Explaining Data-Driven Personas to End Users

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ABSTRACT

Enabled by digital user data and algorithms, persona user interfaces (UI) are moving to digital formats. However, algorithms and user data, if left unexplained to end users, might leave data-driven personas (DDPs) difficult to understand and trust. This is because the data and the way it is processed are complex and not self-evident, requiring explanations of the DDP information and UIs. In this research, we provide a proof of concept for adding transparency to DDP using a real system UI. Furthermore, we demonstrate ways to add breakdown information that can help alleviate user stereotyping associated with the use of personas.

KEYWORDS

Personas; digital interfaces; transparency, information design.

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CSS CONCEPTS

• Human-centered computing ~ Human computer interaction (HCI)

1 Introduction

A persona represents the goals, behaviors and characteristics of a user segment [4, 29]. While personas are typically created qualitatively from user interviews [14, 17], qualitative approaches are newly complemented by data-driven personas (DDPs) that use quantitative methods, algorithms, and online user data [11, 22, 35]. This transition from traditional personas to DDPs is associated with the *digitalization of persona user interfaces (UIs).* While personas are traditionally presented in one or two page paper profiles [6, 26], DDPs are presented in a digital UIs that the persona users can interact with (see example in Figure 1).

Data-driven persona generation is becoming increasingly popular in the industry [27, 34, 35, 43]. The challenge relating to this shift is that while research has been done on traditional paper layouts [28], not much is known about the digital persona UIs and their user experience (UX). Apart from exploratory studies [37, 38, 41], usability problems and interaction patterns in DDP context remain unchartered. More particularly, there has been little research on how to make the digital persona UIs transparent [31]. Transparency refers to providing explanations on how opaque algorithms produce information for end users [13].

This research aims to shed some light into these unexplored areas, with a specific focus on the design goal of making DDPs understandable and trustworthy from the perspective of their users (e.g., journalists, marketers, online content creators, medical professionals, corporate decision makers, and so on).

As a contribution, we demonstrate ways for adding transparency in DDPs by two means: (1) *adding explanations of persona information and how it was produced* and (b) *adding breakdown information of the representative persona characteristics*, towards the goal of mitigating stereotypical thinking.

Therefore, our goals with this research are to demonstrate means to add transparency to DDPs to increase persona users' understanding and trust towards the personas (both being risks noted in previous research [8, 23]); and to add information breakdowns that show the persona is a composite representation of a group of users, thereby providing means to alleviate user stereotyping, a risk stressed in the persona research [15, 22, 46].

2 Related Literature

Personas were introduced as a HCI technique [29] in software development [9, 17]. There are a variety of benefits attributed to personas [1], such as focusing on user outcomes, consensus building among designers and developers, user-centricity, and more granular product targeting [33, 36]. Personas provide communication benefits within teams [7] and organizations [28]. Personas can enable designers to identify with backgrounds different from their own and realize that the user preferences may deviate from their personal preferences [16, 17, 45].

Yet, to achieve the said benefits, it is critical that personas are perceived as credible and trustworthy by their end users [32]. To achieve trust credibility, one proposed technique is explaining how the personas were created, what design choices were made and why. Such transparency has been found especially important in algorithmic systems that, due to their complexity, may appear suspicious to end users [10, 13].

