the product — that is, what eco-labels does the manufacturer, the ingredients, the
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40 product and/or the packaging have?

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42 Also, as many modern products are in fact assembled from multiple components that have been
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44 manufactured in distinct locations with different processes, the importance of each component in
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46 the perceived greenness of a product varies (Gershoff and Frels 2015). In general, it is hard to
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48 communicate ecological impact to people with little expertise in the field (Brunson and Reiter
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50 1996).

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52 Regarding the input of the data to identify a product of interest through the interface, we
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54 consider as the main options photographs of packaging, bar codes or a set of typed key words. In
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56 each case, a list of suggested matches needs to be presented for the user to choose from, similarly to
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58 a modern web search engine. As the primary focus of the proposed framework is to support the user

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2 at the time of purchase, in an in-store context this often means that the product is physically at
3 hand or on a shelf in front of the user — items such as fresh produce in a store will not necessarily
4 be packaged with identifying marks, but most countries require stores to display a sign with details
5 of the origin for items such as fruits and vegetables and a photograph of such a sign can also serve
6 as input. For online use, we assume that a user attempting to make a purchase decision is presently
7 looking at a web page with the product information and can provide information such as a screen
8 capture, a copy-paste of some text, or even the URL of the page as input to specify the product
9 in question (the latter requiring some parsing to identify the product information). We are aware
10 that some types of products and services will fall outside the scope of a framework of this type,
11 but we expect it to be feasible to correctly identify a grand majority of supermarket items and
12 household products available through web stores.

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The proposed framework allows for an unlimited number of user-interface modules that permit the consumer to input products and access the generated ecological recommendations. We have implemented two user-interface prototypes:

Augmented-reality interface (Espinosa Cenicerros, Schaeffer, and Garza Villarreal 2014). Either through a mobile phone or an AR-headset, the interface accesses the camera to identify the product at the centre of attention of the user and then overlays visual representations of the obtained ecological recommendations.

Web-browser plugin (Urbina Coronado, Schaeffer, and Garza Villarreal 2014). An application developed for the Chrome web browser that parses the pages that a consumer is viewing in a web store and, upon mouse-over on a product, adds a visualisation of the ecological recommendation of the identified product.

4.2. *Processing modules*

User interfaces represent the product to evaluate either with images (in the case of the AR-headset or the mobile phone) or a textual description (in the case of the Web plugin). This requires the addition of *processing modules* to improve the speed and accuracy of product recognition and classification. In general, the framework includes (but is not limited to) several *image processing* modules, a *natural language processing* (NLP) module, and — optionally — a *geo-localisation* module. Let us describe each one:

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2 A module for *Natural Language Processing (NLP)* is necessary to determine the *meaning* of
3 any retrieved text, required for its processing (particularly., whether the information contained
4 is neutral, negative, or positive in terms of ecological impact). Sources of text include the OCR
5 module, the website of the producer and/or the product as well as information on product review
6 websites, and the opinions expressed by users in social networks.
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10 A *geo-localisation* module, upon extracting from the user interface the location of the user,
11 compares it to the location of manufacture (extracted from the packaging or by querying product
12 information repositories) and determines whether a specific production location is local or not to
13 that particular user at that specific moment.
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17 An *image processing* module is necessary to detect the product at hand and its main components.
18 As such, image processing modules have the capacity of recognising the image of a product (what
19 product it corresponds to and what are the words contained in the product's label), an eco-label,
20 a QR code, etc. These modules receive images from the user interface and retrieve information
21 regarding the products that appear in the photographs taken with the phone or the AR glasses.
22 Examples of these modules include the following:
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25 A *logo-recogniser* module aids on the identification of a product (brand, producer) and its eco-
26 certifications. The module compares elements present in the input image to a database of known
27 logotypes using *feature detection*. This permits the incorporation of the information of the presence
28 and absence of such symbols in the computation of an ecological score, no longer requiring the user
29 to recognise and interpret their meaning.
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32 A *code scanner* module retrieves product information which otherwise remains cryptic to the
33 consumer. The module interprets bar codes and two-dimensional QR codes present in the image.
34 The product identification numbers extracted in this manner can be used to consult in-store and
35 online databases for product information, which can also be incorporated into the computation of
36 ecological scores.
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39 Finally, the *Optical Character Recognition (OCR)* discovers other relevant product features: it
40 detects any textual information present in an image and converts it into text in order to extract
41 detailed product information.
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4.3. *Query handler*

A *query handler* is a module that takes care of the communication between the processing modules (image, NLP, geo-localisation) and the green recommendation engine. A *query aggregator* receives information retrieved by the processing modules and combines it into a *bag-of-words* representation that acts as a product query, containing labelled subsets of data such as names of ingredients, place of production, brand name, bar code, company name, and names of ecological certifications present in the packaging. Each subset is a separate bag-of-words that is accompanied with a label. Possible labels include the ingredients used to manufacture the product, the locations at which the manufacture takes place, and ecological labels awarded to that product or manufacturer, as well as possible active boycotts against the manufacturer.

