Investigating Persona Viewing Behavior: An Eye-Tracking Study on Portrait-Format Persona Profile

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ABSTRACT

The study offers empirical evidence on how users visually interact with digital personas. Conducting an eye-tracking study in a major news organization's premises, we analyzed the fixations of 29 participants interacting with a standard portrait-format persona profile. Our analysis of 87 repetitions calculates significant transitions between the persona information elements using n-grams from (a) when the profile is first encountered, to (b) when the profile is presented for the second time, and (c) after the participants are familiar with the profile, seeing it for the third time. Collectively, there are a small number of statistically significant transitions, suggesting an L pattern of persona-viewing behavior, and the L pattern holds regardless of the repetition. Results have implications for the design of persona profiles by placing persona information to accommodate users' natural viewing tendencies.

CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI); Interaction paradigms.

KEYWORDS

Persona, User Experience Research, User Analytics, Eye Tracking

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1 INTRODUCTION

User personas (*personas* henceforth), originating from the human-computer interaction (HCI) and user-centered design (UCD) [20, 58, 68], are imaginary people representing actual user segments [9, 13, 17]. Personas are used in software development, system design, and other domains in which understanding people is critical [51]. Personas are typically presented in *profiles* displaying the attributes of the segment in question [52, 61]. These profiles contain information, such as a photo, name, age, job occupation, etc. From a design perspective, persona profiles can be viewed as *humanized user interfaces* (UIs) to user data [33], used by designers and other stakeholders in various HCI contexts [46].

Many layouts (a.k.a., persona templates [52]) exist in both static persona profiles and interactive persona systems [38, 52, 61]. One of the most common is the portrait persona profile (PPP) which is similar to the dimensions of an A4 paper sheet and stems from the fact that personas are often printed and handed out to stakeholders in meetings. This template offers limited space for information, leading to *persona information selection problem;* that is, selecting enough (but not too much) information to address the information needs of persona users [48, 61, 69]. There is also another design challenge, namely the *persona layout problem* [65], i.e., how to design layouts that communicate details about the persona in the most effective way possible (e.g., using text, images, graphs, tables, gauges, and other visual cues). These two design problems motivate our current inquiry into the PPP format, as understanding how users interact with the PPP can teach us about *persona viewing behavior*, namely, how personas are visually interacted with.

While persona layout challenges could be addressed in multiple ways, the common denominator is the need for empirical analysis, i.e., how persona users visually interact with the PPP. In other words, we must first understand *how* people view personas. To this end, behavioral data is required to obtain valid results on the interaction between personas and people using them, referred to as *persona science* [63]. A critical element of persona science is the measurement of user behavior with reliable instrumentation, such as eye tracking [28, 39]. The findings from eye-tracking experiments can offer insights into what captures users' attention, how they navigate through the information, and what elements are most engaging or distracting [16]. This knowledge is essential for optimizing the persona profile layout to align with natural reading behaviors.

Nevertheless, few studies have examined users' visual interaction with persona profiles using eye tracking [28, 66]. In other contexts, HCI researchers have identified general patterns of information processing (e.g., the widely acknowledged F pattern [25, 72, 73]). Our intuition is that such common visual interaction patterns will also emerge in the persona domain, though research has yet to uncover them. To this end, the current study uses eye tracking to investigate how users view different information elements of a PPP. Our premises are that the information elements, which we denote as *Areas of Interest* (AOIs), have varying levels of importance to the user, resulting in distinct persona viewing patterns (see Table 1), and that these patterns are stable with repeated use of the persona profile. Aligned with these reasonings, we address three research questions (RQs):

RQ1: *How does the attention paid to different information elements (AOIs) on a portrait persona profile vary?*

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Table 1: The key concepts mentioned in the RQs.

Concept	Definition
AOI (Area of Interest)	In eye tracking studies, an AOI refers to a specific screen area that is significant to a particular study or observation. In this study, AOIs represent the different information elements (e.g., picture, persona's interests) in the persona profile.
One-state transitions	In a one-state transition model, the next state in a sequence depends solely on the current state without any influence from previous states. In this study, a one-state transition refers to users' moving their gaze from one persona information element to another.
Two-state transitions	In a two-state transition model, the next state depends on the current state as well as the immediately preceding state, linking the last two states to the upcoming state. In this study, a two-state transition refers to users' moving their gaze from one persona information element to another and then another.
N-gram	An n-gram is a contiguous sequence of *n* items from a given sample of text or speech, used commonly in natural language processing to predict the next item in a sequence. In this study, we use it to predict users' gaze fixation from one persona information element to another.
Portrait persona profile	A common persona profile type that shows the persona's information in a portrait layout (as opposed to landscape).
Persona information element	This term typically refers to a specific piece of data or characteristic within a broader persona profile that helps define and distinguish the persona, such as demographics, behaviors, motivations, or preferences.

RQ2: *What are the statistically significant one-state transitions (i.e., bigrams) between AOIs on a portrait persona profile?*

RQ3: *What statistically significant two-state transitions (i.e., trigrams) among AOIs on a portrait persona profile?*

We formulate these RQs based on the premise that one- and two-state transitions are potentially the most impactful, reserving more extended series for future research. To address the RQs, we focus both on fixation counts and the scan path (i.e., sequence of fixations in chronological order) to analyze users' visual interaction with a persona profile.