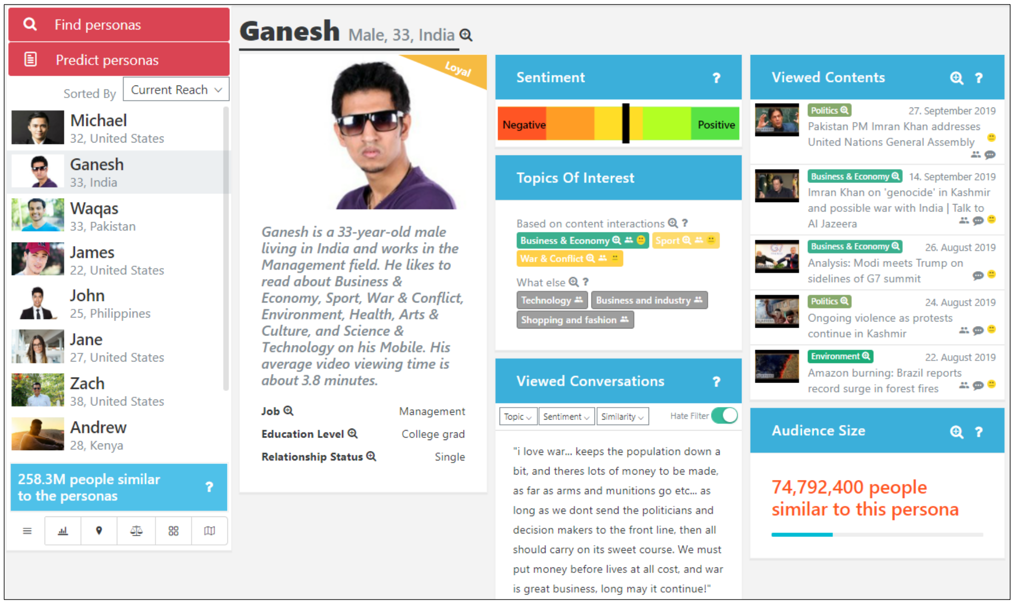

Figure 1: A DDP from a real production system[1]. There are several ways for end users to interact with the system, including, e.g., selecting the persona, changing the number of personas generated, and filtering the comments of the persona.

Persona transparency is an unexplored area in the HCI literature. Among the rare studies focused on persona transparency, Salminen et al. [42] analyze the impact of explanations added in the persona UI on user perceptions. They find that higher transparency (in the form of explanations) increased the perceived completeness and clarity of the shown personas. However, there was an undesirable effect of the explanations decreasing the credibility of the persona. The researchers interpreted this as an indication of a *transparency trade-off*, according to which the technical explanations disrupt the façade of personas being perceived as real people.

It is also worth to note that Salminen et al. [42] implemented the explanations "forcefully", meaning that they were shown as open pop-up type of boxes to the users (see Figure 2). In contrast, we implement the explanations as interactive tooltip definitions that the users can reveal by hovering over the tooltip icon.

Overall, computational techniques are becoming more common in persona development, with several researchers presenting their versions of algorithmically generated personas [2, 3, 24, 47]. The users are given access to the generated personas through system UIs where they can interact with the personas, including selecting each persona and viewing their information The users of these DDPs may question the information in persona profiles because they are unsure of how it was produced. This is a special concern for DDPs because their creation relies on opaque algorithmic processes that are often difficult to communicate in layman terms [5]. This difficulty can be seen from the findings of user studies that report issues of confusion and information design of algorithmically generated DDPs [36–38, 41].

The advice from the previous research is that persona creators should seek to experiment with novel designs of transparency for DDPs [42]. To this end, we present some explanations and data breakdowns we have implemented in a persona system. Note that these findings represent only the added explanations and breakdowns and do not include an empirical user study on their implementation on the persona UX. Such a study is a planned next step in the research agenda.

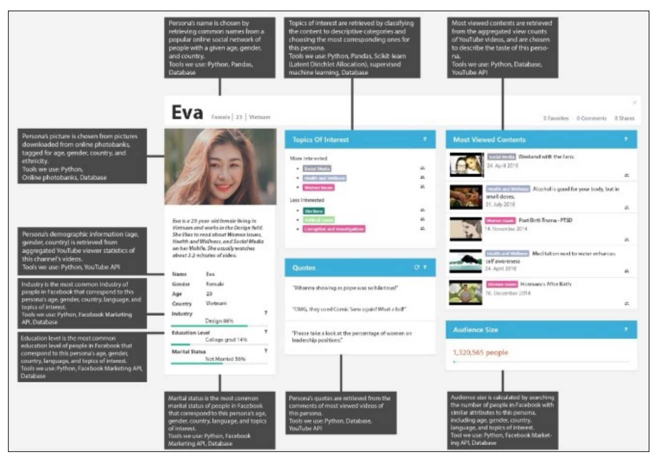

Figure 2: Explanations implemented in Salminen et al. [42]. These were shown "forcefully" without giving the users ability to enable or disable the explanations.

[1] https://persona.qcri.org

Table 1: Explanations implemented in the DDP system. Adapted from Salminen et al. [42].

