



DESIGN SPACE OF INTERACTIVE PERSONA SYSTEMS: A SYSTEMATIC LITERATURE REVIEW OF THE EVOLUTION OF PERSONAS IN THE AGE OF GENERATIVE AI

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ABSTRACT

Aim/Purpose	The purpose of this study is to address the gap in methodologies, data sources, and validation frameworks for interactive persona systems as they evolve from static design artifacts to AI-driven simulators.
Background	Research on personas has traditionally focused on their use as static tools for communicating user requirements to designers. However, the evolution of Artificial Intelligence has transformed these narratives into dynamic systems that simulate real user behavior.
Methodology	The systematic search resulted in 1096 records, of which 985 abstracts were screened, reducing the relevant citations to 65 full-text papers assessed for eligibility. Ultimately, 42 studies met our inclusion criteria. They were analyzed for creation methods, domains, and interaction types, and graded using the Technology Readiness Level (TRL) assessment, a nine-point scale measuring system maturity from concept to deployment.
Contribution	This paper presents the first comprehensive mapping of the design space for interactive persona systems. To support applied settings, it introduces a Practitioner's Toolkit, featuring a Design Framework and a decision matrix, that provides a structured, evidence-based path to select, build, and validate interactive persona systems based on specific project constraints. Furthermore, the review maps four core system types (Behavioral Simulation, Persona Management, Autonomous Personas, and Interface Personas) to distinct use cases and validation goals, providing guidelines to build personas that serve as a fundamental bridge for human-AI alignment.

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Findings	The technology readiness assessment revealed that the field is still in developmental stages, with only 8.6% of systems achieving high and operational maturity levels (TRL 6-9). A critical gap was noted regarding empirical validation: 52% of systems lack any empirical validation. Interactive personas are most prominently applied in UX research, education, gaming, and social simulation, with web applications representing the dominant mode of user interaction. This validation gap directly undermines the reliability of human-AI alignment in design, as systems that have not been empirically tested against real users cannot be assumed to faithfully represent human behavior.
Recommendations for Practitioners	Practitioners are advised to utilize personas to humanize AI systems in human-AI collaboration, integrate personas as core interface components, and leverage them to advance Human-AI alignment.
Recommendations for Researchers	Researchers are urged to develop standardized validation frameworks to assess persona alignment with real users to advance Human-AI alignment.
Impact on Society	Interactive personas advance computing for social good, such as training and advocacy, by providing safe simulation environments. They enable privacy-preserving research through anonymized, aggregated population models.
Future Research	Future work must balance empirical validity with cost constraints and establish ethical metrics to ensure interactive persona systems authentically represent human behavior.
Keywords	HCI, personas, user stories, AI, large language model, human AI alignment

INTRODUCTION

In the human-computer interaction (HCI) vocabulary, personas are recognized as hypothetical users that guide designers and system engineers in crafting digital experiences that resonate with human expectations (Karolita et al., 2023). Personas have long been employed to capture and communicate user requirements. As information technology has advanced, personas have evolved and transformed from static user narrative documents to interactive systems (Salminen, Guan, et al., 2021).

The evolution of AI technology has enabled interactive persona behavior, transforming them into dynamic systems that simulate real user behavior (Kaate, Salminen, Jung, Xuan, Azem, et al., 2025). This AI-driven transformation has heightened the need for advanced design methods and validation frameworks, as personas now serve as living representations of users rather than mere design guidelines (Chen et al., 2025).

The scope of personas has widened from representing only human users to encompassing non-human stakeholders such as animals (Frawley & Dyson, 2014) and plants (Tomitsch et al., 2021). This wider perspective contributes not only to human-centered design but also to the emerging area of planet-centered design (Talgorn & Ullerup, 2023). Beyond serving as design guidelines, personas have become integral components of interactive systems themselves, manifesting as agent personas in interactive voice interfaces (Dubiel et al., 2024). Personas are no longer just documents that describe users but have become the personality of human-AI interactions (Pradhan & Lazar, 2021), and the boundaries between persona, interface, and user are imploding (du Preez, 2024).

The use of personas has moved beyond the commercial space to benefit society by tackling complex social issues through the creation of design interventions and the consideration of the sociocultural implications of designing new technologies (Guan et al., 2023). In healthcare, personas guide efforts to improve service delivery (Ten Klooster et al., 2022). In politics, they inform initiatives to enhance civic participation (Bødker et al., 2012). In education, personas optimize pedagogical services and en-

hance learning opportunities (Schmidt, 2022). Personas focused on sustainability promote ecological awareness (Guan et al., 2023). In cybersecurity, personas model attackers and enhance the mitigation of digital vulnerabilities (Moeckel, 2018). In criminology, personas provide insight to minimize harmful behaviors by modeling criminal motivations (Guan et al., 2023; Hilton & Irons, 2006).

Modern approaches to creating personas address the limitations of traditional personas by making them dynamic, data-driven, and adaptable across contexts (Salminen, Guan, et al., 2020). Ten Klooster et al. (2022) suggested that the continuous updating of personas aligns with the digital twin concept, particularly in eHealth development, as personas focus on maintaining up-to-date descriptions of user groups rather than individuals (Ten Klooster et al., 2022).

While previous systematic inquiries have primarily focused on personas as artifacts for guiding design decisions (Salminen, Guan, et al., 2021; Salminen, Wenyun Guan, et al., 2022) and requirements engineering (Karolita et al., 2023), there remains a significant gap in the literature regarding the methodologies, data sources, applications, and interaction techniques associated with personas when utilized as standalone systems. This gap has become increasingly consequential with the emergence of generative AI. Existing frameworks were designed for static or periodically updated personas and do not account for the architectural demands of LLM-driven systems, which generate dynamic, contextually responsive behavior in real time, introduce new risks of bias and hallucination, and require fundamentally different validation approaches.

This study addresses this gap by conducting a systematic literature review that explores novel approaches to creating and using interactive personas in human-centered computing. We defined Interactive persona systems as interactive computational environments that enable direct engagement with personas as user archetypes—distinct from Jungian (Giles, 2020) personas, which represent individuals’ social masks.

We map the evolution of interactive personas across a decade by identifying domains, methods, data, interaction mechanisms, and implementation readiness of interactive persona systems, and we identify opportunities for future research in persona science. Based on a systematic review of 42 systems presented in Appendix A, this study identifies four core system types, ten use cases, and comprehensive validation frameworks. Researchers will find value in the systematic mapping of methods, domains, and technology readiness levels. Practitioners who design or deploy AI-powered systems will find the newly introduced Practitioner’s Toolkit highly actionable. Educators and instructional designers will also find this toolkit especially relevant to training, simulation, and educational technology contexts. Beyond mapping the field, this study produces a Practitioner’s Toolkit that connects system types, use cases, and validation strategies, providing researchers and practitioners with a structured path for building, evaluating, and deploying interactive persona systems. Within this toolkit, a Design Framework serves as a practical entry point, and a summary Decision Matrix helps readers choose the exact system type that fits their specific project constraints.

The remainder of this paper is organized as follows. The Background section traces the history of persona development from its origins through AI-driven approaches and situates the present study within prior systematic reviews. The Materials and Methods section describes the systematic literature review protocol, including the search process, inclusion and exclusion criteria, screening procedures, and the Technology Readiness Level (TRL) assessment framework. The Results section presents findings organized around the four research questions: persona creation methods, data sources, attributes, and validation (RQ1); domains of application (RQ2); human-persona interaction mechanisms (RQ3); and the technological maturity of current systems (RQ4). The Discussion and Conclusion sections synthesize these findings into actionable insights, including a *Practitioner’s Toolkit*, offering actionable guidelines for researchers and practitioners building next-generation persona tools, and outlining directions for future research.

BACKGROUND

This section traces the history of persona development from its origins to its current AI-driven form, establishing the conceptual foundation for the systematic review that follows.

The term “persona” originated in Jungian psychology to refer to the social face an individual presents to the public, which may differ from their true self. Over time, this terminology has evolved and been employed in other domains, such as art, marketing, and design (Giles, 2020).

Alan Cooper created the first persona, named “Kathy,” in 1985, when he was struggling to create user-friendly software (Cooper, 2020) to focus his design decisions on the specific needs and goals of the end user. Kathy was created to represent the target users of a project management software system, based on interviews with eight potential users. In his book, Cooper emphasized the importance of being specific about users, noting that in engineering usable systems, the focus should not be on everyone and that there should be specific personas, allowing decision making for design to be goal-specific to the goals of these personas (Adlin et al., 2006; Cooper, 1998, 1999; Pruitt & Grudin, 2003). Each persona is a synthesized description of patterns of a segment of users’ behavior, goals, and motives (Blomkvist, 2002).

Personas guide design teams in various domains to focus on specific user characteristics. Personas are highly flexible tools for advancing interactive systems. They facilitate communication within teams, prevent self-referential design, and provide design inspiration. Personas can even define initial social skills and features needed in human-robot interaction. This flexibility offers substantial opportunities for experimental endeavors in research (Salminen et al., 2021).