4.4. *Scoring and recommendations*

Each *scoring module* is an independent system that provides a numerical score: it receives a set of bag-of-words queries from the recommendation engine, processes that information, and produces a score for each category that produced a match within the information handled by that scoring module, if any (a null response is sent if there are no matches). At the end of this section, we briefly describe the social networking module for the sake of clarity.

An individual scoring module does not need to respond on all categories for all products; it may be specific for a certain type of product or only operate on a limited subset of categories. For instance, there could be a module that applies only for food and drinks.

The information arriving from the query handler is sent through a *recommendation engine* that acts as a proxy between the query aggregator, the scoring modules, and the user interfaces. The recommendation engine maintains a registry of active scoring modules, sends to each those bags-of-words that the module has registered to receive (all if no filter is in place), and waits for a determined timeout for each scoring module for a response. The response consists in (category, score) pairs; all arriving pairs are then combined within the recommendation using a scoring function that produces a single score per each category that appeared in at least one scoring module response (options include statistical measures like average or median or fuzzy computation to combine the individual scores, with the option of expressing user preferences in terms of weights). The aggregated (category, score)-pairs are then sent to the user interface that originated the recommendation request.

Figure 2 illustrates the communication between the recommendation engine and the scoring

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2 Figure 2. The phases of interaction between the recommendation engine and a scoring module of the architecture presented
3 in Figure 1.
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6 modules: initially, a scoring module sends a message to the recommendation engine, indicating its
7 interest to be included as a scoring module in the framework. Then, upon adding the scoring module
8 into the register, the recommendation engine sends back a data model that informs the scoring
9 module of the categories currently employed by the framework and the scoring scale to be used in
10 each category as well as the types of bags-of-words that are included in a query. A scoring module
11 may then inform the recommendation engine which subset of the bag-of-words it will process and
12 to which categories it may provide scores; this is to optimise the performance and avoid sending
13 unnecessary information. Every time the recommendation engine modifies the available query data
14 or the categories, it re-sends a package like this to any registered scoring module.
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21 Upon receiving a query from the query aggregator, the recommendation engine sends it to
22 any scoring module in its registry. If no reply has been received from a scoring module within a
23 predetermined time limit (for example due to network malfunction or discontinuation of the scoring
24 module by its provider), the aggregator increments the inactivity count of that particular scoring
25 module. When a scoring module has an inactivity count above a threshold, it is removed from
26 the registry (until it re-registers); the inactivity count is reset to zero as soon as a scoring module
27 replies to a query. The query replies are then combined by the recommendation engine as input to
28 the scoring function.
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35 To speed up the retrieval, a *cache* module is recommended to store information on recently
36 queried products in case the user wishes to reconsider among options, thus avoiding the computa-
37 tional overhead of having to consult the same information again.
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40 Each reply that a scoring module produces includes an identifier (a unique ID within the re-
41 sponses of that module in a 24-hour time period) that can be used if the user interface that
42 generated the query requires access to a textual description of what information contributed to
43 the score. If the user selects to consult the details of a specific score, this ID can then be used by
44 the recommendation engine to retrieve details without a need for the scoring module to recompute
45 this information. The details are not sent automatically with the original response to minimise
46 communication overlay, as the number of modules and categories may increase and the amount of
47 detail in these responses may grow significantly; this would be a problem for mobile-data access.
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2 in a web-view beside the score-visualisation gadget upon user request. We recommend combining
3 colours and symbols for visualising to the user the scores — merely displaying a number is slower
4 to grasp for a user operating in a context of constant distractions such as supermarket, and making
5 the user read a text on each product would risk interrupting the flow of decision-making.
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10 **Example: Social networking module.** To illustrate the function of the scoring modules, let us
11 describe the design of the social networking scoring module, which is one of the modules we propose.
12 In general, this module would gather *opinions* from the product's greenness, rate each opinion, and
13 provide a general score that reflects the overall opinion with regard to the eco-friendliness of the
14 product. Its main task consists of retrieving comments (e.g. tweets) about the product, which can
15 be easily performed via automated tools, such as the Twitter API¹. These tools permit to download
16 a considerable number of real-time comments given a set of keywords (in this case brand, product,
17 and eco-related keywords).
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24 A second important task is to distinguish between opinions and objective text, while also being
25 able to distinguish between *positive* and *negative* opinions. Currently, this is possible with methods
26 from *sentiment analysis* (Liu 2012). The simplest approach is to use a dictionary that contains
27 *polar words*, i.e., words that express a positive or negative opinion; this dictionary is called *lexicon*.
28 Normally, in a lexicon each polar word has a *weight* that indicates if it is negative (weight less
29 than zero) or positive (weight greater than zero). If a word is not found in the lexicon, its weight
30 is zero, which means it is neutral. The rating of each comment is the sum of its weights. The final
31 step consists of calculating an overall score that will be returned by the module. In part, this can
32 be done by combining the individual ratings of the retrieved comments.
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40 *Another issue consists of how to ensure content quality and correctness. Reputation systems*
41 *usually handle environments where the existence of controversial content is possible; it is not un-*
42 *common to see this kind of system applied to social media. The traditional approach for reputation*
43 *systems consists of voting or rating contents to establish their quality or confidence. In Wikipedia,*
44 *for example, content-based reputation systems based on contribution persistence have been pro-*
45 *posed (Adler and de Alfaro 2007); consequently, contributors whose content frequently gets edited*
46 *have a low confidence score. Reputation can also be established via metadata collection, virtual tro-*
47 *phies — these have also been used in eco-friendly applications (Massung et al. 2013) —, feedback,*
48 *profiles, bot identification, statistical filtering, user promotions, and runtime analytics (Daniel et al.*
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56 ¹Available at <https://dev.twitter.com/overview/api>.
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2018). More sophisticated methods include logical argumentation (Sklar et al. 2016), which is an extension of automated reasoning and negotiation in an agent-based environment to reach agreements when conflicting information is presented. However, it has been stated that crowd-sourcing itself is a truth-converging tool (Goodchild and Li 2012).