Section	Explanation provided	Implemented (✗ = No, ✓ = Yes)
Name	Persona's name is chosen by retrieving common names from a popular online social network of people with a given age, gender, and country. Tools we use: Python, Pandas, Database	✗
Picture	Persona's picture is chosen from pictures downloaded from online photobanks, tagged for age, gender, country, and ethnicity. Tools we use: Python, Online photobanks, Database	✗
Demographics	Persona's demographic information (age, gender, country) is retrieved from aggregated YouTube viewer statistics of this channel's videos. Tools we use: Python, YouTube API	✗
Job	Job is shown based on Facebook audience sizes. The system collects Facebook audience sizes based on persona's demographic, interests, and language.	✓
Education Level	Education Level is shown based on Facebook audience sizes. The system collects Facebook audience sizes based on persona's demographic, interests, and language.	✓
Relationship Status	Relationship Status is shown based on Facebook audience sizes. The system collects Facebook audience sizes based on persona's demographic, interests, and language.	✓
Topics of Interest	Topics of interest are retrieved by classifying the content to descriptive categories and choosing the most corresponding ones for this persona. Tools we use: Python, Pandas, Scikit-learn (Latent Dirichlet Allocation), supervised machine learning, Database	✓
Most Viewed Contents	Most viewed contents are retrieved from the aggregated view counts of YouTube videos and are chosen to describe the taste of this persona. Tools we use: Python, Database, YouTube API	✓
Viewed conversations	Persona's quotes are retrieved from the comments of most viewed videos of this persona. Tools we use: Python, Database, YouTube API	✓
Audience Size	Audience size is calculated by searching the number of people on Facebook with similar attributes to this persona, including age, gender, country, language, and topics of interest. Tools we use: Python, Facebook Marketing API, Database	✓

3 Implementing DDP Transparency

We adopted a simple design principle for transparency: *explain to the user what the information is and where it comes from*. The explanations were then crafter by one of the researchers for all the information elements in the persona UI, as defined in Table 1. After this, the other researchers gave feedback on the wording and content of the explanations. Finally, after being reviewed by everyone in the research team, the explanations were implemented in the persona system.

Note that the explanations are the same as the ones used in a previous user study [42]. That study, however, tested only persona mockups, not a live system. Here, we implement the explanations in a live system for real client organizations[1].

3.1 Persona System

The persona system is called Automatic Persona Generation (APG) and it has been widely reported in previous research [2, 3, 18, 19, 39]. APG is both a system and methodology for generating personas from online analytics and social media user data. The system uses application programming interfaces (APIs) to automatically collect online user data with channel owners' permission. It then carries out algorithmic data analyses and outputs a set of DDPs that the end users can interact with using the system UI. APG uses a robust Web framework for Python (Flask) and a stable back-end database (PostgreSQL). It supports multiple online analytics and social media platforms, including Facebook Insights, YouTube Analytics, and Google Analytics.

Thus, we implement the explanations of the previous user study [42] in APG. The following sections demonstrate the implementation through practical examples from the UI. We first demonstrate the explanations and then the data breakdowns. Note that all explanations require the user to hover either the tooltip icon (the small question mark in Figure 4) or the element itself to show. The breakdowns require the user to click on the breakdown icon (the small magnifying glass in Figure 3).

3.2 Explanations

Figure 3 demonstrates the explanation for the stability indicator. The stability function informs the user of how frequently this persona appears in different persona sets over time. If the persona appears often, he or she is labeled as a "Loyal" persona. Otherwise, the persona is labeled as a "Occasional" persona.

Figure 4 shows the sentiment explanation. Sentiment score is calculated as an aggregate score from the comments associated with the persona and describes the persona's overall attitude.

Figure 5 shows the explanation for topics of interest. Topics are reflective of the content consumption preferences of online audience personas [39]. Similarly, most viewed contents describe the content that the group corresponding to the persona has most viewed (see Figure 6). The comments shown in the persona profile are inferred from this content (see Figure 7). Each persona has

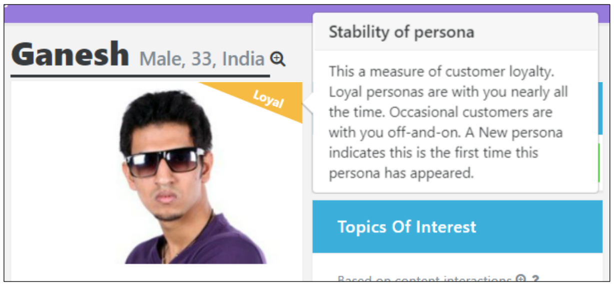

Figure 3: Explanation for the stability of the persona.