CRITICISM OF PERSONAS

While personas offer recognizable benefits and opportunities in user-centered design, as outlined above, the HCI community is actively addressing certain shortcomings. Personas have faced criticism in several aspects. The research community expressed concerns about the credibility, consistency, resource intensity, and representational accuracy of personas (Salminen, Jung, et al., 2020). Chapman and Milham (2006) argued that personas lack the empirical rigor required to function as reliable design tools, contending that their construction rests on assumptions that are rarely tested or falsified. Ronkko (2005) demonstrated empirically that organizational constraints, project structures, and contextual pressures frequently prevent personas from being used as intended, regardless of how well they are constructed. Turner and Turner (2011) raised a deeper concern about the representational logic of personas, finding that the process of creating archetypes from user groups inevitably introduces stereotyping that can undermine the very inclusivity personas are meant to promote.

Another important shortcoming of personas is their lifespan, which requires updating them as the target study group’s context or behavior changes. Some argue that personas often rely more on “fiction” than on real-world data, suggesting that researchers need to develop ways to create personas grounded in evidence and empirical data (Bødker et al., 2012).

Despite their rich contextual elements, personas developed through qualitative methods, such as interviews, are criticized for representing limited demographics and for lacking the ability to present testable hypotheses (Jansen et al., 2021). Another problem with qualitative methods is that addressing changes in the user population requires new, costly data-collection efforts, such as subject recruitment for interviews (Jansen et al., 2021). Quantitative methods utilizing API data have emerged as a solution to the previously mentioned problems; they respond to real-time changes in population behavior and deliver testable observations of behavior (Jansen et al., 2021). However, not all researchers have access to or can collect quantitative data for their intended purpose. Additionally, statistical weight and algorithmic bias could mask outliers and discriminated groups, potentially leading to a lack of inclusivity for diverse demographics (Jansen et al., 2021; Salminen, Guan, et al., 2021).

TRANSFORMATIVE DRIVERS

The widespread adoption of Large Language Models marked a transformative shift in persona architecture. Unlike earlier data-driven approaches that produced static or periodically updated profiles, LLMs enable personas to generate dynamic, contextually responsive, and conversational behavior in real time. This shift fundamentally expanded what persona systems can do — and introduced new challenges around validation, bias, and representational fidelity — necessitating the systematic mapping and classification framework presented in this review. With the emergence of large language models (LLMs) and the advancement of generative artificial intelligence (GenAI), AI-generated personas have become a new approach to creating personas by asking LLMs for their vast knowledge of world dynamics. For example, Salminen et al. (2024) have prompted LLMs to generate 450 personas of people with addiction to study their perspective, while these efforts raised concerns about reproducing the bias and hallucination of LLMs in the design process (Kaate, Salminen, Jung, Xuan, Häyhänen, et al., 2025). Empirical work on LLM-simulated human behavior consistently finds that representational fidelity is conditional rather than guaranteed — dependent on the strength of the relationship between persona variables and the behavior being simulated, the quality of conditioning, and the demographic specificity of the prompts used (Argyle et al., 2023; Dillion et al., 2023; Hu & Collier, 2024). This conditionality echoes foundational concerns raised in situated action theory, which holds that human behavior is inherently embedded in local, contingent contexts that resist abstraction into generalized plans or scripts (Suchman, 1987). Therefore, fidelity cannot be assumed based solely on model capabilities; it must be established through empirical validation with real user populations.

PREVIOUS SYSTEMATIC LITERATURE REVIEWS OF PERSONAS

Previous literature reviews over the past five years have examined data-driven personas (Salminen, Guan, et al., 2021), quantitative approaches (Salminen, Guan, et al., 2020), the context of persona use (Salminen, Wenyun Guan, et al., 2022), and systematically mapped personas in requirement engineering (Karolita et al., 2023).

The systematic literature review of quantitative persona creation articles from 2005 to 2019 (Salminen, Guan, et al., 2020) highlighted three stages in persona research. (1) In 2005-2008, early quantitative methods emerged. In this period, surveys and statistical methods were employed in software development, game development, and e-commerce. (2) Between 2009 and 2014, the dominant theme was diversification. The research community, by employing surveys and collecting behavioral data, has created personas. In this period, gaming and knowledge management systems emerged as new contexts for using personas. (3) From 2015 to 2019, the personas method has become more sophisticated by using online analytics APIs, big data, and large-scale surveys, and has been employed in new domains such as health, privacy, and fashion. During this period, understanding approaches to creating quantitative personas becomes fragmented. Furthermore, the scope of persona creation has been extended beyond human users to include non-human actors such as animals and robots. Another trend in this period was the development of novel systems that created the space for interactions between users and personas. Salminen, Guan, et al. (2020) noted an increase in the use of persona creation automation tools.

Salminen, Guan, et al. (2021) have explored data-driven approaches in creating personas and recognized that these methods evolved through three distinct periods:

In 2005-2008, quantification was a dominant theme, and the early experiments for creating quantitative methods for data-driven personas were conducted.

In 2009-2014, diversification of persona creation methods was identified as the dominant theme. They identified that various methods for using data and algorithms have been used in the literature.

In the 2015–2020 period, with access to social media analytics APIs and advancements in data science, the digitization of personas emerged as the theme.

They identified human-persona interaction as well as fully automated Interactive persona systems as new trends in persona science. Human-persona interaction was recognized in the literature as the research area of developing systems that facilitate interaction with personas beyond the reading of posters like personas. This new trend allows users to consume information by interacting with these personas. Conversations with personas and browsing online profiles of personas have emerged as methods of interaction with personas (Salminen, Guan, et al., 2021).

A systematic review of 95 articles on persona use cases revealed that personas have been employed across diverse domains to facilitate communication with target populations and inform design (Salminen, Guan, et al., 2022). Their usefulness in social science and social computing—along with emerging applications addressing the 17 United Nations Sustainable Development Goals—marks a novel direction for persona research (United Nations, 2015). Personas can promote social good by addressing political polarization and supporting conflict resolution through bridging opposing perspectives.

Karolita et al. (2023) have studied the use of personas in requirement engineering (RE), and reported on the creation and presentation of personas, including challenges and benefits of personas. They also found that qualitative, quantitative, and mixed-methods approaches are the main approaches to constructing personas. They identified interviews, focus group discussions, brainstorming, workshops, observation, field studies, statistical cluster analysis, secondary sources such as forum posts, and questionnaires as techniques used in persona construction in RE.

In regard to the benefits of using personas, Karolita et al. (2023) identified that personas can support better understanding of end users, help validate requirements, improve developer engagement, facilitate risk mitigation, and work as a communication tool in both inter and intra engagements for stakeholders and software developers. Personas are found to be useful in representing cultural variations. Cultural personas can reflect on people’s thinking processes and guide user experience design and have been used to provide a holistic view of large societies and countries to deliver cross-cultural user experience (Lachner et al., 2015). Overall, employing personas in software engineering promotes user satisfaction.

Table 1. Overview of SLRs on personas

Area of Focus	Key Findings and Contributions	Analytical Period	Reference
Quantitative persona methods	Identified three-stage evolution of quantitative approaches with emerging automation tools.	2005–2019	Salminen, Guan, et al. (2020)
Data-driven persona creation	Introduced human-persona interaction systems and digitization methods. Framed interactive persona systems around conversations and profile browsing	2005–2020	Salminen, Guan, et al. (2021)
Use cases for Personas	Mapped persona usage across domains, and framed persona usage for social impact	<2021	Salminen, Wenyun Guan, et al. (2022)
Requirement engineering	Identified challenges including bias and resource intensity while establishing RE-specific practices	2000-2023	Karolita et al. (2023)

Research gap

Despite this growing interest in interactive personas and their potential applications, there appears to be a significant research gap in understanding the nuances and implications of human-persona interaction. As highlighted by Salminen, Guan, et al. (2021) understanding the use and evolution of hu-

man-persona interaction has emerged as an interesting area of research. This study investigates interactive personas from the perspective of the Information Technology discipline (Said et al., 2021), recognizing them as IT solutions that help people by delivering information through human-like behavior.

This study aims to address this research gap by conducting a systematic literature review focused on novel approaches to creating and using personas in human-centered computing and presenting the design space of persona system development. The following research questions were developed to guide our investigation into both the theoretical foundations and practical implementations of these systems:

- RQ1:** How are interactive personas created?
 - **RQ1.1:** What methods are being used to create interactive personas?
 - **RQ1.2:** To what extent do interactive personas rely on empirical data?
 - **RQ1.3:** What attributes are used to define interactive personas?
 - **RQ1.4:** How are these Interactive persona systems validated?
- RQ2:** In what domains are interactive personas used?
- RQ3:** How do users interact with these persona-based systems?
- RQ4:** What is the technology readiness level (TRL) of the Interactive persona systems?

MATERIALS AND METHODS

The study followed the SLR guidelines proposed by Kitchenham and Charters (2007) for the data collection and followed the approach of Azeem et al. (2019) for the analysis of primary studies. The procedures for data collection and analysis are detailed in the following paragraphs and illustrated in Figure 1.