5. Experiments and Results

In this section we describe experiments carried out with two prototypes — one for web stores and another for regular retail using augmented reality. Both evaluations indicate that providing a consumer with information regarding the ecological impact of products affects their behaviour.

5.1. Methodology

We concentrated on these experiments on groceries, while the proposed platform can also include other types of goods and services. The user groups for our experiments consisted in residents of Northern Mexico, of ages 18 to 40, who had purchased something within the last month and expressed interested in testing a shopping prototype.

The online-store interface was tested by 24 users (12 being a control group that used an regular web store and the other half accessing the web store with our prototype plugin that displays ecological information). For the AR-prototype experiments, twelve people (half of them female) were asked to indicate their brand preferences before and after using the AR prototype that displays ecological information. The recommendation engine for these prototypes was a simple database with simplified, artificial ecological information; the products, however, were real, and hence the users may have previous knowledge and/or opinions regarding these products. The goal was to examine how the prototypes affect the users perceptions of the products.

5.2. Web store

With the aim of discovering if just-in-time information orients the consumer towards “greener” choices, in the first experiment, we employed a browser plugin for online shopping. This plugin displays information related to the eco-friendliness of a product (Urbina Coronado, Schaeffer, and Garza Villarreal 2014) by following these steps:

- 1 (1) Once the product is selected, its associated information is identified by the plugin and a query
2 is generated.
3
- 4 (2) A recommendation engine, which runs on a separate web server, receives the query.
5
- 6 (3) The query is processed by the server; if there is ecological information available to fulfil this
7 query, a response is produced with such information.
8
- 9 (4) The plugin places the response within the browser by adapting the styles and sizes on the
10 website.
11
- 12 (5) The user is able to interact with the generated visualisation to access additional details.
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16 In the web-store test, each user was given a list of nine products to buy at the supermarket
17 (Comité fronterizo de obreros 2013). The website to used to perform the test was that of Soriana,
18 a large chain of supermarkets in Mexico, <http://www.soriana.com>. For each requested product,
19 there were different brands and the choice was up to the user. We registered the prices and the
20 ecological score of the selected products in order to determine whether the users of the plugin
21 were willing to pay more in exchange for greener products; our basic assumption is that such
22 willingness would reflect an increase in their environmental awareness at the time of purchase —
23 the willingness to pay a higher price has been demonstrated for organic products (Napolitano et al.
24 2010) as well as products derived from animals with higher levels of welfare (Napolitano et al.
25 2008). However, Schnettler et al. (2009) found no apparent willingness to pay more for animal
26 welfare in a developing country, although the origin of a product does outweigh the price.
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29 In our experimenters, users of the plugin systematically chose alternatives with higher ecological
30 scores, even though this increased the price of the purchase, than the control group. The ecological
31 scores with the plugin were on average 41 percent higher, whereas the average increase in price was
32 8 percent. The difference in the total price of the shopping cart is statistically significant, with a
33 p -value of 0.00096 in a pairwise t -test performed with R². It is important to note that there was
34 no actual exchange of money involved and that expressions of willingness to spend more money
35 do not necessarily guarantee that more money would in fact be spent; further experimentation in
36 collaboration with a store is required to examine consumer behaviour (Chandon, Morwitz, and
37 Reinartz 2005).
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52 ²An open-source tool for statistics, available at <https://www.r-project.org/>.
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3 Figure 3. The *difference* in the frequency of selection of brands into a set of ten favourites, before and after using the AR
4 prototype (the frequency of selections *after* the usage minus the frequency of selections of the brand *before* the usage — positive
5 values indicate a change in favour of the brand whereas negative ones indicate a change against it) versus the ecological score
6 assigned to each brand.

7 **5.3. Augmented-reality interface for retail**

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10 Our AR prototype detects logotypes when the user holds a product package and displays the
11 ecological score if a match is found in the database (Espinosa Cenicerros, Schaeffer, and Garza
12 Villarreal 2014). The interface hardware was a *Vuzix ST AR 1200XLD* headset that functions both
13 as output (screen) of the client application and and input (camera) for processing the user's field
14 of vision; it is somewhat heavy and partially limits the field of vision, for which the experience of
15 wearing it (especially for a first time) may divert the user attention towards the headset itself and
16 away from the task.
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22 Each user was requested to indicate ten of their favourite brands from an image containing
23 several brand logotypes, both before and after using the prototype that displays ecological scores.
24 Our goal was to examine whether the preferences are altered by viewing environmental information
25 through the prototype. The results are shown in Figure 3: brands that were displayed with a high
26 eco-scored got selected more after using the prototype (a positive change in selection frequency),
27 whereas low-scored brands got selected less (a negative change in selection frequency). We examined
28 the statistical significance with an analysis-of-variance model in R and the effect of the score in
29 the change of selection frequency is significant with a *p*-value of 0.0006.
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38 **6. Conclusions**