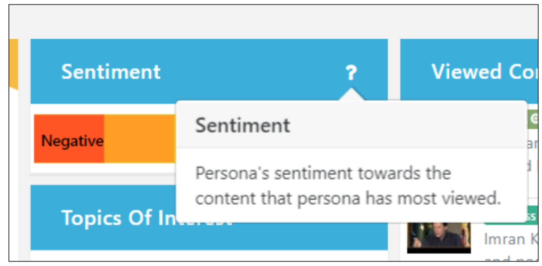

Figure 4: Explanation for the sentiment of the persona.

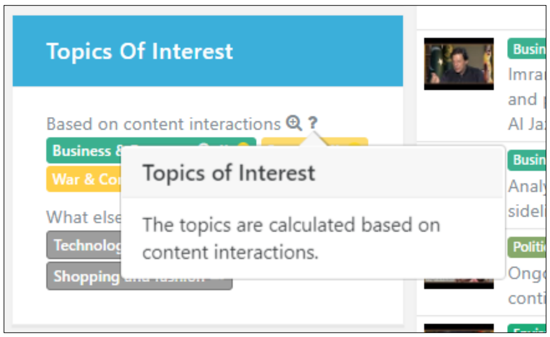

Figure 5: Explanation for topics of interest.

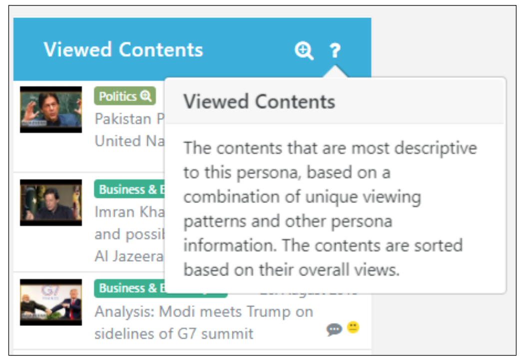

Figure 6: Explanation for the viewed contents.

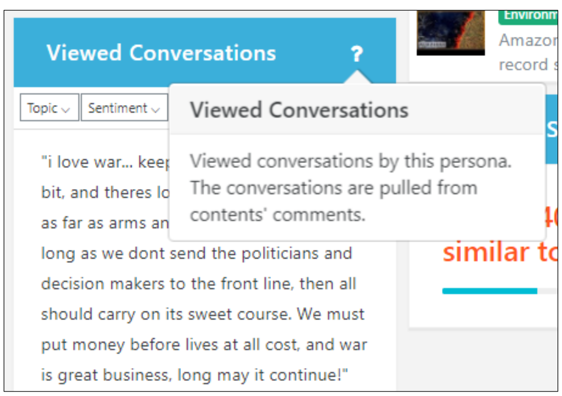

Figure 7: Explanation for the quotes.

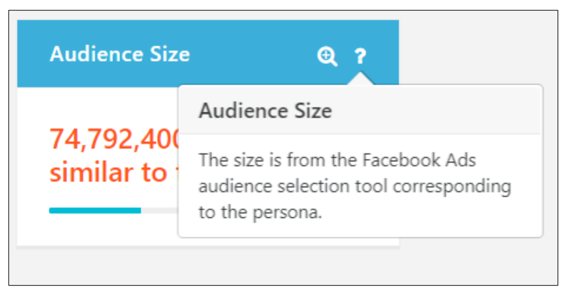

Figure 8: Explanation for the audience size.

demographic traits (age, gender, location) and topics of interest. Based on these, audience size is calculated. This corresponds to the number of people with the said characteristics (see Figure 8).