SEARCH PROCESS

The research began by familiarizing the search results through several iterations to find articles that described interactions with personas. We noticed that the relevant results were not discoverable with straightforward terminology, as articles used different terms such as “dynamic personas,” “generative personas,” and “interactive personas.” To eliminate potential bias in identifying a specific type of interaction, generic terminology was used to screen more studies. The Association for Computing Machinery (ACM) Digital Library, which indexes articles from the Special Interest Group on Computer-Human Interaction (SIGCHI), was selected as the primary database. This choice is consistent with Stefanidi et al. (2023), whose systematic review of 189 HCI literature reviews established that ACM SIGCHI venues represent the core intellectual landscape of the field. IEEE Xplore was included to broaden coverage to relevant computing systems research outside the ACM ecosystem. Scopus was evaluated but ultimately excluded; the broad term “persona” returned thousands of irrelevant records spanning psychology, marketing, and security, making manual filtering impractical.

The following search string was applied to the abstract fields of both databases: (“persona” OR “personas”) AND (“interactive” OR “interaction” OR “system” OR “agent” OR “simulation”). In ACM Digital Library, the query was executed using the advanced search with abstract field restrictions. In IEEE Xplore, the same string was applied to the abstract metadata field. No additional filters on publication type were applied at the database level; venue and format filtering was handled during abstract screening. The search was conducted on July 8, 2024, and results were filtered to publications between 2014 and 2024, a timeframe chosen because prior studies identified this period as marking the emergence of sophisticated interactive persona systems (Salminen, Guan, et al., 2020, 2021). This step returned 427 ACM articles and 347 IEEE articles.

In addition, the top 20 HCI publication venues identified through Google Scholar (a major academic search engine) were selected to expand the literature coverage. Following Caraban et al. (2019), the articles retrieved for each venue were manually collected to identify relevant studies outside the ACM and IEEE digital libraries. These publications were identified based on their Google Scholar h5-index ranking at the time of data collection. For each venue, the proceedings page or journal archive was searched using both “persona” and “personas” within the venue’s own search interface. Only article titles and abstracts were screened at this stage; full issues were not manually browsed. The list of these publications is presented in Appendix B. Twelve of these publications were from ACM and IEEE and were not searched again in this step. For the remaining publications, a hand search was conducted for articles published between 2014 and 2024, adding 109 articles.

As suggested by Kitchenham and Charters (2007), the study used forward snowball sampling by searching recognized systematic literature reviews on personas (Karolita et al., 2023; Salminen, Guan, et al., 2020, 2021; Salminen, Wenyun Guan, et al., 2022) to collect articles that might fall outside IEEE and ACM coverage. Forward sampling identifies papers that cited a particular source, helping surface relevant articles beyond the initial database search. Google Scholar serves as a valuable resource for conducting snowball sampling (Wohlin, 2014), an increasingly popular technique in systematic literature reviews. This step added 212 articles.

INCLUSION AND EXCLUSION CRITERIA

This study employs systematic inclusion and exclusion criteria to ensure the selection of relevant literature that contributes to our understanding of interactive persona systems. The criteria are designed to focus on articles that examine systems in which users directly engage with personas beyond static documentation, encompassing computational environments in which personas serve as interactive entities across diverse application domains. The exclusion criteria filter out traditional UX persona documentation, technical machine learning improvements that mention personas in passing.

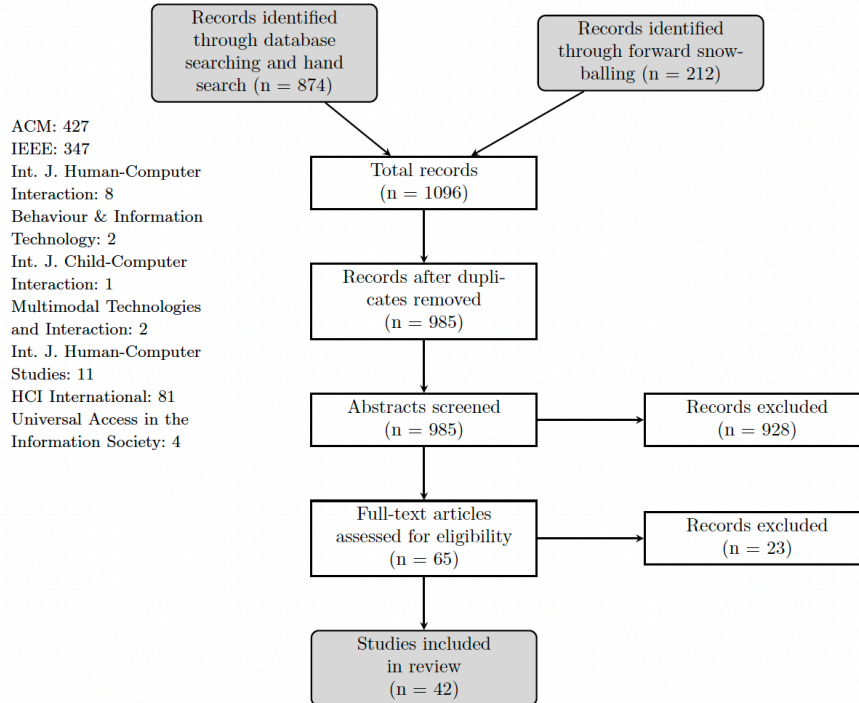


Figure 1. Data Collection Overview

ABSTRACT SCREENING

The study employs systematic inclusion and exclusion criteria to guide article selection, as outlined in Table 2. This review examines Interactive persona systems from an HCI and system development perspective. Chatbot and conversational agent papers were included when the persona functioned as a structured system entity used to support interaction design, user research, or human-AI collaboration. Papers were excluded when the focus was AI model optimization, prompt tuning, or conversational performance — areas outside the HCI scope of this review. After screening the abstracts of 985 articles, 65 articles were selected for full-text review. To assess screening consistency, the first author re-screened 111 abstracts (~11%) after a six-month interval. When it comes to borderline cases, through discussion with the second author, the articles were labeled. Intra-rater reliability — the degree to which the same screener reaches consistent decisions across two independent passes — was measured using Cohen’s Kappa (0.899), indicating almost perfect stability (Landis & Koch, 1977). In the seven inconsistent cases, the first author re-examined the full text against the criteria; two were ultimately included.

Table 2. Inclusion and Exclusion Criteria for Article Selection

Inclusion Criteria	Exclusion Criteria
Articles describing systems where users can directly interact with personas (beyond reading static documents)	Articles that focus on Cooper’s definition of personas as fictional representations of users
Articles exploring persona creation methodologies and interaction	Articles focusing on Jungian psychology personas (social masks)
Articles in Computer Science, Information Technology, or Human-Computer Interaction domains	Articles on persona detection for security or identity recognition
	Systematic literature reviews and meta-analyses, book covers, conference proceeding covers, Thesis
	Articles describing only static, non-interactive persona creation methods
	Articles focused solely on traditional paper-based UX personas without interactive elements
	Articles focused primarily on machine learning optimization, or chatbot optimization
	Articles that are less than two pages (excluding references), as they do not contain enough information for analysis

Full-text Screening And Quality Assessment

The 65 full-text articles underwent comprehensive screening for eligibility and quality assessment using the following criteria.

Quality Assessment Criteria:

- **Relevance to Research Focus:** Is the paper directly applicable to research on interactive persona systems? (Articles were compared against the conceptual framework established by Salminen, Guan, et al. (2021) for human-persona interaction)
- **Methodological Clarity:** Does the paper provide sufficient information about persona creation methods and system implementation?

- **System Description:** Does the paper adequately describe how users interact with the persona system?
- **Empirical Foundation:** Does the paper clearly describe the data sources and validation approaches used?

Articles that did not meet these quality criteria or fell outside the scope of interactive persona systems were excluded. Following this full-text screening and quality assessment, 23 articles were excluded, leaving a final collection of 42 for analysis which is presented in Appendix A. The overview of this process from data collection to final selection is illustrated in Figure 1.

DATA EXTRACTION AND CODING RELIABILITY

Following the final selection of 42 primary studies, the first author conducted data extraction using a structured spreadsheet. Each study was assigned a primary-study identifier (P1–P42) corresponding to its entry in Appendix A. For each study, the following variables were coded: system type, creation method, empirical data source, interaction type, use case, domain, persona attributes, validation goal, validation method, and Technology Readiness Level. The full coding scheme, including variable definitions and coded values, is provided in Appendix C. To improve extraction consistency, the first author re-coded all 42 studies after a 2-month interval, and any discrepancies between the two rounds were reviewed and resolved by both authors before finalizing the analysis.

TECHNOLOGY READINESS LEVEL ASSESSMENT

To evaluate system maturity, the Technology Readiness Level (TRL) assessment method was used to grade each solution. Technology readiness level was introduced by the National Aeronautics and Space Administration (Mankins, 1995) to assess technological maturity (Lacueva-Pérez et al., 2018) and has been employed in systematic literature reviews (Seegrün et al., 2023) and assessing HCI technologies to study the maturity of existing solutions (Lacueva-Pérez et al., 2018). This approach is particularly valuable for evaluating emerging and in-progress solutions such as augmented reality (van den Oever et al., 2024).

Evaluating technology maturity involves analyzing the levels of system development and the validation methods. This study adapted the definition of Martinez Plumed et al. (2020) as presented below:

Table 3. Technology Readiness Levels, adapted from Martinez Plumed et al. (2020)

Level	Description
TRL 1	Basic principles observed
TRL 2	Technology concept formulated
TRL 3	Experimental proof of concept
TRL 4	Technology validated in lab
TRL 5	Technology validated in relevant environment
TRL 6	Technology demonstrated in relevant environment
TRL 7	System prototype demonstration in operational environment
TRL 8	System complete and qualified
TRL 9	Actual system proven in operational environment

The first author reviewed included studies to assess the technology’s readiness, considering the development stage (e.g., concept, implementation, deployment), evaluation, and the evaluation context.