In broader terms, the study focuses on the user behavior of stakeholders using personas–these can be, e.g., designers, software developers, marketers, or other stakeholders working on UCD [51]. While stakeholders can be any individuals interested in learning about different user types through personas, in our study, the stakeholders are journalists using personas to better understand their audience segments. We report the journalists' visual interaction patterns over multiple engagement repetitions with a persona, which we believe reflects an actual work environment where the stakeholders repeatedly use a persona in various scenarios. Via these repeated visual interactions, the users of the persona profile gain some degree of familiarity, which may affect their viewing patterns from the initial usage.

2 RELATED WORK

2.1 Designing Persona Templates

As a humanized representations of "people data" [36], personas are a visual approach for representing segments of the target populations by presenting data in a form that most people can relate to—that of another person [35]. As such, personas are widely developed in many domains and organizations [74]. Personas have also been evaluated in multiple ways, including statistical evaluation for segmentation identification tasks [62], with various positive benefits reported in the literature [27]. Personas are used for various tasks in organizations, including communication, objective setting, and planning [13, 24, 58]. Given that communication across teams is "one of the most significant obstacles [designers] face" [31] (p. 20), personas aim to provide a shared mental model of the end users [54]. For this, a common portrait-shaped template of the persona profile has been developed [52] that includes a short, one-page textual description and a photo, most often a headshot or a picture, along with supporting text and graphs. The persona profile we test in this study adheres to this common template for the *portrait persona profile (PPP)*, leaving other profile types for future work.

Increasingly, persona profiles are served in online systems that provide stakeholders with access to the personas in real time [37–39, 47, 63]. Given such systems, understanding users' visual interaction with persona profiles is increasingly important, because the information elements in web-based persona profiles can be altered in terms of position, size, shape, and so on [63]. This also makes studies investigating visual interaction with *other* web-based UIs (e.g., websites, search engines) relevant for understanding the use of persona profiles because these studies can contain insights that could also apply to persona design. Overall, persona templates are important design conventions, i.e., standard ways of organizing content and information [30]. Design conventions have value in reducing the cognitive cost of viewing persona information. For example, typically, the persona's name and picture are placed at top-left region of the layout [52, 61], following a general notion of a "user profile" akin to social media profiles or CVs. Not placing these elements in their conventional positions might cause confusion and add extra mental load on the user. On the other hand, a lot of the information in a persona profile could be reorganized, and some of that reorganizing might benefit the information-extraction process and the persona's overall usability [31]. So, studying templates matters.

However, a *unified theory on persona design* is missing. For example, merely knowing to what elements users pay more attention does not necessarily result in improved action unless we tie it to a concrete goal. *Do we want people to read all the information? Should we remove the information that people normally do not care about? Should we place the most important information at the beginning (to make it more convenient), or at the end (to make people go through the other information)?* These are questions currently left unanswered by persona studies. However, using the analogy of search engines, we can consider what the purpose of personas is. For search engines, the purpose is to enable the user to find the information they are looking for [10]. Adopting this thinking, we could argue that personas are "search engines" for user understanding. However, the creator of the persona does not necessarily know what information the persona user is looking for, and furthermore, the requested information might vary among designers using the same persona (or the same designer using the persona for different tasks). So, a good persona should provide either *more* information, corresponding to the set of information required by all stakeholders using the persona, or it should be dynamic and provide *less* information, meaning that the information is tailored [1] for each user at a given time.

2.2 Using Eye Tracking to Understand Users' Information Viewing Behavior

Eye tracking is widely used to study users' visual interaction with systems and UIs [11, 21, 32, 42, 43]. Eye tracking can reveal interaction patterns toward navigational and content elements and provide design recommendations [4, 5, 16]. Overall, eye-tracking experiments in online UX focus on analyzing information architecture, navigating websites, understanding users' visual search behavior and content interaction, testing usability and UX, and optimizing online forms and surveys [7]. Guan and Cutrell [25] analyzed navigational and informational task performance in an online search UI. They placed relevant search results at the bottom of the search page and observed decreased search performance, as users are not inclined to view the bottom of the search results page. Goldberg et al. [21] studied online search tasks and concluded that key information should be placed on the top-left of the web page. Others have called this typical pattern a "golden triangle" or *F pattern* [11, 23, 44]. Craswell et al. [14] and others [6, 41, 75] refer to this effect as *position bias*, highlighting that the first results in a search listing tend to receive a click-through rate.

In the persona UI context, these findings would suggest that the information at the bottom of the profile is not viewed as much as the information at the top. However, while there is repetitive support for the F pattern [15, 72], other studies have challenged the pattern's predominance. Navalpakkam et al. [49] found that nonlinear website designs with rich information content on the right column may deviate from the F pattern as users are drawn to information-rich content. In another study, Roth et al. [60] found that high-saliency content seems to break the conventional F pattern. Because the F pattern has been both supported and challenged in the study of information processing, it is meaningful to investigate if this (or some other) pattern holds within the context of persona profiles.