3.3 Data Breakdowns

To reduce stereotyping and to facilitate the understanding of the data, APG provides breakdowns of information. Figure 9 shows the demographic groups that have the highest quantitative association with the content engagement pattern that the persona is based on. The point is to show to the users that even though the persona has a representative demographic group (in this case, Male 25-34 India), there are also other demographic group that fit, with different degrees of association, to the behavioral pattern of this persona. In other words, there is diversity within the persona. In a similar vein, Figure 10 illustrates the distribution of topics of interest. It shows how much, in quantitative terms, the persona prefers, or does not prefer, a given topic. Again, as these measures are calculated using machine learning models (see [3]), we can obtain and present a probabilistic score for the persona users.

3.4 Explaining Algorithmic Process of DDPs

One challenging – perhaps even the most challenging – aspect of explanation in DDPs is the functioning of the core algorithm. This has previously been done using equations [2, 3, 39, 40] and figures (see Figure 12).

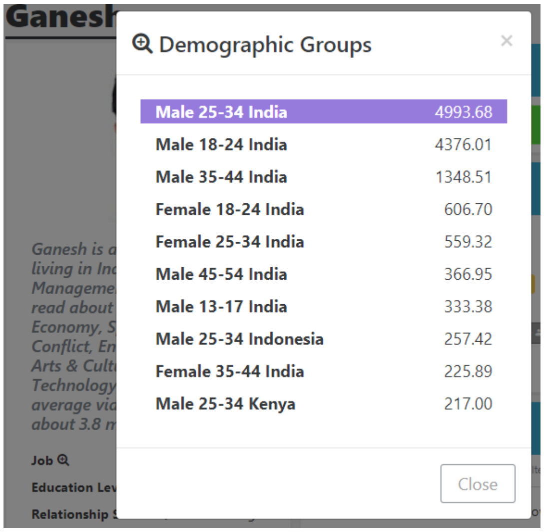

Figure 9: Breakdown of demographic groups, intended to decrease stereotyping by showing that not only one demographic group corresponds to the shown persona. For example, figure shows that although the dominant demographic group is male, also females (e.g., Female 18-24 India) correspond to the behavioral pattern of the persona.

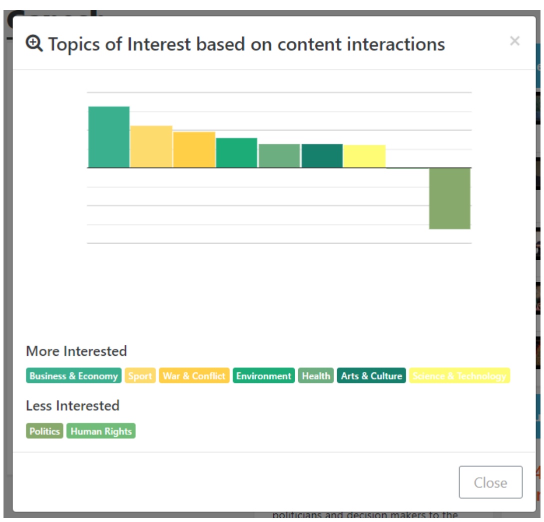

Figure 10: Distribution of the persona's topical interests.

To generate the personas, APG uses the underlying data to obtain a grouped interaction matrix V ($V = g * c$), where the columns of the said matrix, for our task, are video content (c) and the rows represents demographic user groups (g). The element in the matrix are the view-counts of the videos for each demographic group. The system then applied non-negative matrix factorization (NMF) [20] to V to discern p latent video viewing behaviors, using the resultant weights from the NMF. These groups, p, are then enriched by adding attributes, including a name, profile picture, their topic of interest among others.

Various ways to explain this algorithmic approach have been attempted in previous literature, including a simple stepwise list (see Figure 11) and complex mathematical denotations (see Figure 12) explanations. Essentially, communicating algorithmic processes is a hard problem to solve as the process has many steps and a high degree of technical complexity. Explaining these processes in a simple graph, text, or table seem not very user-friendly. As a future course of action, we are planning to produce an explainer video – the advantages of a video are many: we can use different screens, views, and animations to simplify the algorithm; we can break down the process into a logical narrative; we can give examples that make the storyline more concrete; and we can support the conveying of the message with visual, textual and auditory information (i.e., voiceover). This facilitates learning and understanding by different user types.