RESULTS

Figure 2 illustrates the number of articles in each year from 2014-2024. In the following paragraph, we discuss the results for each research question in the corpus.

HOW ARE INTERACTIVE PERSONAS CREATED?

In the following paragraphs, the methods that were employed in the primary articles are discussed and articulated:

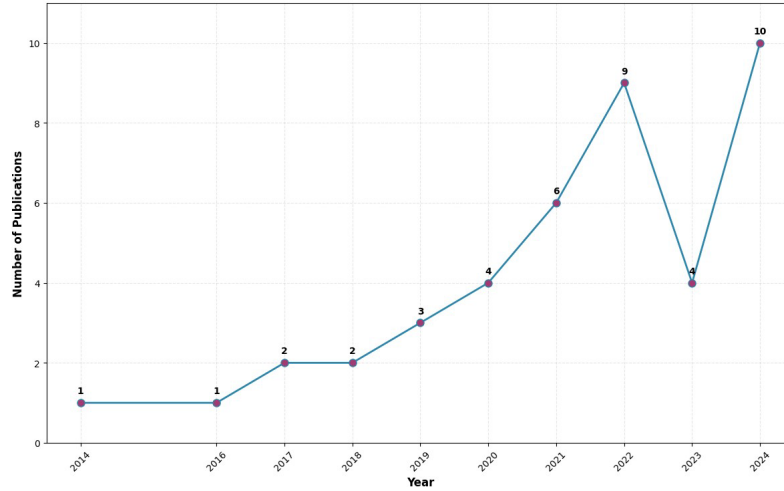


Figure. 2 Number of Articles in Each Year

WHAT METHODS ARE BEING USED TO CREATE INTERACTIVE PERSONAS?

Figure 3 provides an overview of the methods used for creating personas, and we explore them in detail in the following lines:

Algorithm-based methods

In these methods, statistical analysis techniques common in machine learning, such as clustering (Kikuchi & Takahashi, 2021), were used alongside quantitative data collection methods. Notably, this category includes generative procedural persona techniques, which represent advanced quantitative approaches. Procedural persona generation is an important subset of data-driven approaches for persona creation that relies on algorithms (Bell, 2017) and has been employed in several studies (e.g., Alvarez et al., 2022; Holmgård et al., 2019; Mugrai et al., 2019).

Mugrai et al. (2019) created procedural player persona agents, and each agent has its own goals in a tile matching game. They proposed that the simplicity of the tile-matching game could allow researchers to use it as a benchmark for testing procedural personas. Holmgård et al. (2019) have defined the main objectives of player personas in a dungeon game: reaching the exit, killing monsters, collecting treasures, and interacting with game objects such as potions.

Unlike the previously mentioned works that personas play the games, Alvarez et al. (2022) worked on personas that can design the games. They collected data from participants who designed rooms for a dungeon game and used clustering algorithms.

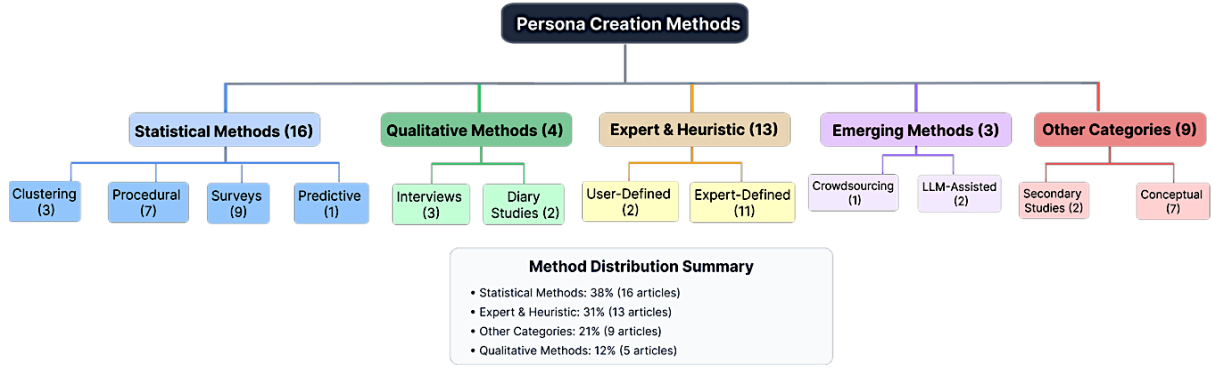


Figure 3. Methods of Creating Personas: Eight (8) articles multiple methodological approaches for creating interactive personas.

Barthet et al. (2022) have elevated the state of the art of player persona by capturing both the interaction data of players and their emotions with a racing game as a test bed. They clustered these data to create player personas that behave like humans and simulate the behavior of humans. They suggested this approach can be used for exploring the behavior of players. They used an algorithmic approach that explores the state space of the game, which is the racing track in this case, and a reward function that balances between player behavior and emotional intensity.

Automatic persona generation is identified as a promising method for creating personas, which is based on algorithmic analysis (e.g., Jung et al., 2018; Salminen, Jansen, & Jung, 2022; Salminen, Jung, et al., 2020). In developing systems for automatic persona generation, the capability of the systems in identifying outliers is a crucial element (Salminen, Jansen, & Jung, 2022). There are limitations in automating the creation of personas, such as processing open-ended answers (Salminen, Jansen, & Jung, 2022), which it limits the depth of automated persona generation.

Bell (2017) proposed the concept of a marketplace system for automatic creation of personas. In their proposed systems, consumers upload their own data into a digital vault, and a data mining engine processes all of the user data to identify rare characteristics, and new personas are generated based on this data marketplace, and buyers can target and bid for personas in this marketplace.

Survey

In seven (7) studies surveys and questionnaires were employed (Alazraki et al., 2021; Bouzekri et al., 2024; Hsu et al., 2024; Kikuchi & Takahashi, 2021; Matias et al., 2024; Salminen, Jansen, & Jung, 2022; Salminen, Vahlo, et al., 2020). The surveys were utilized to collect remotely information on user behavior, needs, and backgrounds. These studies demonstrated that surveys can be used as a foundation for automation of persona creation in two studies (Salminen, Jansen, & Jung, 2022; Salminen, Vahlo, et al., 2020). In the data collection through surveys, Salminen, Vahlo, et al. (2020), enhanced the experience of respondents by connecting the survey form to a database of 130,495 game tiles, and enabling auto-complete suggestions.

QUALITATIVE METHOD

User interviews were used in three (3) articles (Hsu et al., 2024; Maruhn et al., 2023; Navarro Sainz & Prabhakar, 2022), and diary studies were discussed in two articles (Aragon Bartsch et al., 2022; Navarro Sainz & Prabhakar, 2022). Qualitative methods in these studies helped the researchers to gather in depth, and contextual knowledge about users. Hsu et al. (2024), in their proposed method for the creation of predictive personas, used interviews at the first step of data collection, and suggested that interviews are necessary for understanding the target study group.

For creating system personas of voice user interfaces, Navarro Sainz and Prabhakar (2022), used both diaries and interviews. They suggested that system personas that facilitate voice interactions should include voice, tone, and personality.

Diary studies were also used for creating personas in career guidance. Aragon Bartsch et al. (2022) recruited two former HCI students, one of whom worked as a software developer, and the other worked as a marketing manager. These two students represented the two personas with different career choices. These students record their daily work tasks over one week in conversations. The researchers augmented these data with weather information to create the illusion of real-time interaction with personas in the proposed system.

Expert-defined/Heuristic methods

Seven (7) studies (Andriella et al., 2019; Bonnardel & Pichot, 2020; Bouzekri et al., 2024; Karahasanović et al., 2021; Murali et al., 2022; Pillis et al., 2024; Rinott & Shaer, 2024; Zhao et al., 2024) relied on researchers' experience or definitions to create personas. While these methods are based on a qualitative understanding, they don't follow formal qualitative research methods. Andriella et al. (2019) developed personas based on collaborations with caregivers and doctors. Alvertis et al. (2016) combined customer data with software engineer experience.

Crowd sourcing

Alvertis et al. (2016) presented a novel approach to persona creation in software engineering through their Persona Builder tool, which leverages crowdsourcing and anonymized user data. They proposed a system named Persona Builder, which offers three main functionalities: custom persona creation using "predefined parameters", exploring and choosing from a pool of "pre-defined personas", and the ability to reuse and modify existing personas from public or private repositories. This approach allows software teams to create dynamic personas based on real but anonymized user data collected from various online sources, thereby expanding the representativeness of personas and enabling them to be continuously updated as users' skills and traits evolve, without compromising privacy.

Predictive personas

Hsu et al. (2024) have proposed and validated a method named predictive personas, which blends the benefits of both quantitative and qualitative methods in persona creation with supervised modeling techniques. This method consists of the following steps: (1) User Research (Potentially interviews), (2) Data Collection (Questionnaire design & Survey), (3) Data Preparation (Partitioning), Modeling, Evaluation, and Persona Creation. They integrated shopping preferences factors such as quality, demand, price, risk taking for buying new products, and past experiences in developing predictive models.