Perhaps surprisingly, there has been limited eye-tracking research exploring how users visually interact with persona profiles [12]. There has been work on the effect of images [28] and numbers [65] on users' visual interaction with personas, but these studies do not describe distinct scan paths along the whole profile. Goodwin [22] discussed visual design aspects of personas, emphasizing their importance, but not providing an analysis of *how* users visually interact with personas. Matthews et al. [45] reported on the design and layout of persona profiles, along with how different design elements can impact user engagement and comprehension, but they do not present empirical evidence of users' viewing sequence. Overall, to our knowledge, previous research has not explicitly investigated users' information viewing sequences in persona profiles. The closest to this purpose is Hill et al. [28], who examined showing multiple persona photos, including both men and women and found that several photos did not significantly decrease engagement with the personas. However, their study did not investigate the sequence of information viewing among the users. Overall, personas studies have often employed surveys and interviews to understand persona users' perceptions of personas [67], while attempts to understand the persona profile as an interface have been much more limited.

Because personas are an established and commonly applied technique for presenting information, it is essential to determine how users visually interact with persona profiles. So, this is the research gap we address. Overall, there is a need to present information about users in a compact yet recognizable format [11], as both the screen space and human cognitive processing impose constraints on the number and positioning of informational elements included in a persona profile [55]. Deciding what information to contain and exclude and how to present that information best is one of the fundamental questions in HCI research.

3 METHODOLOGY

3.1 Participants

The study was conducted in the workplace of a major worldwide media network with extensive broadcast and online presence. The study spanned one work week, with participants volunteering to participate in the study. Thirty participants participated in the study. One participant was discarded because the eye-tracking device could not be calibrated correctly, so we report the results of 29 participants. The participants were not financially compensated for taking part in the study. The 29 useable data recordings (see Table 2) have a nearly equal representation of males and females (Female: n = 14, Male: n = 15), with no other genders being identified. The average age of participants was 33 years old (SD = 6.6). The average experience of participants in the news industry was seven years (SD = 5.6), and the average experience in the current company was three years. Their expertise with personas varied, so some needed to familiarize themselves with the concept before the study. However, we explained each participant the concept.

Overall, the participants reflect the staff working with news content daily. They formed a diverse pool of individuals from 19 countries (e.g., Egypt, Georgia, Germany, Syria, the UK, USA, etc.). *Producers* are the primary content creators of news articles

Table 2: Participant age, identified gender, and experience information by role.

	Male	Female	Total
Producers	n = 11	n = 7	n = 18
Editors	n = 3	n = 5	n = 8
Others	n = 1	n = 2	n = 3
Avg. age (years)	28.5	30.2	32.6
Avg. exp. in news industry (years)	7.1	7.5	7.3

and videos for the web and television, whereas *editors* prepare the content for final publication, mainly for social media channels. The participants were journalists and social media content creators working in said organization to produce a hypothetical story for the audience segment of their social media channel that the persona represented, so there was a logical reason for them to use the persona in this study.

3.2 Experiment Design and Apparatus

We designed a within-subjects user study in which each participant completed three repetitions. Each repetition involved using the same persona, but the scenario was altered for the subject of the story [International Affairs / Refugees / Israel-Palestine], which the journalist was asked to consider as the context of using the persona.

We applied eye tracking to capture the visual attention given by the participants to different information elements in the persona profiles. The study had two stations, each equipped with a desktop computer, the *EyeTribe* eye-tracking device, and associated software for logging the sessions. The EyeTribe tracker has an average accuracy of approximately 0.5 degrees of visual angle, eye movement with sub-millimeter precision, and a sample rate of 60 Hz. To ensure data quality, a separate workstation monitored the real-time recording of the eye-tracking device. Besides one participant we excluded, combining the warm-up task and the real-time monitoring ensured a valid gaze sampling percentage [29]. We detected no significant downtime of the eye-tracking software or device. We also inspected the data afterward to see if any participants had substantially fewer fixations than others but observed no anomalies.

3.3 Study Procedure

We instructed all participants at the beginning of the study about the usage of the device and the procedure. To begin each trial, we welcomed the participant, introduced ourselves, briefly explained the study (i.e., using eye tracking to investigate how they interact with personas), and answered any questions about the study. After completing an IRB consent form, we assigned each participant a unique ID and had the participant complete a demographic survey. We then calibrated the eye-tracking device using the nine-point calibration provided by the software. Each participant also completed a 'warm up' task (i.e., *Find Lunch*, which was finding the picture of food on the screen) to get familiarized with the eye-tracking equipment before completing the repetitions. This also allowed us to ensure that the eye-tracking device recorded the gaze correctly.