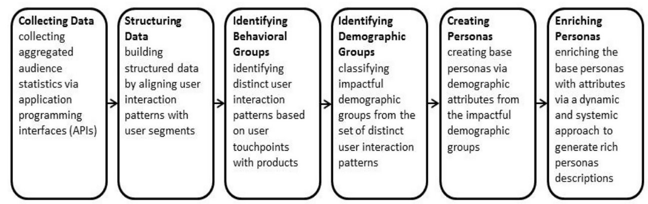

Figure 11: Stepwise explanation of the APG algorithm [3].

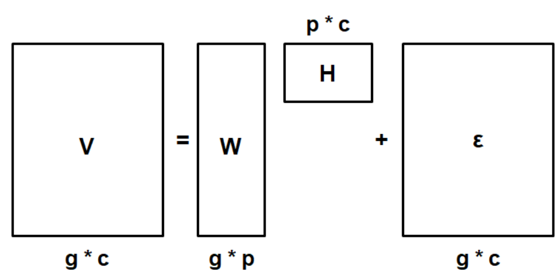

Figure 12: Symbolic explanation of the APG algorithm [2].

4 Discussion

4.1 Contribution

Personas are said to be cognitively compelling [4] and empathetic [21, 25], as they put a human face on otherwise obscure user data. Pruitt and Grudin [30] outline that psychological theory explains why personas should be engaging, pointing out that personas provide a conduit for conveying a broad range of user attributes.

Yet, personas have been repeatedly challenged in the literature for their "imaginary" nature [8], abstraction and lack of credibility [23, 32]. DDPs provide features and functionalities that can provide partial or complete solutions to long-standing persona weaknesses, such as being slow to create and rapidly expiring [2] and being subjective instead of fact-based [3, 8]. In addition, personas have been criticized for lack a real value to enhance user insights, especially in the modern environment with many other analytics tools are available for probing into online audiences [1]. Using digital persona UIs could potentially provide ailments to enhance the value decision makers get from personas.

Nonetheless, due to prevalence of *paper* as the default choice of UI for personas, there is currently a lack of empirical studies focused on investigating the UX of digital persona UIs, as most persona interfaces have not been available in Web systems. According to previous literature [37, 38], the concerns relate to navigation, understanding, and credibility. Users also have questions about the algorithm behind the personas.

To this end, this research provides design suggestions and ideas for information breakdowns that aim to explain the information content in the DDPs and challenge the assumption that the persona is just one person, instead of being representative of a whole group.

4.2 Future Work

First, empirical user studies to test the design ideas outlined here are highly called for. The real impact of explanations on UX needs to be corroborated. Particularly, it is essential to address two core design questions:

(a) *do the explanations really increase users' understanding about the persona information?*

(b) *Do breakdowns really reduce stereotypical thinking about the persona?*

Second, user-specific differences towards explanations can affect their implementation [12]. One aspect that makes adding explanations challenging is the technical savviness among users. For some users, more technical information can be irrelevant and even alienate them for the "easily approachable" personas, while others crave for such information. Thus, a design challenge is to provide technical explanations for those who need them without interfering with the self-explanatory nature of the persona UI.

Third, experimenting with new explanation types (e.g., innovative use of video, graphics, product walkthroughs…) is needed. This research focused on a very specific implementation of tooltip explanations, whereas software systems enable other complementary approaches that should be tested.

Fourth, the described explanation approaches were generic across all personas. They are tied to shared components such as sections, datasets, and algorithms, but not specific to the current persona being shown. For example, users may wonder why the current persona is of specific age and has specific interests. The generic explanations are indirect and may require users to figure out the exact answers independently. For this reason, *persona-specific* explanations may be needed.

Overall, even though APG contains tooltip definitions of each information section, its algorithmic transparency [44] may not be adequate but additional explanations may be needed.

4.3 Practical Implications

Finally, the frequency of understanding issues reported in related research [36–38] implies there is a need for system-specific training. For optimal usability, self-explanatory features would be the ideal design goal. However, interactive persona UIs and DDPs can become complex, prompting the use of various educational means, such as explainer videos, video tutorials, and collaborative workshops. For persona adoption in the target organization, explanations can be useful but not necessarily enough.

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