The other notable observation were the efforts to expand the lifespan of data and consequential personas by using existing data, forecasting, and generating data of future external environment factors. Kikuchi and Takahashi (2021) demonstrated this approach by augmenting questionnaire responses with simulated future data to create "virtual lives" for personas. This approach considers external factors such as inflation, asset succession, and price fluctuations of risky assets in social simulations to create personas that consider future changes. In addition, they expanded the empirical foundation of personas beyond current questionnaire responses by forecasting projections of potential future states.

LLM assisted persona creation

An emerging approach is using large language models to generate personas (J. S. Park et al., 2022). In one notable example, J.S. Park et al. created 10 seed personas and fed them to GPT-3 to generate 1,000 unique but relevant personas, aiming to simulate the social behavior of an online community. Also, six (6) studies (Azzopardi et al., 2022; Godwin et al., 2024; Markel et al., 2023; Noufi et al., 2023; Porter et al., 2014; Rea & Young, 2020; Vandenberghe, 2017) did not clearly articulate their methods and mostly described them only at a conceptual level, and one article relied on secondary studies (J. Liu et al., 2022).

TO WHAT EXTENT DO INTERACTIVE PERSONAS RELY ON EMPIRICAL DATA?

The analysis reveals a spectrum of approaches (see Figure 4), ranging from systems deeply grounded in large-scale empirical datasets to those primarily based on artificial synthetic data.

Several studies employed **sizeable empirical datasets** to create their systems. An et al. (2018) analyzed data from the social media accounts of an international broadcasting company, including 30 million interactions across 4,200 videos. (S.-G. Jung et al., 2021) leveraged publicly available Instagram data from a mobile telephone operator. Salminen, Jung, et al. (2020) created their system on survey data from 15,000 respondents. Salminen, Jansen, & Jung (2022) employed multiple datasets, including two real-world surveys and an artificial dataset. Hsu et al. (2024) collected 2,240 real user data points to create and validate predictive personas. While large-scale data collection is mostly common in quantitative approaches, one study stood out for the extensive qualitative data collection: Maruhn et al. (2023) created their VR personas on 8000 face-to-face interviews.

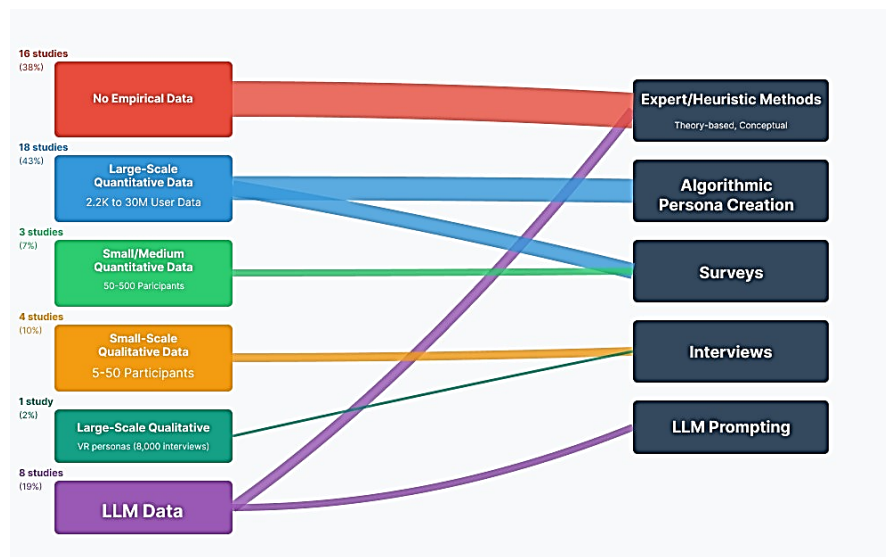


Figure 4. Overall Visualization of Methods and Their Reliance on Empirical Data

Some studies relied more on **researcher experience**, leading many to use researcher-defined personas in their work (Bouzekri et al., 2024; Karahasanović et al., 2021; Markel et al., 2023; Murali et al., 2022; Zhao et al., 2024).

Several studies focused on using **human play data** to develop interactive personas. Holmgård et al. (2019) and Mugrai et al. (2019) used actual player behavior data to create procedural personas. Player data can include intentions, actions, or emotions (Barthet et al., 2022). Fernandes et al. (2021) proposed trained personas from human play data or hand-coded approaches.

Data Marketplace for Dynamic Persona Creation was another discussed approach to extend the reliance of personas on empirical data, although it remained as a concept (Bell, 2017). This concept suggests using a marketplace to create personas based on real user data from those willing to sell their data for persona creation. This conceptual platform offered dynamic persona creation by data mining on traded personal data.

Matias et al. (2024) proposed a knowledge database and machine learning models. They used an existing persona library named “Volere” in their research for simulating personas which was a widely used requirements specification template in software engineering.

Other studies presented unique approaches: (Wang et al., 2021) used data from a persona management system, and (Aragon Bartsch et al., 2022) collected data from diary studies for their mobile app personas.

Several works did not explicitly discuss their data sources (Rea & Young, 2020; Vandenberghe, 2017). These works primarily focused on the conceptual aspects of creating personas.

WHAT ATTRIBUTES ARE USED TO DEFINE INTERACTIVE PERSONAS?

The outcome of employing the above methods was constructing personas. These personas were defined through a variety of attributes that are discussed in following paragraphs.

Demographic and basic information were discussed in almost all articles, except two articles, which were mostly focused on interaction with personas (Rinott & Shaer, 2024; Zhao et al., 2024). Demographic information can include age, gender, ethnicity, name, country (An et al., 2018; Bonnardel & Pichot, 2020; Jung et al., 2018; Kikuchi & Takahashi, 2021), and household composition (Kikuchi & Takahashi, 2021). Professional and academic background were discussed in the literature (Aragon Bartsch et al., 2022; J. Park & Choi, 2023; J. S. Park et al., 2022). Studies that focused on usage of LLMs described these attributes with more details such as years of work experience, career goals, and even publications of the personas (Aragon Bartsch et al., 2022; J. Park & Choi, 2023; J. S. Park et al., 2022). The personas constructed for very niche and specific domains, such as aviation, consist of domain-specific job information. For instance, LLM-driven pilot personas were defined with aircraft familiarity (e.g., Boeing 747, 787), Airline (KLM, United), Seat (e.g., captain), and Safety focus, which indicates the level of emphasis of the persona on safety matters (Bouzekri et al., 2024). LLM-driven personas of students included year, major, and programming experience (Markel et al., 2023; J. Park & Choi, 2023).

Narrative and scenarios were other attributes that were used to define personas in the literature examples are composing biographies, stories (Porter et al., 2014), quotes (Jung et al., 2018), working narratives (Wang et al., 2021), and social media posts (Azzopardi et al., 2022). Narrative elements that relied on qualitative data were used to provide context for persona interactions, especially to raise awareness of privacy decisions. It was used to communicate the online behavior of the personas (Azzopardi et al., 2022).

The literature revealed that the research community, by using a diverse set of research methods, was able to identify **behavioral patterns** and use them to define personas. These factors including Hours of doing activity (Rinott & Shaer, 2024), companionship (Rinott & Shaer, 2024), buying, traveling, entertainment consumption (Bell, 2017), social activities (Murali et al., 2022), and playing strategies (Fernandes et al., 2021; Holmgård et al., 2019) were specially useful in creating interactive personas. Moreover, financial background together with behavioral economic factors such as risk taking in investment (Kikuchi & Takahashi, 2021), and purchase intention frameworks (Hsu et al., 2024) were used to create personas that can respond by predicting (Hsu et al., 2024) and forecasting (Kikuchi & Takahashi, 2021). Psychological traits were used to predict personas' anticipated reactions, such as emotional intensity (Hsu et al., 2024).

The other interesting factors which is very relevant to technology design is defining attributes that can define the interaction of users that personas representing with technology, such as **level of control over system** (Rinott & Shaer, 2024), **confidence in technology** (Bouzekri et al., 2024), **digital literacy** (Porter et al., 2014) and **devices user owns** (Wang et al., 2021). Wang et al. (2021) went deeper in defining personal attributions of target users. They become more specific about **visual factors** such as skin tone and clothing preferences.

Moreover, in order to facilitate engineering inclusive software, AlRyalat et al. considered defining special conditions such as vision type, and protanopia (a form of color blindness where individuals cannot perceive red colors properly). Along these lines, Andriella et al. (2019) considered **cognitive factors** such as memory, reactivity, hearing, and attention in persona construction.

Alvertis et al. (2016) proposed that personas should include aggregated attributes, such as an age range, together with cosmetic attributes. They defined cosmetic attributes as attributes that make personas identifiable for the teams without revealing the identity of actual user data such as real name. Quotation and fictional profile pictures are examples of cosmetic attributes which discussed.

Defining **interests** and **hobbies** was another important attribute that not only gives human-like adjectives to personas but also allows designers to map users' needs to representative personas (Benhararak et al., 2024). It can include favorite media categories (An et al., 2018), most-watched videos (An et al., 2018), favorite games (Salminen, Vahlo, et al., 2020), hobbies or general interests (Benhararak et al., 2024).

