A Dynamic Approach to Information Quality in User-Generated Content

Research-in-Progress

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Abstract

Information quality (IQ) plays a critical role in ecommerce consumers’ purchase decisions, and product-related user-generated content (PUGC) is an increasingly important source of information. Nevertheless, vendors currently do not take full advantage of PUGC since PUGC is mainly used for evaluation purposes. Integrating PUGC into earlier phases of the purchase-decision process might be promising. However, little is known about which dimensions of IQ consumers evaluate as being most important in different phases of the purchase process. To close this gap, we design a survey study that investigates the perceived relative importance of various IQ dimensions in each of three purchase phases (i.e., screening, filtering, and evaluation). Conceptually, we thus extend the concept of IQ to a dynamic approach. Practically, our findings can inform the design of ecommerce websites that integrate PUGC about how to best support the purchase-decision process with respect to dynamic IQ.

Keywords: Information quality, User-generated content, Recommendation agent, Consumer decision making, Consumer purchase funnel
Introduction

Information quality (IQ) plays a critical role in ecommerce consumers’ purchase decisions (Tsai and Chuang 2011; Narwal and Kant 2014; Napitupulu and Kartavianus 2014; Chen et al. 2009) as there is no opportunity to physically interact with products when shopping online. User-generated content (UGC) is an increasingly important source of information when it comes to product-selection and decision processes. With its advantages of richness, authenticity, and independency, UGC also comes with challenges like fraud, subjectivity, and diverse forms of heterogeneity. Of special interest is a subset of UGC that deals with product-related information. For example, for laptops, this would be statements like “bright display,” “annoying fan,” or “long-lasting battery.” Although the presence of product-related UGC (PUGC) has become common on ecommerce sites, it is questionable if vendors and intermediaries take full advantage of PUGC. Today, PUGC is heavily used for evaluation purposes. That is, PUGC is typically not accessible on ecommerce sites before the corresponding product has been found (Lee et al. 2008). PUGC is mostly treated like an extension to the vendor’s product description, and it is necessary to access the product site before accessing the associated PUGC.

Nevertheless, decision making entails earlier phases (e.g., screening of opportunities, reduction of a consideration set, selection of candidates, confirmation, evaluation), but PUGC does not find its way into decision phases other than evaluation. When PUGC is only used for evaluation purposes, it turns out to be a time-consuming process for users as they have to read the full texts of several reviews and iteratively refine their search according to the insights obtained. We believe there is a need to integrate PUGC in earlier phases of the purchase-decision process. As more and more product reviews are written, the need to organize and rearrange PUGC becomes more important (Hu and Bing 2004), getting away from vast full-text displays of reviews. Issues of questionable IQ however constrain the use of PUGC in earlier search phases. Using PUGC in an early search phase (e.g., screening of opportunities or reduction of a consideration set) implies pulling the relevant PUGC information “in front of the product” and presenting the content in an aggregated and consolidated way. However, it is challenging for information system designers to provide filters or condensed information in appropriate quality in a screening or filtering phase for some obvious reasons: PUGC mostly covers only a few aspects of a product, and single reviews are like illuminating a product in the dark with a spotlight—they never give a full picture. As completeness of information is one problem, proper aggregation and consolidation of PUGC turns out to be another. We therefore want to examine the IQ needs of users throughout the purchase-decision process.

A widely accepted definition of IQ is that of “fitness for use” of data/information for data consumers (Wang and Strong 1996; Madnick et al. 2009; Ballou et al. 2003). Fitness for use implies a user-centric view of IQ issues that is related to a specific task, and it reflects that “use” can be different depending on the situation. Thus, fitness for use is an appropriate IQ definition to study potentially changing IQ evaluations throughout the purchase-decision process, during which the user is confronted with different situations and tasks.

From IQ research, we learned that IQ does not only comprise accuracy, believability, and other intrinsic dimensions but also contextual, representational, and accessibility dimensions (Wang and Strong 1996). This emphasizes that changing the representation, the context, or the accessibility of the information will not only result in a different assessment of IQ but will also impose different IQ needs on the user side.