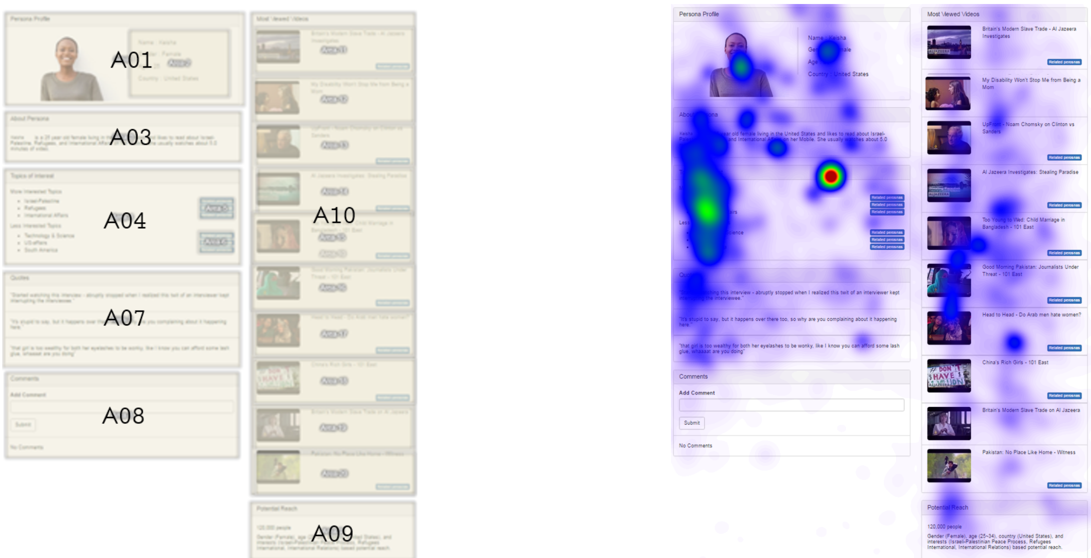
After the warm-up task, the actual task started. We read the participants a scenario before they engaged with the persona profile. The scenario was identical except for the subject of the story [International Affairs / Refugees / Israel-Palestine] that the journalist was interested in writing: "*You are creating a news video about [International Affairs / Refugees / Israel-Palestine]. You want to get some insights on how to pitch your story. As part of your investigation, you view the following persona page, looking for content on the page to see if it can help you pitch your story.*" After completing one scenario, the participant moved to another. The scenarios were presented in random order in different sequences (e.g., S1-S2-S3) which were counterbalanced within the study. The study completion time was approximately thirty minutes per participant.

3.4 Tested Persona Profile

The persona was created based on the organization's user data using a data-driven persona generation approach that has been reported and validated in prior work [2, 3]. The persona thus represents a typical user group of the target organization's social media channels. Structurally, the PPP adhered to the standard PPP [52], which was corroborated by collaborating with a researcher who has more than 20 years of experience in persona research. The profile was subdivided into AOIs, as shown in Figure 1. In eye tracking, an AOI is a selected subregion of a displayed treatment permitting the measurement of key indicators (e.g., fixation, gaze duration) only for those sub-regions. AOI descriptions are presented in Table 3. The persona was served to the participants using a cloud-based research system in which the participants could freely view the profile as a static image.

3.5 N-gram Analysis

As mentioned in the introduction, n-gram analysis allows us to capture sequences of profile views, which can reveal common patterns in how users navigate through different information elements in the persona profile. Overall, n-grams have been deployed in a variety of contexts to investigate, for example, system log data [71]. Here, we conducted an n-gram analysis looking at one and two-state transitions. To clarify to the reader, n-gram analysis is a data mining technique to identify the most frequent 2-grams, 3-grams, etc., in a sequence of items [50, 59]. When the transitions between two states (in our case, informed by the frequency of transitions) are represented by a probability, this is called a Markov model, a probabilistic modeling approach for predicting the next item in a sequence, in which n is the gram (i.e., subsequence or sub-pattern) from the complete sequence or pattern. An n-gram model predicts



(a) **(b)**

Figure 1: (a) AOIs of the persona profile used in the eye-tracking experiment (see details in Table 2). Overall, the AOIs permitted us to (b) measure participants' gaze fixations for key areas of the persona profile – the fixations are illustrated as a heatmap in the picture, with stronger color density indicating more visual attention paid to the particular AOI.

Table 3: AOIs (a.k.a., States). Vis-à-vis Figure 2, some AOIs are grouped under one more prominent unit for the analysis (e.g., A04 contains A05-06, as these two AOIs are located inside this larger AOI). The table explicates these AOIs in parentheses ("includes…").

START	State before the participant fixates on the persona profile. It is used for analysis and is not an AOI on the persona profile. Therefore, it was something not seen by participants.
A01	Image of the persona with name, age, country
A03	Biographical snippet
A04 (includes A5-6)	Topical interests, including most and least preferred
A07	Quotes from the persona gleaned from social media accounts
A08	Comment block for end users
A09	Segment size represented by this persona
A10 (includes A11-20)	Videos most interested in by this persona
END	State when the participant is no longer fixating on the persona profile. It is used for analysis and is not an AOI on the persona profile. Therefore, it was something not seen by participants.

state x_i using states x_i-1, x_i-2, x_i-3, ... x_i-n. The probabilistic model is then presented as $P(x_i|x_i-1, x_i-2, xi-3, \ldots x_i-n)$, with the assumption that the next state depends only on the last n states. For instance, when n=1, the n-gram model is the same as the Markov chain model, whose next state depends only on the current state. We identified statistically significant transitions among the n-gram paths using a binomial analysis that identifies a significant difference for a given value; in our case, this is the average probability of a state transition. We assume an equal probability of a transition among states, a reasonable assumption given that the participants were familiar with the profile in two repetitions. As these are initial findings from the study, we did not investigate longer n-gram paths or the difference in n-grams path among the three repetitions (e.g., first encounter, second encounter, and third encounter), reserving these analyses for future work.