The other notable category of attributes in the literature was user-defined attributes. These systems allow users to define custom attributes (Benhararak et al., 2024; Ha et al., 2024). This flexibility of persona construction was enabled by the generative capabilities of LLMs (Benhararak et al., 2024; Ha et al., 2024).

How are these interactive persona systems validated?

A critical finding is that 22 studies (52.4%) provided no empirical validation of their systems. Among the studies that conducted validation, researchers pursued diverse validation goals as outlined in Table 4.

Studying Human Alignment, conducting direct comparisons with representative users (Bouzekri et al., 2024) or predictive accuracy testing (Hsu et al., 2024) were used to assess how accurately personas represent real human behavior and characteristics. Learning Effectiveness of participants in testing was measured to investigate educational outcomes and skill development when users interacted with educational personas (Aragon Bartsch et al., 2022; Markel et al., 2023). Population Coverage validation measured that personas adequately represent target demographic groups and their requirements (An et al., 2018; Salminen, Vahlo, et al., 2020). Studies focused on Interaction Quality examined conversation quality, engagement, and the social effectiveness of persona interactions (Ha et al., 2024; Pillis et al., 2024). More technical approaches included Persona Management validation, assessing system effectiveness in managing, monitoring, and operating personas (Godwin et al., 2024; Jung et al., 2021), and Task Performance validation, measuring functional effectiveness and task completion capabilities (Benhararak et al., 2024; Zhao et al., 2024). Expert Approval for domain assessment (Noufi et al., 2023) and Social Dynamics validation studying social behaviors and group interaction patterns (Bubna et al., 2020).

Table 4. Validation of Interactive Personas

Validation Goal	Description	Primary Studies	Total
Persona Simulation Validation: Does the persona accurately represent real human behavior or population?			
Human Alignment	Assessing how accurately personas represent real human behavior and characteristics	P1, P21, P27, P33, P34, P37	6
Population Coverage	Ensuring personas adequately represent target demographic groups and their requirements	P5, P9, P10, P13, P18, P42	6
Representativeness	Subject matter expert assessment of persona quality and appropriateness	P38, P40	2
Social Dynamics	Studying social behaviors and group interaction patterns to assess behavioral authenticity	P38	1

Validation Goal	Description	Primary Studies	Total
Interaction Effectiveness Validation: Does the system work well for users to achieve intended outcomes?			
Persona Management	Validating system effectiveness in managing, monitoring, and operating persona interactions	P13, P18, P41	3
Interaction Quality	Evaluating conversation quality, engagement, empathy building, and social effectiveness	P29, P39	2
Learning Effectiveness	Assessing educational outcomes, training effectiveness, and skill development	P22, P27	2
Task Performance	Evaluating functional effectiveness and task completion capabilities	P30, P35	2
No Empirical Validation — 22 studies (52.4% of corpus)			
P2, P3, P4, P6, P7, P8, P11, P12, P14, P15, P16, P17, P19, P20, P23, P24, P25, P26, P28, P31, P32, P36			22

DOMAINS

The analysis identified that systems are applied across a diverse range of domains and industries. These novel systems are finding utility for using personas in both conventional fields and emerging fields, as presented in Table 5.

In the user experience and market research fields, interactive personas are enhancing our understanding of user or customer behavior and preferences. For instance, Jung et al. (2021) employed an interactive persona system to analyze user interactions in the tourism sector. Bouzekri et al. (2024) interviewed with pilot personas to study the cognitive behavior of pilots about an automation system in airplanes.

Moreover, interactive personas enhance the requirements engineering process. Wang et al. (2021) proposed a virtual reality-enabled approach to requirements engineering using interactive personas. Alvertis et al. (2016) explored the use of crowdsourced and anonymized personas in requirements elicitation. Simulating personas to provide their predictive feedback was also used in the requirement engineering of national electronic services to enhance the electronic government state (Porter et al., 2014). These applications of personas are enhancing the efficiency of software engineering and the success of IT projects.

The gaming industry has shown particular interest in these systems and brought innovation to this domain. For example, Barthet et al. (2022) demonstrated the use of interactive personas in game design and player modeling.

Social simulation is another emerging area of persona use, as discussed by Kikuchi and Takahashi (2021) and J. S. Park et al. (2022). For instance, J. S. Park et al. (2022) generated a large number of personas as the members of an online community in the Reddit social network (a large online community platform) and used large language models to generate behaviors of these personas by creating their posts and comments. People created a virtual community of synthetic users that can provide feedback on the input. Although this system cannot predict the absolute truth about the future, it can provide insights into potential social behaviors about a topic.

In education and training, interactive personas are opening up new possibilities. J. Park and Choi (2023) developed a system for public speech practice using LLM-simulated audiences. In this system, the LLM serves as the personas of the audience and helps speakers practice public speaking by receiving feedback from simulated personas. In another notable work in the education field, Markel et

al. (2023) employed LLMs to act as the personas of the students, which enabled novice teaching assistants to practice and gain experience through interaction with these LLM-simulated personas. Murali et al. (2022) used interactive personas to train lay counselors in vaccination promotion and increase vaccination rates. These applications are examples of interactive personas in skill development and professional training.

Personas are also enhancing users' health and wellness. Navarro Sainz and Prabhakar (2022) designed a voice user interface using interactive personas for everyday stress care, and Alazraki et al. (2021) created an empathetic AI coach for self-attachment therapy.

One distinct domain was integrating personas in software to enhance the productivity of computer-supported work (Ha et al., 2024; Rinott & Shaer, 2024). Personas were integrated into these systems, and users interacted directly with them as part of their task completion.

In the media distribution industry, interactive personas have worked as a directory of audiences. An et al. (2018) created a system that gave a face to the audience of a broadcasting network.

The field of robotics and human-robot interaction is also leveraging interactive personas. Rea and Young (2020) investigated the use of on-screen agents to influence teleoperation. For example, Andriella et al. (2019) developed a high-level abstraction of a persona-behavior simulator for learning robot policies, reducing the need for lengthy sessions that can be exhausting for patients who use these robots.

In career development, Aragon Bartsch et al. (2022) introduced a novel approach using scheduled mobile chat messages with interactive personas for career guidance.

Using Interactive personas in knowledge support systems was studied in one research to enhance task performance (Zhao et al., 2024).

In the insurance sector, Maruhn et al. (2023) used interactive personas to represent sociodemographic attributes of insurance buyers, namely education, living environment, and leisure behavior, for facilitating business strategy development, growth strategy planning, and content creation.

Lastly, in the domain of cybersecurity, Azzopardi et al. (2022) developed a persona system for evaluating awareness of online risks and harms and enhancing digital literacy. In their system, users explore different personas and the content these personas shared on social media, and they provide feedback on the behavior of these personas.

Table 5. Domains of Interactive Persona Systems in Primary Studies

Domain	References
General Theoretical Contribution	P2, P3, P6, P12, P13, P14, P18, P23, P40
Game Design and Testing	P8, P9, P10, P17, P20, P25
Education and Training	P21, P26, P27, P29, P32, P37, P39
Marketing	P4, P16, P34
Health and Wellness	P7, P15, P18, P19, P31
Digital Content Distribution	P5, P6
Robotics	P7, P11
Career Guidance	P22
Cyber Safety and Risk Awareness	P23
Computer Supported Work	P29, P30, P32
Electronic Government	P1

Domain	References
Social Simulation	P16, P24
Knowledge Support	P35
Aerospace Industry	P33, P36
Tourism	P13, P38
Insurance	P28
Social Justice	P39

INTERACTION WITH PERSONAS

The analysis of the 42 articles identified diverse methods for user interaction with interactive persona systems, as their frequency is presented in Figure 5.

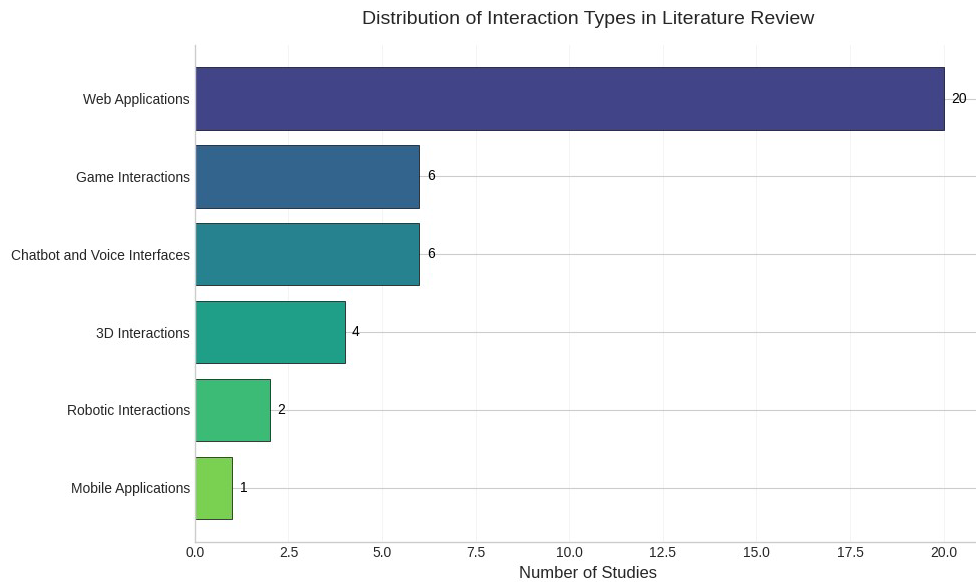


Figure 5. Interaction with Personas in the Primary Studies

Web applications

Twenty (20) studies (Alvertis et al., 2016; Azzopardi et al., 2022; Bell, 2017; Benharrak et al., 2024; Godwin et al., 2024; Ha et al., 2024; Jung et al., 2021; J. Liu et al., 2022; Markel et al., 2023; Matias et al., 2024; Murali et al., 2022; J. Park & Choi, 2023; J. S. Park et al., 2022; Pillis et al., 2024; Porter et al., 2014; Rea & Young, 2020; Rinott & Shaer, 2024; Salminen, Jansen, & Jung, 2022; Salminen, Jung, et al., 2020; Zhang et al., 2024) employed web applications for delivering interaction with personas. These web applications range from simple tools for displaying data to more complex systems that you can interact with. For example, Benharrak et al. (2024) presented a web-based text editor that integrated a tool allowing writers to define AI Personas of target readers, such as University professors or PhD students, to provide feedback as reviewers on the writing.