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41 We described a computational framework for providing consumers with ecological information on
42 the products they consider buying at the time of purchase. We discuss the structure of such a
43 platform and provide experimental results on two conceptual prototypes, one for a web store and
44 another for in-store purchases that uses augmented reality. We found that timely information of
45 products can affect consumer perception of these and stimulate greener choices; observing such an
46 effect for two distinct user interfaces demonstrates the flexibility of our framework as a tool for
47 ecologically conscious decision making at time of purchase.
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53 According to the results of the experiments, the availability of ecological information at time of
54 purchase can affect the perception of the consumer towards preferring products that are said to
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2 be ecological, even if this goes against their own previous preference or the cost of the alternative
3 products. Such an increase in the awareness may well result in behavioural changes in consumer
4 behaviour, the measurement of which is left to future work.
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7 The Mexican users in our experiments also expressed a willingness to pay more for ecological
8 products, in agreement with the findings of Prakash and Pathak (2017) in India. Both agree with
9 the studies of Fleith de Medeiros, Duarte Ribeiro, and Nogueira Cortimiglia (2016) with Brazilian
10 consumers and the results of Hussain, Khokhar, and Asad (2014) with Pakistani students; the
11 overall conclusion is that recognised brands and companies that are known to be eco-friendly are
12 preferred. The present study — alongside with the cited studies that were carried out in Brazil,
13 Pakistan, and India — indicates that providing information on the ecological impact in an easy-
14 to-absorb fashion is able to steer self-assessed consumer preference towards eco-friendly products
15 even for a higher price.
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23 Future work includes the full-scale implementation of such a system using existing online infor-
24 mation sources such as <http://world.openfoodfacts.org/>. One practical concern is vulnerability
25 to spam and misleading information (the internet has plenty of both). This requires the introduc-
26 tion of administrative mechanisms where a super-user can block abusive scoring modules, as well
27 as a decentralised reputation mechanism where the users can vote for the reliable modules and
28 then the scoring function weighs the scores received from the modules in terms of the reputation