However, there is little knowledge about users’ IQ preferences throughout the phases of the purchase-decision process. Researchers have not yet revealed in which contexts PUGC becomes most valuable on product platforms or how to build information systems that can leverage the value of PUGC. To close this gap, we enhance the understanding of PUGC IQ by combining IQ with purchase-decision process phases in order to obtain a more differentiated view of IQ for the same PUGC content over time or, more concisely, process phases. We propose to pursue a dynamic approach to IQ to optimally support the purchase-decision process in the different phases. Hence, we specifically ask the following research question:

RQ: Does a user’s prioritization of IQ dimensions change depending on the phase of the search process in which PUGC is integrated?

The remainder of this paper is organized as follows. First, we introduce related work from three fields: IQ frameworks, purchase-decision process models, and approaches to integrating PUGC into early purchase
process phases. Then, we depict our research approach of dynamic IQ by combining IQ with a purchase phase model, which is followed by the formulation of our proposition and the presentation of our conceptual model. Afterwards, we explain our survey instrument and data analysis propositions. We conclude with the contributions that we want to achieve.

**Related Work**

First, we relate to existing literature in the field of IQ and purchase-decision processes as we combine both concepts in our research. Further, we give an overview of corresponding approaches and methods to extract relevant product features from PUGC as a basis for its use in early phases of the purchase process.

**Information quality**

Typical research questions related to IQ are (1) how can IQ be defined, (2) how can IQ be measured, and (3) how does IQ relate to other concepts, such as user satisfaction and information system success.

Relating to the first point, different authors have proposed a variety of definitions. As already mentioned, the fitness-for-use definition was introduced by Wang and Strong (Wang and Strong 1996) and has since been the conceptual basis for various IQ frameworks (e.g., Lee et al. 2002; Kahn et al. 2002) and research studies (e.g., Nelson et al. 2005; Otto 2011), including applications in online contexts (Arazy et al. 2011; Scholz and Dorner 2013). Another common definition proposed, for example, by Orr (Orr 1998) and Shanks and Darke (Shanks and Darke 1998) is that of IQ being the degree of correspondence of information with external phenomena (i.e., accurately representing real-world entities and their attributes). Shanks and Darke (Shanks and Darke 1998) and Price and Shanks (Price and Shanks 2005) proposed a definition of IQ based on semiotic theory, which integrates different perspectives and defines IQ on three semiotic levels: syntactic (conforming to rules), semantic (corresponding to external phenomena), and pragmatic (user-centric perspective).

Regarding the second point—measuring—IQ definitions are usually operationalized through a set of dimensions like accuracy, timeliness, completeness, consistency and ease of understanding (for an overview of definitions, see, for example, Knight and Burn (2005); Jayawardene et al. (2013); Lee et al. (2002)). The dimensions chosen to be relevant in order to assess IQ in specific contexts depend on the task and formal specifications and expectations of the consumer (Lee et al. 2002; Kahn et al. 2002). Dimensions are then measured through technical means (e.g., structural and textual features of UGC (Wang et al. 2011; Vir Singh et al. 2014)) or via user surveys (e.g., Liang and Xue (2013); Blanco et al. (2010)).

Under the third point to mention is that IQ has been shown to positively influence information system success (DeLone and McLean 2003; DeLone and McLean 1992; Petter et al. 2013) and user satisfaction (Wixom and Todd 2005; Doll and Torkzadeh 1988).

However, the assessment of the relative importance of different IQ dimensions has received less attention. From the perspective of information users, this problem can be defined as follows. Given a set of IQ dimensions (e.g., accuracy and timeliness), there are several tradeoffs (e.g., the more accurate information is supposed to be, the less timely can it be provided and vice versa) as well as different contexts and tasks (e.g., phases in the purchase-decision process): which IQ dimension should be prioritized first, second, third, and so forth? Developers, website providers, and e-commerce vendors (and probably others) could use such insights to adapt information processing and presentation to such dynamic IQ prioritization profiles.

