Design Issues in Automatically Generated Persona Profiles:

A Qualitative Analysis from 38 Think-Aloud Transcripts

Joni Salminen
Qatar Computing Research Institute, HBKU; and Turku School of Economics
Doha, Qatar
jsalminen@hbku.edu.qa

Sercan Şengün
Northeastern University
Boston, Massachusetts, USA
s.sengun@northeastern.edu

Soon-gyo Jung
Qatar Computing Research Institute, HBKU
Doha Qatar
sjung@hbku.edu.qa

Bernard J. Jansen
Qatar Computing Research Institute, HBKU
bjansen@hbku.edu.qa

ABSTRACT

Increased access to data and computational techniques enable innovations in the space of automated customer analytics, for example, automatic persona generation. Automatic persona generation is the process of creating data-driven representations from user or customer statistics. Even though automatic persona generation is technically possible and provides advantages compared to manual persona creation regarding the speed and freshness of the personas, it is not clear (a) what information to include in the persona profiles and (b) how to display that information. To query into these aspects relating information design of personas, we conducted a user study with 38 participants. In the findings, we report several challenges relating to the design of automatically generated persona profiles, including usability issues, perceptual issues, and issues relating to information content. Our research has implications for the information design of data-driven personas.

KEYWORDS

User study, personas, automatically generated personas, data-driven personas, information design

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1 INTRODUCTION

Increased access to data and computational techniques [20, 24] enable innovations in the space of automated customer analytics. A potent example is automatic persona generation (APG) [1, 2] that creates data-driven representations from user or customer statistics, such as YouTube video views or in-house customer relationship management (CRM) data.

Even though automatic persona generation offers advantages relative to manual persona creation, such as the speed and freshness [1], automatically generating personas via an online system poses various challenges.

For example, two important problems emerge for information design: (a) it is not clear what information should be included in the persona profiles and (b) how to display that information to the end users of personas. To provide insights into these aspects relating to the end users of personas, we conducted a user study with 38 participants in a large non-profit organization.

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2 RELATED LITERATURE

Personas are an interactive design technique [9] and an alternative form of analytics [6], with wide-ranging application in software development [18], marketing [21], and other fields. A persona simplifies numerical data into an easily understandable representation: another human being [17]. Personas enhance the communication of user data within an organization, so that content, marketing, or product decisions can be made while keeping end users in mind [10].

However, a drawback of personas relates to their creation. The traditional way of creating personas involves lengthy and costly manual work [7]. In addition, the resulting personas can quickly stale as shifts in the underlying customer base take place, especially in the fast-moving online content industry [23]. Even when user behavior is changing slowly, the validity of the generated personas should be regularly reviewed.

To solve the shortcomings of traditional persona generation, researchers have suggested automatic persona generation, which is defined as a methodology for automatically creating personas from online analytics data [1, 3]. These automatically generated personas are (1) rapidly created, within a matter of hours, (2) behaviorally accurate, as they are inferred from users' interaction patterns with online products, and (3) periodically updated through API-supported data collection and re-computation [14].

The methodology of APG (1) retrieves data on demographic segments' interaction with online products (e.g., video views), (2) generates a segment-content matrix using the interactions as elements, (3) applies non-negative matrix factorization to detect latent behavioral patterns, (4) associates the behavioral patterns with demographic data, (5) applies topic modeling to classify the content, and (6) outputs rich persona profiles by dynamically adding characteristics, such as names, photos, and descriptive quotes obtained from social media [1, 3, 14].

Even though automatically generated personas can address many shortcomings of traditional persona creation, they are not entirely immune to the general challenges of persona creation. For example, the risk of information inconsistency from unrelated datasets [4] still exists. Moreover, it is possible that end users perceive automatically generated personas as confusing [22] or lacking credibility [7]. As perceptual challenges have been found to be associated with the application and use of personas within real organizational use cases [13, 19], clarifying end user perceptions toward automatically generated personas is a priority matter for both research and practice.

3 METHOD

3.1 Data Collection

We conducted an eye-tracking user study, in which we showed automatically generated persona profiles to the end users of the persona generation system. We wanted to track both the visual engagement (eye-tracking) as well as the qualitative feedback from the end users. This manuscript focuses only on reporting the findings from analyzing the qualitative feedback.