Data systems

Three (3) studies (Hsu et al., 2024; Kikuchi & Takahashi, 2021; Matias et al., 2024) discussed data processing methods for personas, one for predicting customer behavior in target marketing (Hsu et al., 2024), one discussed creating a persona system for social simulation using data augmentation (Kikuchi & Takahashi, 2021), and the other one discussed a system that deliver dynamic personas that respond, and updated according to behavioral change of users (Matias et al., 2024). While this

study does not directly discuss the interaction method itself, it contributed to knowledge for implementing interactive persona systems.

3D interactions

Five (5) studies presented systems which were benefited from the immersive environment to deliver engaging personas (Andriella et al., 2019; Bonnardel & Pichot, 2020; Bubna et al., 2020; Maruhn et al., 2023; Wang et al., 2021). Wang et al. (2021) presented a system that creates personas automatically, including 3D avatars, and automatically simulates different environmental factors to simulate the user experience of different personas using virtual reality and a head-mounted display. Maruhn et al. (2023) have introduced a VR persona system that allows designers to experience the home of personas from the standpoint of an insurance company and experience a recorded interview with the avatars of personas in a virtual reality environment.

Game interactions

Six (6) articles were developed to create dynamic personas through video game environments (Alvarez et al., 2022; Barthet et al., 2022; Fernandes et al., 2021; Holmgård et al., 2019; Mugrai et al., 2019; Murali et al., 2022). Murali et al. (2022) developed a virtual agent persona in Unity to help train the healthcare workforce to address the concerns of anti-vaccine people. The other articles focused on enhancing game development through automated playtesting, content generation, and designer modeling. The concept of automated playtesting, as discussed by Barthet et al. (2022), Holmgård et al. (2019), and Mugrai et al. (2019), relies on procedural personas. These personas are AI agents engineered to simulate various player types.

Fernandes et al. (2021) presented a system that uses player personas to customize procedurally generated game content. Designers can interact with this system by defining persona attributes, and the game generates content tailored to the play preferences of different player personas. Alvarez et al. (2022) took a unique approach by modeling game designers themselves. This system creates “designer personas” based on the styles and patterns observed in game designs.

Mobile applications

One study (Aragon Bartsch et al., 2022) presents a mobile application sending scheduled chat messages from personas throughout the day in order to familiarize the students with career guidance by helping them experience daily life events of their future career.

Chatbots & voice interfaces

Personas are being utilized in a bidirectional manner with Conversational Interfaces: they are used to give personality to chatbots and voice interfaces (Alazraki et al., 2021; Navarro Sainz & Prabhakar, 2022; Rinott & Shaer, 2024; Zhao et al., 2024), while simultaneously, these same conversational interfaces are proposed to interact with personas during processes such as design (Vandenbergh, 2017). Alazraki et al. (2021) created a set of empathetic personas with different age groups and connected that is backed by a dataset of verbal emotions to deliver as a self-attachment therapy coach. Navarro Sainz and Prabhakar (2022) created user personas and crafted three system personas to deliver stress care through voice-based interactions.

TECHNOLOGY READINESS LEVEL

The analysis of articles indicated different levels of maturity across different studies. Figure 6 presents the chronological representation of articles and their maturity. In Figure 7, the maturity level and the distribution of articles are visualized. The assessment of systems indicates that the majority of persona systems in the primary studies fall within the low to medium maturity range, as the interactive personas are not validated or are at a preliminary validation stage. Only three systems with high maturity levels have been identified in the literature. This distribution implies the notable need and opportunities for further research about interactive persona systems. One explanation could be that

the emergence of new technologies for interaction with data, including LLMs and virtual reality, opened new directions for persona-based systems.

In the following paragraphs, the details about these systems at the assessment of their maturity are discussed:

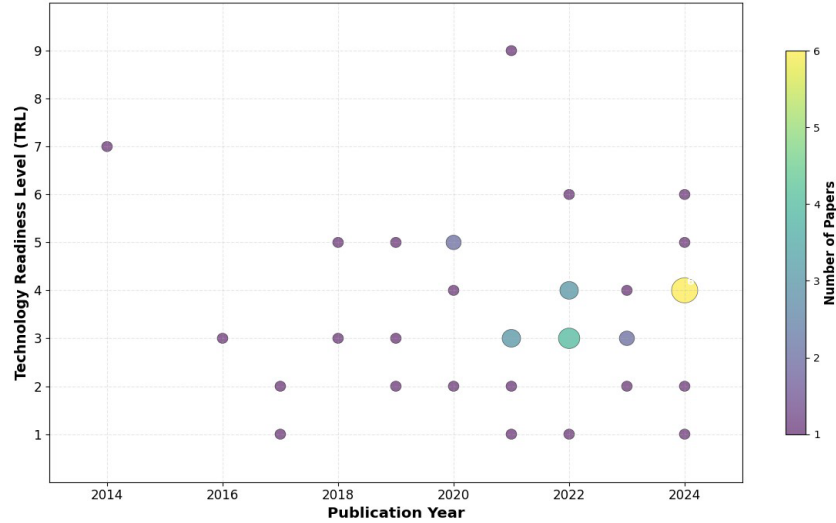


Figure 6. Maturity of Interactive Persona Systems

Fully operational maturity (TRL 9)

One system demonstrates the highest level of maturity. A fully operational interactive persona system with mouse-tracking capabilities achieved TRL 9. The system was used to create a tourism solution, and the persona-creation method was validated in a previous study. The system was then upgraded to incorporate functionality for tracking interactions with personas to analyze the behavior of persona users and even facilitate the creation of personas for persona users (Jung et al., 2021).

High maturity (TRL 6-8)

Three (3) systems show high maturity, as they have been used in real-world scenarios, including an e-government service framework at TRL 7 (Porter et al., 2014), a system for generating personas from survey data (Salminen, Jansen, & Jung, 2022), and a system for awareness and simulating LGBTQIA+ advocacy (Pillis et al., 2024) found to be matured at level 6.

Medium maturity (TRL 4-5)

Sixteen (16) systems fall in this range (An et al., 2018; Aragon Bartsch et al., 2022; Benharrak et al., 2024; Bonnardel & Pichot, 2020; Bouzekri et al., 2024; Ha et al., 2024; Hsu et al., 2024; Markel et al., 2023; Mugrai et al., 2019; Murali et al., 2022; Salminen, Vahlo, et al., 2020; Zhao et al., 2024). It includes applications such as generating personas from social media data (An et al., 2018), automated playtesting (Mugrai et al., 2019), predictive personas for marketing (Hsu et al., 2024), customizable AI personas (Ha et al., 2024), writing assistance (Benharrak et al., 2024), career guidance (Aragon Bartsch et al., 2022), game design (Salminen, Vahlo, et al., 2020), pilot opinion simulation (Bouzekri et al., 2024), counselor training (Murali et al., 2022), education (Markel et al., 2023), knowledge support (Zhao et al., 2024), and virtual dynamic personas for collaborative creativity (Bonnardel & Pichot, 2020). These studies have developed a solution, and the usefulness of the interactive personas is validated at a limited scale in a lab setting or in a context relevant to the operational goals.

Experimental maturity (TRL 3)

Twelve (12) systems are at the proof-of-concept stage (Alazraki et al., 2021; Alvertis et al., 2016; Az-zopardi et al., 2022; Barthet et al., 2022; Fernandes et al., 2021; Holmgård et al., 2019; Jung et al.,

2018; Maruhn et al., 2023; Navarro Sainz & Prabhakar, 2022; J. Park & Choi, 2023; J. S. Park et al., 2022; Wang et al., 2021. These experimental solutions probed diverse areas of interaction with personas including voice interfaces for stress care (Navarro Sainz & Prabhakar, 2022), VR-enabled requirements engineering (Wang et al., 2021), digital psychotherapy (Alazraki et al., 2021), game design, game content generation (Fernandes et al., 2021), automated playtesting (Holmgård et al., 2019), VR personas for user understanding (Maruhn et al., 2023), automatic persona generation (Jung et al., 2018), generative personas for game testing (Barthet et al., 2022), configurable LLM-generated audiences (J. Park & Choi, 2023), evaluation of online personal data revelations (Azzopardi et al., 2022), social simulacra for prototyping (J. S. Park et al., 2022), and crowdsourced personas in software development (Alvertis et al., 2016).