1 Though Orr (1998) and Wand and Wang (1996) actually speak of “data quality,” we use “data (quality)” and “information (quality)” synonymously as it is common practice in IQ research (Madnick et al. 2009). In some contexts, it is necessary to differentiate between data and information, or, respectively, data quality and information quality. Some studies do so but often do not share a common understanding regarding these and other terms (Kahn et al. 2002; Madnick et al. 2009; Price and Shanks 2005; Wand and Wang 1996). For our research objective, we do not need to differentiate between data quality and information quality.
In fact, there are some studies on the tradeoffs between IQ dimensions and their relative importance. Fehrenbacher and Helfert investigated tradeoffs between the perceived importance of selected IQ dimensions (Fehrenbacher and Helfert 2012), and Seethamraju studied the relative importance of web quality dimensions (Seethamraju 2005). However, to the best of our knowledge, this problem has not been investigated in the context of the purchase-decision process.

**Purchase-decision process models**

Information processing theory identified three decision-making phases (Cook 1993; Simon 2001) in pre-internet times—intelligence, design, and choice—which have since been adapted to online purchase decision making (Gao et al. 2012). In general, when talking about the purchase-decision process, the consumer purchase funnel model (Evans 2008) is widely used in various forms and under differing names (e.g. as the consumer decision journey (Court et al. 2009)) or in diverse “funnel models,” such as the ecommerce funnel, sales funnel, or conversion funnel. The consumer decision model (Engel et al. 1995; Jobber 1995) proposes seven phases: need recognition, search for information, pre-purchase alternative evaluation, purchase, consumption, post-purchase alternative evaluation, and divestment. Several other theories have been applied to the decision-making process, such as mental accounting theory (Gupta 2006). Vázquez et al. presented a novel analysis and classification of UGC in terms of how it is involved in the phases of the consumer decision journey (Vázquez et al. 2014). Depending on the perspective, purchase decision models have a different number of phases (most commonly four to seven) with different names.

**PUGC in early decision process phases**

Integrating PUGC into early decision phases is one of the aims of content-based recommender systems. Whereas in general, “the recommendation problem is reduced to the problem of estimating ratings for the items that have not been seen by a user” (Adomavicius and Tuzhilin 2005, p. 2), a recommender system’s goal in a broader view is not only to estimate ratings for items that a user has not seen yet but also to provide relevant information for items the user has not seen yet. Content-based recommender systems do not take user behavior or collaborative filtering into consideration but perform this task relying on content only.

Content-based recommender systems are rooted in information-filtering (Belkin and Croft 1992) and information-retrieval research (Salton 1989), providing automatic feature-extraction techniques for textual data. An overview of text-extraction techniques is given in Jiang’s work (Jiang 2012). Further, Lee, Li, and Wei integrated traditional information-retrieval relevance rankings with database aggregation to model the knowledge within online product reviews and product descriptions in order to provide a needs-centric search whereby users can input free-text queries (Lee et al. 2008). Dave et al. proposed a classifier that draws on information-retrieval techniques for feature extraction and scoring in order to generate a list of product attributes (quality, features, etc.) and aggregate opinions about each of them (Dave et al. 2003). Aggregating subjective opinions is a challenge but leads to more intersubjective information, referred to as “objectivity by averaging” (Parameswaran and Whinston 2007).

Social business intelligence (social BI) approaches (Francia et al. 2014) make up an interdisciplinary research area and combine data-mining technologies, natural language processing, and other promising techniques to summarize PUGC. Gallinucci et al. proposed a way to aggregate topics for social BI (Gallinucci et al. 2013), and Hu and Bing proposed an approach to mine and summarize the customer reviews of a product, focusing on product features only and generating feature-based summaries (Hu and Bing 2004). Further, Popescu and Etzioni constructed an unsupervised information-extraction system, which mines reviews in order to build a model of important product features (Popescu and Etzioni 2005).

Especially for content-based recommender systems, which—per definition—rely solely on content, it is vital to extract and present content in an appropriate way. Nevertheless, although diverse techniques exist to extract product features from full-text data and approaches have been proposed to integrate PUGC into early purchase process phases, in practice, we rarely see an application of these approaches. Most importantly, it remains unclear which IQ dimensions—from the perspective of the consumer—PUGC should be adapted to when designing recommender systems in order to correspond to relative IQ prioritization on behalf of users.
Research Approach

In our research approach, we combine two models: a purchase funnel model and an IQ framework. In the following, we depict how we apply both models to our research objective.