Figure 1 shows an example of the personas shown to the end users, with the following information sections in the persona profile: Topics of Interest, Quotes, Most Viewed Contents, and Audience Size, along with basic information of the persona, including picture, name, age, gender, and location. This information pieces are defined in related work [21].

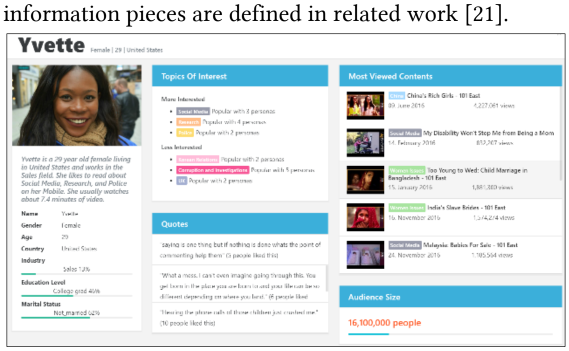

Figure 1: Example of the personas. Another persona, "Anar", was also shown to control for gender effects.

Our participants for this study were digital content creators from a major non-profit organization. This organization was chosen because they utilize personas to achieve their goals for external stakeholder communication, and the people in the organization generally have a satisfactory baseline knowledge of the persona technique.

There were 38 participants (27 males and 16 females). The average age of participants was 34 (min. 21; max. 57; std. 9.6) years old. The participants were selected to reflect the staff within the organization and interested in the organization's users. Forming a diverse pool of individuals, the participants came from a variety of job positions, ranging from data analysts, engineers, editors, social media, copy writers, and content specialists. The participants' experience with personas was 1.9 (*Slightly experienced*), with a minimum of 1 (*Not experienced at all*), a maximum of 4 (*Highly experienced*).

The participants were not financially compensated. The experiment took place in the participant's workplace. The sessions lasted approximately thirty minutes per participant. We instructed all participants in the same way about the usage of the devices and the procedure. For each treatment, the participants were presented a scenario prior to engaging with the persona profile. The scenario involved creating digital content for the user group that the persona represents (i.e., a marketing video that would interest the persona). The participants were encouraged to think aloud [12] when viewing the persona profiles. We made voice recordings and transcribed these recordings for the qualitative analysis.

3.2 Data Analysis

The qualitative analysis of the transcripts was performed by two of the researchers.

The first researcher conducted an exploratory analysis on the transcripts and, during that process, created a codebook [11] that guided the qualitative coding of the second researcher. The second researcher used this codebook to identify passages from the transcriptions that related to the code categories. The passages belonging to a category were stored in a database and manually analyzed for meaning. The identified passages were also coded as negative or positive for sentiment.

The following section presents the findings by category and by participant group. Table 1 gives a summary of the results.

4 FINDINGS

4.1 Findings by Category

Negative Emotional Response: This category was used when the participants voiced an emotion with negative sentiment. *Confusion* was used when the participant was unsure about what to do next or what the presented information meant (e.g., "Honestly I just want to have an idea, when we have quotes, how am I expected to react?" –P33).

Disapproval was used when the participant was criticizing the way the personas were presented (e.g., "That's a lot of things to read." –P17; "There's a lot of uncertainty." –P26). *Negativity* was used as a stronger version of *Disapproval*, wherein the participant was put off by the persona (e.g., "It's scary!" –P3; "I think this is a horrible presentation [...]" –P33).

Table 1: Frequencies of coded instances. Counts refer to the number of coded passages in the transcribed text that belong to the category. Negative and Positive Emotional Responses show the totals, the categories below them show the breakdown.

Category	Code	Count		% of Total Codes	
Negative Emotional Response	Confusion	66		14.2%	
	Disapproval	24		5.2%	
	Negativity	10		2.1%	
Positive Emotional Response	Appreciation	30		6,4%	
		Positive	**Negative**	**Positive**	**Negative**
Persona Perception	Authenticity	25	7	5.4%	1.5%
	Credibility	22	48	4.7%	10.3%
	Similarity	4	6	0.9%	1.3%
Information Elements of Persona Profile	Audience Size	3	13	0.6%	2.8%
	Basic Information	18	38	3.9%	8.2%
	Picture	23	8	4.9%	1.7%
	Quotes	9	32	1.9%	6.9%
	Topics of Interest	8	32	1.7%	6.9%
	Most Viewed Content	10	15	2.1%	3.2%
User Interface	Colors	3	2	0.6%	0.4%
	Scrolling	-	10	-	2.1%
NOTE: We did not code instances with neutral sentiment.					