4 RESULTS

4.1 Overview

In this research, we present several results and implications concerning the visual attention paid to different sections of persona profiles and how these sections are employed in conjunction with other sections. In our analysis by repetition, there were no significant differences in the number of states among repetition one (M = 8.90, SD = 0.41, Max = 9, Min = 7), repetition two (M = 8.69, SD = 0.71, Max = 9, Min = 6), and repetition three (M = 8.69, SD = 0.54, Max = 9, Min = 7) nor bigrams or trigrams. As our focus is

Table 4: AOIs and counts of fixations. Ordered by % of fixation counts, absolute, and then normalized for the size of the AOI. Rank change with normalization is also shown.

AOI	Rank	Fixation Count	%	Rank (Normalized)	Fixation Count (Normalized)	% (Normalized)	Rank Change with Normalization
A10	1	17,327	42.51	4	2,027	13.64%	-3
A04	2	6,672	16.37	2	2,774	18.67%	0
A03	3	5,294	12.99	1	4,578	30.81%	+2
A07	4	4,939	12.12	3	2,053	13.82%	+1
A01	5	4,766	11.69	5	1,963	13.21%	0
A09	6	1,200	2.94	6	1,200	8.08%	0
A08	7	560	1.37	7	263	1.77%	0
Total		40,759	100.00		14,858	100.00%	

on global persona profile viewing and streamlining presentation, we present the overall results, with counts of the top occurring bigrams and trigrams by single repetition in the appendices (Tables A1 and A2). In the discussion section, we comment on differences indicating possible future research.

4.2 AOI Fixations

As shown in Table 4, more than 42 percent of absolute fixations occurred on A10. However, once normalized for screen space of the AOIs (the normalization was done because the saliency of larger screen objects could affect participants' viewing behavior), A03 received the most fixations, followed by A04. A10 (the persona's top content) "lost" the most in rank comparison after accounting for AOI size. In turn, A03 (a text overview of the persona) and A07 (the persona's quotes) gained one and two ranks, respectively. For other AOIs, the rank remained unchanged. The results in Table 4 also show that A01 which is placed, according to the F pattern's idea, in the most optimal position of the screen (i.e., top-left), does not rank first in terms of fixation frequency.

4.3 Bigrams

We then analyzed bigrams (e.g., a single transition between states). There were 46 unique single-state transitions, for a 2.17% probability of a single transition between states. We conducted a binomial analysis to identify the significant state transitions. As shown in Table 5, there were eleven statistically significant unigram transitions of the 46 total transitions (23.9%) based on a binomial test. These eleven n-grams represent more than 53% of all single transitions among AOIs.

As seen in Table 5 and Figure 2a, there was a significant trend in the bigram analysis of the participants viewing the image, biographical, topical interests, and social media quotes in combination (i.e., A01, A03, A04). We can observe an L pattern (e.g., A01→A03, A03→A04, A07→A08, A08→A09) based only on the significant transitions, with only a few significant patterns deviating from this L trend (e.g., A01→A10, A07→A09, A08 →END). The A09→END transition (i.e., exiting the persona profile from the bottom-right) fits the L pattern, as does START→A01 (i.e., entering the persona profile from the top-left). As noted in Table 5, a bidirectional n-gram also occurs (i.e., A08→A09 and A09→A08), although both transitions fit the L pattern.

Table 5: Results from the bigram analysis. Statistically significant bigram transitions; binomial test (p<0.05). See Figure 2 for the display of the L pattern trend. Note: START and END are not AOIs on the persona profile; they denote entry and exit from viewing the persona profile.

N-grams	Count.	%	Cumulative %
A09 →END	44	6.52	6.52
START →A01	43	6.37	12.89
A01 →A03	37	5.48	18.37
A08 →END	36	5.33	23.70
A03 →A4	34	5.04	28.74
A07 →A08	33	4.89	33.63
A04 →A07	30	4.44	38.07
A08 →A09	29	4.30	42.37
A01 →A10	27	4.00	46.37
A09 →A08	25	3.70	50.07
A07 →A09	22	3.26	53.33