**Purchase funnel**

The consumer purchase funnel model is widely used in various forms and under different names, with different numbers of and naming for phases. In our research approach, we decided to use a parsimonious model of a purchase funnel that consists of three phases (see Figure 1): (1) a screening phase, during which the user gathers an overview about products; (2) a filtering phase, during which the user narrows down the consideration set, and (3) the evaluation phase, during which the user reads product information (i.e., descriptions and reviews) in detail.

<table>
<thead>
<tr>
<th>Purchase funnel</th>
<th>User action</th>
<th>Examples of PUGC content in each use context</th>
</tr>
</thead>
<tbody>
<tr>
<td>Screening</td>
<td><strong>Screening phase:</strong> user gathers overview about products</td>
<td></td>
</tr>
<tr>
<td>Filtering</td>
<td><strong>Filtering phase:</strong> user narrows down the consideration set</td>
<td></td>
</tr>
<tr>
<td>Evaluation</td>
<td><strong>Evaluation phase:</strong> user reads product information in detail (i.e., descriptions and reviews) in detail</td>
<td></td>
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- **Screening phase:**
  - Battery duration (short, OK, long)
  - Screen (bright, dark, convenient, disturbing reflections)
  - Fan (noisy, silent, not hearable)

- **Filtering phase:**
  - □ bright screen (8)
  - ☑ long-lasting battery (13)
  - ☑ high-quality chassis (7)
  - □ silent fan (11)

- **Evaluation phase:**
  - “Since I like to work on the balcony, it is very important to me that the device has a bright display. In this regard the laptop outperformed my expectations. I was however disappointed from the battery, it does not last longer than 3 hours.”

When dealing with the fitness-for-use approach for IQ dimensions, we not only deal with content but content in a specific use context. The research object of fitness for use is therefore a combination of content and use context. In the following, we give an overview what PUGC means in the three different fitness-for-use situations.

**PUGC in the screening phase.** Screening PUGC is the first step in our decision process. “In the beginning phases of purchase, a buyer lacks experience, his choice criteria is not well-developed and he doesn’t have any knowledge of various brands and their potential” (Gupta 2006, p. 27). PUGC necessarily has to be aggregated, consolidated, and condensed to be presentable in the screening phase.

**PUGC in the filtering phase.** Filtering by PUGC is the second step in our decision process. If PUGC is used for filters, it necessarily has to be aggregated, consolidated, and condensed just like PUGC in the screening phase. The big difference between PUGC for screening and filtering is not the presentation of the content but what users want to do with this content (i.e., the use context).

**PUGC in the evaluation phase.** Evaluating PUGC is the last step in our decision process. In this phase, the user reads detailed information about the product (i.e., the full text of the review).

Examples of PUGC in each phase are presented in Figure 1.

**Conceptual model**

Our basic proposition is that users evaluate the IQ dimensions differently depending how close they are to checkout and the completed purchase. For example, in a very early phase, completeness might be the most relevant IQ in order to get an overview of relevant product features, some of which might be critical...
for the user’s later purchase decision. Further, amount of data may also play a leading role in combination with completeness in order to grasp the overview quickly. When narrowing down the consideration set by filters, believability and relevancy might be the most important IQ dimensions because users might fear filtering possibly interesting products out and never getting to take them into consideration again (i.e., believability) and because relevancy is the basic idea of filtering out irrelevant products. After narrowing down the number of alternatives to a certain product (i.e., when the user reads reviews and evaluates a single product), timeliness of the information might be one of the most relevant factors for users. Furthermore, ease of understanding may also be important since poorly written reviews hinder a quick evaluation.

Assuming that the user’s prioritization of different IQ dimensions changes with closeness to the purchase, we put forth the following proposition and present the conceptual model, as shown in Figure 2.

**Proposition**: A user’s prioritization of IQ dimensions will change depending on how close he or she is to checkout.

![Figure 2. Conceptual model](image)

**Research Method**

We pursue an empirical approach to IQ as we want to explicitly focus on the subjective perspective of the information consumer. The empirical approach to IQ leads back to the work of Wang and Strong (1996). The approach of Wang and Strong (1996) fits well with our empirical consumer-centric view. We will conduct our research in a survey approach to answer our research questions. We will ask consumers how they assess different IQ dimensions in different phases of the decision-making process (i.e., screening, filtering, or evaluation).