Positive Emotional Response: This category was used to mark the segments that had positive remarks about the presentation of personas in general (e.g., "Their names are very interesting." –P9; "[The personas] had background, education, where they come from, the demographics and stuff. I think it gives interest and not interested things, I think they cover a lot of the important things." –P29).

Persona Perceptions: This category was used when the participants commented on the personas as if they were real people and compared the personas to themselves. These codes were marked as negative or positive.

Authenticity was used when personas were viewed as real people (e.g., positive: "Alright, I think I know Anar pretty well." –P16; negative: "He is a real person but he is a predator." –P19). *Credibility* was used when participants commented on the consistency of the shown information (e.g., positive: "I found this profile more coherent [...]" –P7; negative: "I don't believe this guy is actually American, (...) there is something wrong because he's writing in British English here." –P6).

Finally, *Similarity* was used when the participants relate to the personas on a personal level whether negatively or positively (e.g., positive: "[...] In fact we can be born in the same place and have different lives." –P21; negative: "I don't agree with his opinions, and I don't belong to his group." –P12).

Information Elements of Persona Profile: This category collects the remarks made about specific sections of the persona profile, including (a) Audience Size, (b) Basic Information, (c) Picture, (d) Quotes, (e) Topics of Interest, and (f) Most Viewed Content. Typically, each section is presented as a box in the persona profile page (see Figure 1).

By calculating a positive-to-negative mention ratio (Equation 1), it is possible to sort the information in the order of perceptual preference by the participants.

$$\text{ratio}_{\text{positive to negative}} = n_{\text{positive comments}} / n_{\text{negative comments}} \quad (1)$$

Audience Size was the weakest section ($r_{p/n} = 0.23$), with most of its segment overlapping with confusion (e.g., "Audience size is not clear, I guess it's about how much this persona covers, the audience represented by this persona, I'm not sure." –P13; "What does this mean, audience size? How many are watching?" –P17; "Audience size is a bit vague." –P30). The other ratios are: *Topics of Interest* ($r_{p/n} = 0.25$), *Quotes* ($r_{p/n} = 0.28$), *Basic Information* ($r_{p/n} = 0.47$), *Most Viewed Content* ($r_{p/n} = 0.67$), and *Picture* ($r_{p/n} = 2.88$).

Some information was considered redundant: "Why do I need to know 'less interested' [topics of interest]?" (P16). Some information was considered unclear based on its headings, e.g. it was unclear for participants whether *Quotes* were from the persona or about the persona, thereby suggesting that more precise phrasing need to be used (e.g., "Quotes by persona").

User Interface: This category contains the remarks of the participants relating to the issues of user interface and user experience. Mainly, these remarks were agglomerated under two categories: *Colors* and *Scrolling*. The scrolling codes refer to in-page scrollbars. These appear in the persona profile elements such as *Quotes* and *Most Viewed Content*.

In almost all cases, participants did not notice that the section was scrollable and those who did were unimpressed by this functionality (e.g., "Oh, there are more videos here. I didn't realize." –P10; "Okay, I see. [reading] I did not scroll down the last time. I can scroll down, I did not see this." –P13; "I don't really like this scrolling." –P1). All codes regarding scrolling were negative. *Colors*, on the other hand, had both positive and negative comments ($r_{p/n} = 1.5$). These comments refer to personal preferences and taste (e.g., "Now the green colour is so bright that I'm wondering if it's more distracting." –P15 vs. "The higher education in topics of interest popped up because of the green." –P32).

4.2 Findings by Participant Group

To compare the participants (P), we divided them into two groups, according to their job roles (see Table 2).

Table 2: Participants by Gender and Profession.