29 of the module, placing a higher importance to the trusted modules.
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35 Personalisation of which scoring modules to take into account and how to weigh between them
36 as well as adjusting the level of detail given by default in the user interface is of importance, as pre-
37 vious studies report high individual differences regarding the amount of information preferred by
38 consumers (Chen, Shang, and Kao 2009). We also believe that incorporating elements of ramifica-
39 tion (that is, giving users “points” or “ranks” for their ecological actions, in the way that Facebook
40 encourages users to validate the information provided by businesses and Duolingo rewards users for
41 completing language lessons) could be useful and their effect should be experimentally determined.
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48 Further experiments are needed to determine the relative importance of various ecological factors
49 for the users, differences between visual and textual representation of information for the ecological
50 factors, and possible differences in the response of different user groups (that is, whether factors
51 such as age, gender, education, or socio-economic status affect the way in which the user employs
52 and interprets the ecological information provided by the proposed framework. We also wish to
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2 measure the degree of knowledge that Mexican consumers have regarding ecological issues and
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4 examine whether this is related to their degree of preference toward eco-friendly products.
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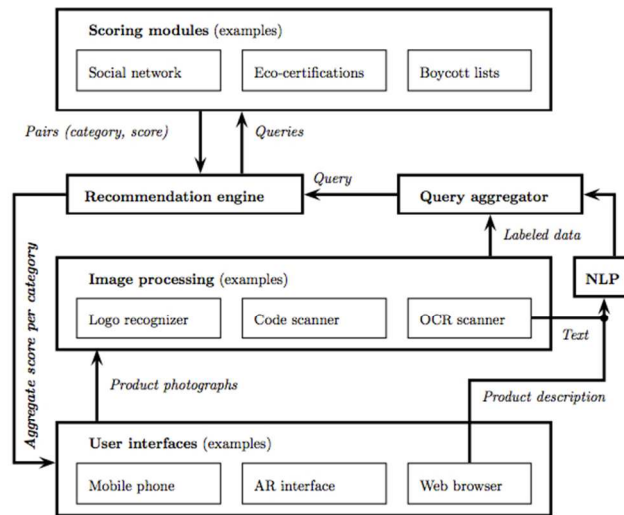
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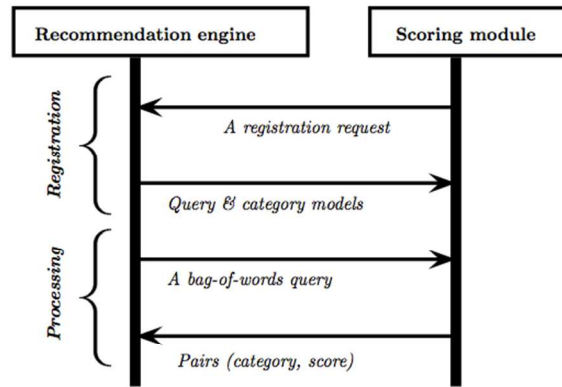
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Principal components of the proposed ecological product- recommendation framework.

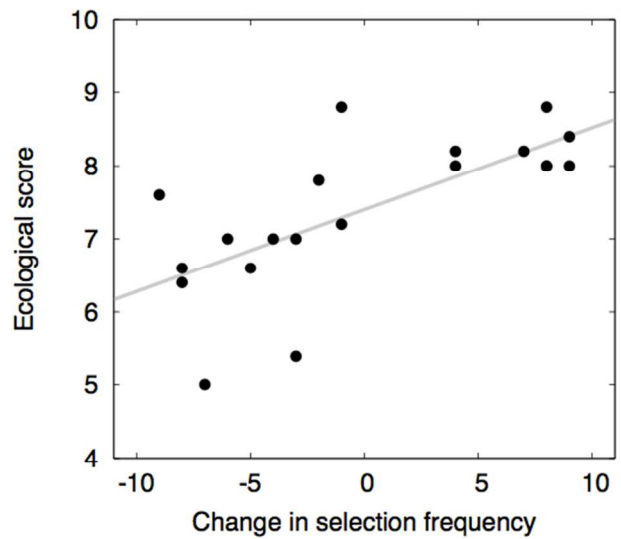
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The phases of interaction between the recommendation engine and a scoring module of the architecture presented in Figure 1.

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The difference in the frequency of selection of brands into a set of ten favorites, before and after using the AR prototype (the frequency of selections after the usage minus the frequency of selections of the brand before the usage — positive values indicate a change in favor of the brand whereas negative ones indicate a change against it) versus the ecological score assigned to each brand.

301x233mm (72 x 72 DPI)