**Selection of IQ dimensions**

As we chose to select Wang and Strong’s IQ dimension set due to its wide acceptance and the fit with our empirical consumer-centric view, we have to deal with 15 dimensions (Wang and Strong 1996). In order to reduce the amount of IQ dimensions to be assessed in the three use contexts, we limit the number of IQ dimensions to 10, leaving out the dimensions that are not applicable or are of general low importance in all three use contexts: namely, accessibility, access security, value-added, interpretability, and concise representation.

On the basis on Wang and Strong's (1996) empirical approach, a set of more recent IQ frameworks have emerged, and various names and definitions of IQ dimensions have been proposed in the literature.
a few papers give detailed definitions of the IQ dimensions, and definitions differ across the frameworks. In our questionnaire, we will mainly stick to the definitions of Wang and Strong (1996), but we also occasionally pick definitions from other authors when we perceive those definitions to be (1) better suited for our research context or (2) easier to understand for survey participants.

**Believability.** It is hard to distinguish believability from similar terms, like confidence (McGilvray 2008). The best definition for our purpose is the one from Wang and Strong (1996, p. 31): “Data are accepted or regarded as true, real, and credible.”

**Timeliness.** Timeliness (McGilvray 2008; Byrne 2008; Loshin 2006; Price and Shanks 2005) is also often referred to as currency (English 2009; Stvilia et al. 2007; Eppler 2006; Redman 1997). We refer to the definition of Price and Shanks (2005, p. 10): “The currency (age) of the data is appropriate to its use.”

**Accuracy.** Accuracy is included in a lot of studies (McGilvray 2008; Stvilia 2007; Gatling 2012; Eppler 2006; Loshin 2001; Redman 1997). We found the following definition to be most appropriate: “Determines the extent to which data objects correctly represent the real-world values for which they were designed” (Gatling, 2012, p. 334).

**Objectivity.** Price and Shanks (2005) discussed several understandings of objectivity. Nevertheless, we stick to the definition of Wang and Strong (1996, p. 32): “Data are unbiased and impartial.”

**Reputation.** The definitions of reputation sometimes point out cultural aspects. Stvilia defined reputational IQ as “the position of an information entity in a cultural or activity structure” (Stvilia 2007, p. 1724). However, as we are not planning a cross-cultural study, we stick to the simpler definition of Wang and Strong (1996, p. 32): “Data are trusted or highly regarded in terms of their source and content.”

**Completeness.** The term completeness can be found in many studies (Byrne 2008; Gatling 2012; Gomes et al. 2007; Loshin 2006; Redman 1997; Wang and Strong 1996) but also under different names with similar meanings (e.g., data coverage) (McGilvray 2008). For our survey, we select the definition of Gomes et al.: “Data is complete if no piece of information is missing” (Gomes et al. 2007, p. 17).

**Relevancy.** From relevancy definitions (English 2009; Lyon 2008; Stvilia 2007), we pick the one from Wang and Strong (1996, p. 31): “Data are applicable and useful for the task at hand.”

**Consistency.** Several definitions for consistency can be found (Gatling 2012; Eppler 2006; Kimball and Caserta 2004; Loshin 2001), of which we pick the following: “Is the information free of contradictions or convention breaks?” (Eppler, 2006, p. 83)

**Ease of understanding.** Ease of understanding is sometimes used synonymously with interpretability (Redman 1997). We decided to drop interpretability from the set of IQ dimensions and use the definition of Wang and Strong (1996, p. 32): “Data are clear without ambiguity and easily comprehended.”

**Amount of data.** “The quantity or volume of available data is appropriate” (Wang and Strong 1996, p. 32).

**Survey instrument**

Several methods exist to gather data with the goal of prioritizing criteria, in this case IQ dimensions. Simple approaches use Likert scales for all criteria and are generally suitable to assess user perceptions (Smith 1997) but allow the user to respond that all dimensions are important to him or her. More sophisticated approaches work with resource limitations and ask users to assign points from a given “budget” to the dimensions, referred to as comparative scaling with constant sum, which allows for better discrimination among criteria without being too time consuming (Malhotra 2009). However, participants have to calculate and sum up points, which makes this method difficult and error prone. As an advantage, both approaches allow operations on a metric scale.