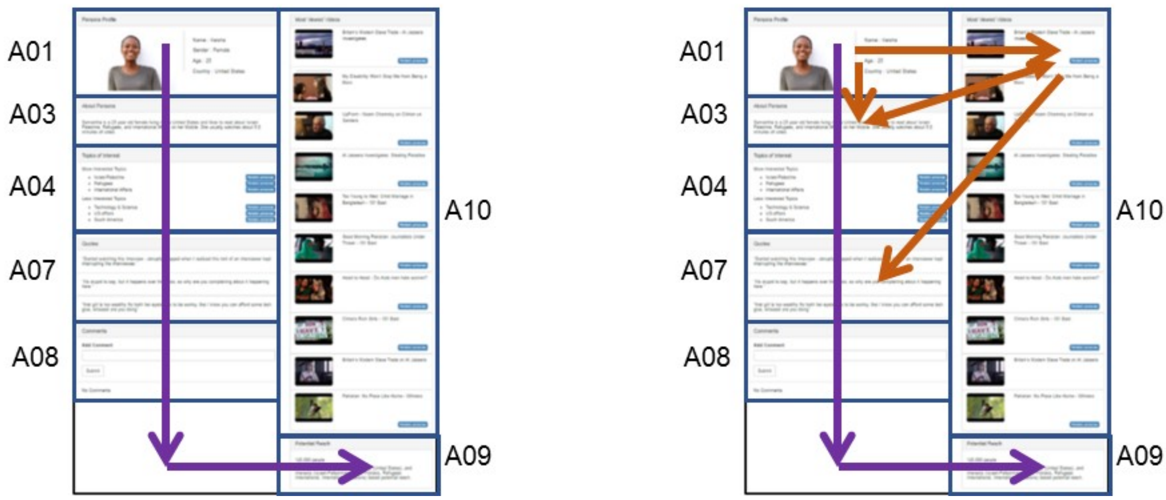
4.4 Trigrams

We then examined trigrams (e.g., two consecutive transitions between states). There were 130 unique single-state transitions for a 0.77 percent probability of two transitions between states. There were 15 (11.54%) statistically significant trigrams based on a binomial test. From Table 6, there was an important trend in viewing the bottom of the persona profiles in sequence and a trend in a horizontal viewing of the top elements of the profile, again with an L pattern, with activity also in the upper sections. As shown in Table 6, 40.14% of the trigrams were statistically significant.

5 DISCUSSION

5.1 Research Highlights

Our results have several interesting findings, summarized as follows.



(a) **(b)**

Figure 2: The L pattern based on the n-gram analysis of significant (a) bigram and (b) trigram scan paths. The L pattern denotes a focused trend on the left and bottom rails of the persona profile, using these profile portions in combinations.

Table 6: Statistically significant trigrams state transitions; binomial test (p<0.05). See Figure 3b for the display of the L pattern trend. Note: START and END are not AOIs on the persona profile; they denote entry and exit from the persona profile.

N-grams	Count.	%	Cumulative %
A8 →A9 →END	29	4.93%	4.93
A9 →A8 →END	24	4.08%	9.01
A1 →A3 →A4	21	3.57%	12.59
START →A1 →A3	21	3.57%	16.16
A7 →A8 →A9	19	3.23%	19.39
A3 →A4 →A7	17	2.89%	22.28
A7 →A9 →A8	17	2.89%	25.17
START →A1 →A10	14	2.38%	27.55
A1 →A10 →A3	12	2.04%	29.59
A10 →A3 →A4	11	1.87%	31.46
A4 →A7 →A8	11	1.87%	33.33
A1 →A3 →A10	10	1.70%	35.03
A10 →A7 →A8	10	1.70%	36.73
A4 →A7 →A9	10	1.70%	38.44
START →A3 →A1	10	1.70%	40.14

Both the bigrams and the trigram scan path exhibit an L pattern. This challenges the conventional F pattern observed in relation to various UIs [73], indicating that there may be something inherently different concerning persona templates, their use in the content creation domain of journalism, or a combination of both. As for why the L pattern emerged (rather than the more expected F pattern), it may be a result of the different nature (i.e., persona template vs. search results or webpage) and the nature of the information seeking (i.e., focus on the use of the persona vs. reading of online content). Addressing these nuances requires further research with a focus on these questions, though we provide more interpretation in the next subsection.

The 11 significant bigrams represent more than half (53%) of all bigrams, and the top 15 trigrams represent more than 40% of all trigrams. These findings suggest that the persona viewing behavior is relatively stable (i.e., similar for different participants), although not completely linear. This finding holds implications for persona user modeling, such as the simulation of persona users' likely gaze patterns for the detection of usability issues or the development of dynamic persona systems that would modify the template based on observed patterns. These directions are beyond the scope of this manuscript but still hold promise.

The L pattern held even with the repeated viewing of the persona profile. Despite repeated viewing of the persona profile, the L pattern was consistent in the participants' visual interaction with the persona. This is an expected result as users typically follow similar information-gathering strategies [56] when presented with consistently formatted displays [34]. Our premise was that the entire number of AOIs would decrease with repeated viewing; however, this was not the case, with only minimal differences in the number of states among repetition one, repetition two, and repetition three. This finding suggests that the content in persona profiles generally draws consistent attention based on placement regardless of the number of times the person interacts with the persona profile. We found increased views of the demographics and right-hand rail in repetitions two and three (see Tables A1 and A2 in the appendix). This opens a need for focused investigation comparing the difference between the persona's first and subsequent use.

5.2 Interpreting the Findings

Results show that, interestingly, A01, in the upper left corner, received only 11.69% of the fixations despite being the "prime real estate" area. This might indicate that, after repeated views, the classic F pattern [73] noted in studies of search engine results pages might not hold for persona profiles. It might also indicate that these participants did not consider demographics useful for their tasks, which is an area for further investigation in future research. Overall, the findings show that end users engage with specific parts of the persona (i.e., the left-hand rail and bottom) much more than other sections, perhaps indicating perceived importance.

Because A03 containing the text summary of the persona received the most attention (after accounting for AOI size), this implies that the users were attempting to process the persona information efficiently. The fact that A03 is not located on the top-left of the screen (which would traditionally be considered optimal for information processing) but is instead located toward the middle of the screen implies that users are behaving purposefully in finding the information they perceive relevant and then focusing on it.