Research Professional (n = 26; 68%)		**Marketing Professional (n = 12; 32%)**	
Male	Female	Male	Female
n = 18; 69%	n = 8; 31%	n = 6; 50%	n = 6; 50%

By calculating a ratio of all positive comments to negative comments by profession (see Equation 2), it is possible to see that marketing professionals ($tr\Sigma p/\Sigma n = 0.51$) were slightly more positive than research professionals ($tr\Sigma p/\Sigma n = 0.49$).

$$\text{total ratio}_{\text{all positive to all negative codes}} = tr\ \Sigma p/\Sigma n = n_{\text{positive comments}} / n_{\text{negative comments}} \quad (2)$$

Moreover, there is a difference of style between the criticism of research and marketing professionals. The research professionals are more likely to comment on *how the information is presented* (e.g., "Usually in the description you provide the exact age, not 40-something." –P12; "Because the labels for me, they seem not correlative with the title of the video." –P5), whereas marketing professionals are more focused on *making generalized inferences from the information provided* (e.g., "I think what I wanted was basic information, which was there, like age, the gender, and stuff like that." –P27; "Yeah, he gives enough information about his most interested." –P28).

Another difference comes from the unpacking of the persona information. For example, the persona contains this information: "works in production [...] interested in research." Many participants from the research profession tried to unpack this information: "So he works in a production field. I actually don't know what production is." –P16; "I don't know what it means production." –P13; "Works in the production field. Not sure what that means." –P22; "I don't know what production field means." –P15; "Works production field. It's not clear what kind of production." –P18; "I don't know what research means here, but I guess it's documentary." –P10; "So, research is a strange, very generic topic. Because in my mind research is something very particular, like scientific research, but it could be other research." –P16. In contrast, no participant from the marketing profession commented similarly on these pieces of information.

Participants from the marketing profession are more likely to understand the personas through narratives pieced together from selective information on the screen. Some examples are: "[...] it showed me Yvette is in the US, she reads these publications, and she's interested in these topics [...]"–P30; "He's a layman, an everyday man, a common man." –P33; "[...] she works in the medical field, but she's looking at videos on Arab language, literacy around the world, so I don't know, I didn't see the connection." –P38.

5 DISCUSSION

Our findings show that automatically generated personas are predominantly perceived authentic (i.e., as real people), despite them being created automatically from data. In this regard, automatically generated personas are similar to manually created personas [9]. This implies that various technologies used for data-driven persona generation, having been developed for over a decade [15], have developed into maturity.

However, it also turns out that data-driven personas inherit the same challenges as traditionally created personas. Most notably, like manually created personas, lack of credibility [7] remains challenging for automatically generated personas, as we found a number of negative mentions about credibility.

Regarding the APG approach, results show that the information regarding *Audience Size* was found to be confusing, indicating potential adverse effects when including numerical information in persona profiles (or when not defining the information content properly). Confusion has also been associated with personas in previous research [22].

Also, both *Quotes* and *Topics of Interest* sections included a high ratio of negative mentions. The main reason was due to the perceived inconsistency, highlighting, yet again, a classical persona creation problem [4]: ensuring that different information elements are presented in a way that end users would perceive as consistent and coherent.

Picture and *Authenticity* were the only categories that had more positive than negative mentions. Interestingly, apart from *Most Viewed Content* that contained thumbnails of videos, the persona picture is the only element with visual information. Previous research asserts that visual information is deemed as more trustable and persuasive by the viewers for digital documents [8] and in cases where the visual and textual information conflict, the visual information was selected as the cannon [5]. The fact that *Authenticity* and *Picture* are the only categories with more positive than negative mentions also suggests a relationship between these two information elements.

The observed interface issues related to the choice of scrolling and the use of dual scroll bars. However, in general, presentation of personas in an interactive system as opposed to the traditional paper format [16] posed no notable usability issues.

6 CONCLUSION

Automatically generated personas, although utilizing efficient computational techniques and quantitative data, are not immune to the perceptual challenges observed in previous persona research. However, the manipulability of the automatic persona generation system also enables low-barrier experimentation with solutions to these problems. Therefore, future research should investigate solutions to the observed persona challenges, particularly relating to credibility, information definitions, and consistency of information elements.

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