Working with ordinal scales, a simple way to collect data about preferences is to ask participants to rank the criteria. However, the results neglect how big differences in perceptions are. It has been proven useful to ask users to select between IQ dimensions (Fehrenbacher and Helfert 2013) in pairwise comparisons. Given the relatively large number of items to compare, however, this is not practical as the number of comparisons increases quadratically.
Applying these thoughts to our research, our primary intention is not to compare the IQ dimensions within one use context but to see changes in the most important dimensions between the three use contexts. Also, considering the exploratory nature of this research, we choose the rather simple method of asking the participant to select the three most important IQ dimensions in each use context (i.e., screening, filtering, and evaluation). This will not allow us to determine how important a specific IQ dimensions is for a certain participant, but we can still determine the relative importance of the IQ dimensions on an aggregated level. Further, data will also be appropriate to answer our research question and investigate our proposition.

In our questionnaire, we will put users in a scenario of searching for a laptop on the internet. We introduce them to the three situations of screening, filtering, and evaluating and give corresponding examples so they gain a good understanding of the use context. In each situation, we present the 10 IQ dimensions that we selected from Wang and Strong’s set (1996). Then, we ask them to identify the three most important of the 10 available IQ dimensions for each of the three phases. To prevent a systematic bias arising from the sequence of the selecting, filtering, and evaluating phases, we change the order of the three situations for each participant and also change the order of the IQ dimensions.

**Sample questionnaire**

The following is a questionnaire example for the scenario screening (Figure 3). We will assemble questionnaires for the use contexts filtering and evaluating accordingly.

![Questionnaire for Scenario Screening](image)

**Data analysis**

Survey results from one participant will comprise three times (for each phase) three out of the 10 IQ dimensions. Summing up responses from all participants will yield statistics on the frequencies of the IQ dimensions, which will reflect the relative importance of the IQ dimensions for each of the three use contexts (i.e., phases). Since our research question and proposition concern whether there are any
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differences in prioritizations of IQ dimensions between the three phases, we will compare frequency distributions between phases. We will use Pearson’s $\chi^2$ test to assess (1) whether phases and IQ prioritizations are independent from each other (across all phases) and (2) whether IQ prioritizations differ when phases are compared in a pairwise manner.

In addition to this confirmatory assessment of our proposition, the results can also be analyzed in an exploratory way regarding which specific IQ dimensions are usually evaluated as being important in each of the three phases.

**Potential Contributions and Further Research**

As we gain more knowledge about information needs throughout the purchase-decision process, we will be able to better design future content-based recommendation systems according to the fitness-for-use paradigm. Insights into user perceptions of IQ of PUGC in earlier search process phases is key to the construction of new product search mechanisms, tomorrow’s recommender systems, and the handling of PUGC in general. Managers of ecommerce sites will benefit from these insights when they need to decide how they can integrate PUGC in earlier process phases, especially when integrating them into filtering options.

Insights into dynamic IQ has implications for the design of ecommerce platforms, too. Future ecommerce sites will surely need to process more and more PUGC and transform the information into product properties that serve the information needs of customers in each decision process phase. While research on IQ needs has been agnostic of purchase-decision process phases so far, we combine the concepts of IQ and decision phases in order to analyze the concept of IQ in a more dynamic way. Our findings will contribute to IQ research and improve IQ frameworks, such as the one presented by Wang and Strong (1996).

With the knowledge of users’ IQ needs across the purchase-decision process comes the potential to design the purchase process more efficiently. However, measuring the quality of the purchase process itself (e.g., with well-known metrics, like a consideration set, time consumed, or quality of the decision) needs further research, for which our findings on dynamic IQ may serve as a basis.

Exploratory results regarding the relative importance of IQ dimensions in each phase can inform theoretical considerations about the relationship between IQ evaluations and the purchase process and may help in building a deeper understanding of dynamic IQ.
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