Similarly, the results show that A01 placed on top of the screen, albeit located in "prime real estate," receives relatively fewer fixations than its position would leave us to assume. Because the information in A01 only contains basic demographics along with the persona's picture, this information may not be considered by the users as highly relevant for understanding who the persona is. On the other hand, the information in A01 contains less text per screen pixel than A03, for example, which implies that it is faster to process. Reading the text on A03, albeit presented in a short summary format, is likely to consume more cognitive effort which then reflects in a higher number of fixations. So, some persona information elements are more prone to rapid scanning, while others make the users pause and focus. Aside from A03, the A07 element (persona's quotes) saw an increase in rank of fixation frequency when adjusting for screen size. The third information element in the "top 3" in terms of relative fixation frequency was the persona's topics of interest.

When putting the results together, alternative explanations loom. However, one that most appeals to us is the idea that the *nature of the persona viewing task* fundamentally differs from the *nature of finding information from a website* such as a search engine results page (SERP). Namely, in SERPs, users would expect the most important information to be located at the top of the page, whereas for personas, the important details of the persona can be located *anywhere* in the profile (i.e., they remain to be discovered by the user). Once the user finds satisfactory information on the SERP, they stop searching. However, to get a fully rounded picture of the persona as a person, the user needs to visit all the information elements. The user still does not focus an equal amount of attention on these elements, but he or she nonetheless scans them. This scanning tends to follow the L pattern which, for the layout that we tested, represents a logical and efficient way to browse the persona information. As such, we interpret the user's visual interaction with the persona to be the product of their purposeful task completion (i.e., learning about the persona as much as they could) and adhering to efficiency in terms of information processing.

It is not evident that research would converge to one optimal layout for personas. On the other hand, neither has search–proven by the fact that Google constantly changes its SERP, for example, by redesigning it to contain rich snippets and AI-generated information. But this does not mean that research on different persona layouts would be a wasted effort. The more we understand the pros and cons, boundaries and limitations of different designs, the better we can make personas serve UCD.

5.3 Design Implications

These insights have direct implications for the design and engineering of interactive computing systems, especially in the context of creating more effective and user-friendly persona profiles. Specifically, the findings offer insights into the design of persona profiles to better align with users' natural viewing behaviors. The identification of an L pattern in persona viewing behavior suggests that *designers of persona profiles should place crucial persona information strategically along this trajectory.* The key information should be positioned in the L-path, where the users of personas are more likely to fixate during their initial and subsequent encounters with the profile. This can enhance the effectiveness of persona profiles in swiftly conveying essential details to persona users.

The three information elements that received the most visual attention were the *short text summary of the persona*, *the persona's topics of interest*, and *the persona's quotes.* These information elements not only serve the general purpose of learning about the persona, thereby supporting the user's goal completion, but they were also prominently placed in the middle of the screen, in close proximity to one another. Thus, including these three information elements in the persona profile, near one another, can be a meaningful design guideline for persona developers.

The findings point to paying careful attention to the visual hierarchy within persona profiles. Elements that are more critical or frequently referenced by those using the persona should be visually emphasized. Understanding which features attract the most attention during initial and subsequent encounters can inform the design of persona templates and the prioritization of information elements. Relatedly, our finding emphasizes treating the *persona as UI.* With any interface design, it is essential to consider users' *naturally occurring* behaviors, such as visual attention patterns. To this end, HCI practitioners should involve users in the design process and conduct usability testing with persona profiles to refine layouts based on actual user preferences and behaviors.

There is plenty of room for developing further experiments using the n-gram paradigm. We offer some thoughts to that end. Most notably, practitioners and researchers can look into the following properties:

- **Predictive applications:** By analyzing frequent n-grams, we might be able to predict which information a user is likely to view next based on their viewing history. The most common n-grams could indicate which combinations of personas are frequently viewed together, potentially revealing underlying user interests or preferences concerning persona information.
- **Generalization to persona sets:** Instead of using persona information as n-gram elements, we could model sequences

of viewing one persona after another. This could be valuable especially when there is a large number of personas that the stakeholders have to deal with [64].

- **Scalability:** N-gram processing is generally considered computationally efficient [19], meaning that n-grams are applicable to large datasets–this implies that a large number of user-persona interactions could be efficiently modeled using the n-gram approach. For example, user logs containing mouse movement and/or clicks in interactive persona systems [40] could be leveraged.
- **Depth:** Finally, we could go beyond trigrams to four, five, or longer sequences. This would make sense especially for more intense persona usage sessions; analyzing longer sequences would teach us more about the depth of stakeholders' use of personas. With n-grams, it is straightforward to change the depth of analysis.

5.4 Key Limitations and Future Work

As with any study, ours comes with some limitations.

For instance, the PPP layout of the currently presented profile may have strongly influenced the present results; the information presented in the in the design may have shaped the current results and the design of the persona (in relation to the (cultural) background of the participants) may have impacted viewing behavior.

First, because persona layouts can vary by context and domain [57], the findings may not generalize to all persona profile layouts, especially those deviating from the portrait design. Especially in different device environments such as mobile, tablet, and laptop usage, optimal persona layouts might vary. Therefore, the study should be replicated with other persona layouts (e.g., horizontal ones). This line of research could be expanded nearly infinitely, as the theoretical space for alternative designs of persona profiles is vast.

Second, the study was focused on the journalism context. Concerning future work in understanding persona viewing behavior, replicating the study in other domains (e.g., interface design, marketing, e-commerce) to see if the L pattern holds for these end users. Similarly, studies in cognitive psychology could reveal insights into person perceptions associated with stakeholders' viewing behaviors.

Third, considering cultural sensibilities in design [26], all our participants were proficient in English, even if English was not their native language. Nevertheless, it would be interesting to replicate the study with sole right-to-left reading participants with the personas in their primary language.

Concerning future research, the approach for analyzing AOIs and transitions among AOIs can be replicated for different persona profile layouts, thus providing an instrument for *persona science* [57], i.e., the use of scientific methods to produce robust knowledge about personas and their users. For example, future research could look into systematically altering the position of information elements and observing if users continue focusing most on marked key elements (e.g., persona summary, topics of interest, quotes) even when their position in the persona profiles changes.

Moreover, it would be interesting to connect the screen sizes of different information elements with the relative share of attention (i.e., gaze duration rather than only fixation counts) they receive to identify any anomalies and connect with the use of this information in a design task.

From information processing it is known that visual attention and fixation are not the same; attention is a deeper concept [16]. Similarly, fixation duration and information uptake are also not to be directly equated. These axioms pose measurement challenges when using eye-tracking data, also in our context. To address these challenges, it would be interesting to combine the eye-tracking analysis with other data sources, such as think-aloud records [8, 18, 53], which would shed more light on what the users found to be the most critical information. Users could be asked to rank the information elements in the persona profile from highest to lowest importance (or relevance, usefulness. . .) after the session and then carry out a correlation analysis to determine whether the self-reported importance ranks by users correlate with the users' actual viewing behavior.

Another line of research could leverage eye tracking to study different ways of presenting personas in a set: *personas in grid vs. list*. This could yield insights into users' information processing strategies for human factors such as persona selection bias [70]. For example, Kammerer and Gerjets [41] changed the layout of a search results page from a list to a grid format, finding that search results received more attention when they were at the top of the list than their share of attention on the grid interface. With the grid interface, the search results received equal attention. Another finding was that the list interface yielded more homogenous and linear viewing patterns than the grid interface, thus lending support to the F pattern. Similar experiments could be done with personas.

While our study investigated aspects of position bias in persona profiles, Wang et al. [75] observed several other user biases, including *vertical bias* (i.e., the preference for vertical blocs over search listing), *trust bias*, and a *revisit bias*. Testing these biases (and discovering new ones!) is in the roadmap for eye-tracking experiments in the persona context.

Finally, recognizing that users tend to revisit persona profiles after becoming familiar with them opens opportunities for persona personalization. While our study focused on persona profiles in a news organization's context using a static persona profile, the L pattern of persona viewing behavior may have broader applications in HCI as well as user modeling and personalization. Future research could explore how data-driven or algorithmically created persona systems could adapt the presentation of persona information based on users' previous visual interactions.

To facilitate the design of further experiments, we provide the script for our eye-tracking experiment in the online supplementary material. We also share the data for research purposes in an anonymized format upon request.

6 CONCLUSION

The purpose of personas is to provide information that helps make more UCD; i.e., consider user requests in the decision-making process. For this, the persona profile is instrumental: it mediates the information about the user group the persona represents. Because personas represent an established and commonly applied technique in HCI, it is important to determine how stakeholders visually interact with persona profiles. Given the limitations of information processing and web layouts, determining the boundaries of persona representation forms a relevant research problem. Our findings challenge the predominant F pattern for persona layouts, offering preliminary evidence that an L pattern for persona viewing more accurately describes persona-viewing behavior among stakeholders in the persona context, when using the portrait persona profile design. Our investigation into the visual attention patterns of persona users sheds light on how to design persona profiles better to align with users' natural viewing behaviors. To this end, our study illustrates the potential of eye-tracking and n-grams for persona science, which other studies can build upon.

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APPENDIX1

Table A1: Results from a bigram analysis by repetition. The top ten most occurring bigrams are shown. Note: START and END are not AOIs on the persona profile; they denote entry and exit from the persona profile.

Bigrams	# Repetition 1	# Repetition 1	# Repetition 1	Total
A9 END	14	16	14	44
START A1	3	20	20	43
A1 A3	14	10	13	37
A8 END	13	11	12	36
A3 A4	5	14	15	34
A7 A8	11	8	14	33
A4 A7	4	12	14	30
A8 A9	11	11	7	29
A1 A10	6	11	10	27
A10 A4	3	7	7	17

APPENDIX2

Table A2: Results from a trigram analysis by repetition. The top ten most occurring bigrams are shown. Note: START and END are not AOIs on the persona profile; they denote entry and exit from the persona profile.

Trigrams	# Repetition 1	# Repetition 1	# Repetition 1	Total
A8 A9 END	11	11	7	29
A9 A8 END	10	7	7	24
START A1 A3	2	8	11	21
A1 A3 A4	1	8	10	19
A7 A8 A9	6	6	7	19
A3 A4 A7	1	7	9	17
A7 A9 A8	6	6	5	17
START A1 A10	0	8	6	14
A10 A3 A4	0	6	5	11
A4 A1 A3	9	0	0	9