Low maturity (TRL 1-2)

Ten (10) systems are at the early research stages (Alvarez et al., 2022; Andriella et al., 2019; Bell, 2017; Kikuchi & Takahashi, 2021; Matias et al., 2024; Noufi et al., 2023; Rea & Young, 2020; Rinott & Shaer, 2024; Vandenberghe, 2017). These works formulated the fundamental theories for using personas and navigated design concepts for engaging with personas, including for discovering new directions for research. A thought experiment was employed to establish the idea of bot personas (Vandenberghe, 2017), AI collaborations in the workspace using personas were discussed (Rinott & Shaer, 2024), and persona design through social simulation for marketing (Kikuchi & Takahashi, 2021). In addition, game designer persona utilization (Alvarez et al., 2022), human robot interactions (Alvarez et al., 2022; Andriella et al., 2019; Rea & Young, 2020), and creation of dynamic updating personas for including user behavior change were discussed and conceptualized in the literature (Matias et al., 2024). Composing a design fiction was a distinctive approach in the study, which conceptualized a data marketplace platform, PersonaMX, for the online creation of dynamic digital personas based on data purchased from real users (Bell, 2017).

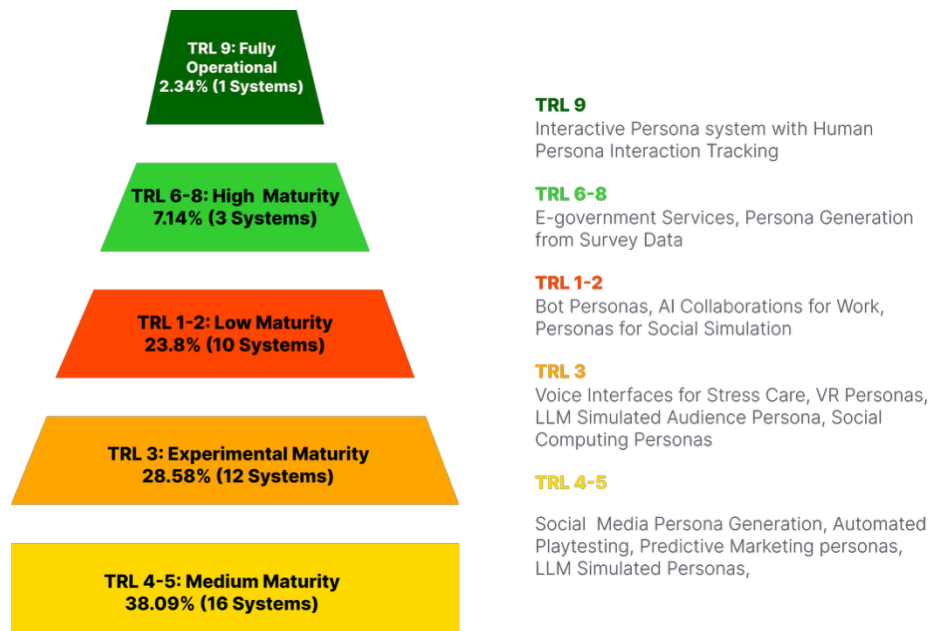


Figure 7. TRL of Interactive Persona Systems in the Literature

DISCUSSION

This systematic literature review provides the first comprehensive mapping of interactive persona systems, revealing how personas have transformed from static design artifacts into dynamic, AI-driven interactive systems. Our analysis of 42 studies spanning a decade (2014-2024) addresses each

research question while uncovering critical gaps and opportunities in this emerging field. Each system type directly addresses a limitation in prior research: Behavioral Simulation tackles static representation, Persona Management addresses data silos, Autonomous Personas reduce manual creation costs, and Interface Personas close the gap between personas as artifacts and personas as active system components. The results reveal that interactive persona systems have evolved into distinct architectures, each serving different goals and interaction models. This consolidates the trajectories identified in prior reviews — the human-persona interaction and automation trends flagged by Salminen, Guan, et al. (2021) have matured into recognizable system types, and the domain breadth documented by Salminen, Guan, et al. (2022) and Karolita et al. (2023) now has a system-level structure to explain it. The TRL analysis adds dimension prior reviews were not positioned to surface — despite a decade of development, 91.4% of systems remain below high maturity, identifying validation not as a peripheral concern but as the central challenge shaping the field’s next phase. The following sections discuss what these findings mean for theory, practice, and research — organized by each research question and the contributions they surface.

PERSONA CREATION METHODS AND DATA FOUNDATIONS (RQ1)

The evolution of persona creation methods reflects a clear shift towards data-driven and automated approaches (An et al., 2018), and the data collection tools, such as surveys (Salminen, Vahlo, et al., 2020), facilitated automating the process of data collection.

However, A notable absence in the reviewed corpus is the treatment of cultural identity as a persona attribute. As shown in Table 6, this dimension is underexplored in the literature, despite evidence that cultural context meaningfully shapes user mental models and interaction expectations (Lachner et al., 2015). This represents an underexplored dimension of persona systems, particularly relevant for global deployments.

Table 6. Persona Attributes

Attribute Category	Examples	Primary Studies
Demography	Age, gender, name, ethnicity, education, marital status, household composition, birthday, population	P1, P5, P6, P10, P13, P15, P16, P18, P21, P22, P27, P31, P33, P37, P41, P42
Behavior	Buying behavior, traveling patterns, TV watching, commenting behavior, walking speed, activity patterns, game behavior	P4, P9, P24, P31, P34, P37, P38, P41
Psychological	Emotional intensity, empathy, anxiety levels, risk preferences, personality traits, mindset, characteristics	P11, P15, P19, P20, P27, P39
Cognitive	Memory, attention, knowledge, decision-making style, state recognition, perception, time perceptions, reactivity	P7, P29, P36, P37, P38, P40, P42
Physical/Appearance	Pictures, images, voice, appearance, skin tone, clothing preferences, visual representation, 2D avatars	P1, P6, P10, P11, P14, P15, P18, P19, P23, P29, P36, P37, P40
Temporal/Activity	Hours of activity, temporal aspects, sport time, work time, daily activity patterns, timelines	P14, P22, P32, P38, P41
Social/Interaction	Social activities, communication tendency, social media posts, dialogue patterns, social relationships, trust	P21, P23, P36, P38, P39, P40

Attribute Category	Examples	Primary Studies
Technology-Related	AI behavior, level of control with system, technology readiness, algorithm capabilities, aviation technology	P7, P14, P26, P32, P33, P35, P36, P38, P40
Contextual	Background, living space, workplace roles, physical context, environment, seat preferences	P14, P27, P28, P33, P36, P39, P40
Goal/Motivation	Career goals, designer goals, interests, hobbies, challenges, requirements, motivations, frustrations	P10, P14, P25, P26, P30, P37, P41, P42
Gaming-Specific	Playing style, playing strategy, game designer goals, designing strategies, emotional intensity in gaming	P8, P9, P17, P20, P25
Work/Professional	Job roles, work experience, career goals, publications, resume, leadership skills, aircraft familiarity, safety focus, occupation	P10, P22, P24, P26, P33, P37, P39, P41
Financial/Economic	Financial status, cash flow, asset balance, stock data, risk preference, investment types, purchase intention	P16, P34
Accessibility	Vision issues, hearing impairments, accessibility barriers, physical issues, special conditions	P7, P14, P42
Not Specified/General	Potential benefits discussed, aggregated attributes, cosmetic attributes, attributes not explicitly defined	P2, P3

Interestingly, reliance on LLM knowledge, as discussed in previous studies (Salminen et al., 2024), emerged in the reviewed literature (Benharrak et al., 2024; J. S. Park et al., 2022). In some studies, the researcher defined the persona, and AI generated it for the researcher’s goal, as discussed in previous studies (Dubiel et al., 2024). This blend of human expertise and AI capabilities suggests a promising direction for improving the efficiency of persona use in software engineering.

While this approach can reduce persona-creation costs and enhance flexibility and efficiency by allowing designers to rapidly explore various scenarios, it requires further investigation. The validity and representativeness of these AI-generated personas require careful investigation and validation. In addition, the disparity between the time of the training data and changes in the real-world state needs to be validated and augmented with human input.

Although the crowdsourcing approach is discussed in only one study (Alvertis et al., 2016), considering the broader landscape of persona science, this approach provides a valuable foundation for capturing diverse user needs and expanding the data scope, and it can be especially useful for potential uses of personas in domains such as social good that impact a wide range of people. This method can potentially aggregate the information about a large population into a smaller number of personas. By aggregating individual attributes in smaller groups of fabricated people, this approach represents people in information systems without sacrificing their privacy.

The patterns observed across the corpus reveal a recurring tension in persona development. Systems with the strongest empirical grounding — such as those built on large-scale surveys (Salminen, Vahlo, et al., 2020) or thousands of face-to-face interviews (Maruhn et al., 2023) — required substantial resources to assemble. In contrast, LLM-based systems that reduced creation cost introduced representativeness concerns noted by the primary authors themselves (Bouzekri et al., 2024; Salminen, Jansen, & Jung, 2022). No single system in the corpus simultaneously achieved strong empirical grounding, broad representativeness, and low creation cost — pointing to a fundamental trade-off between these three properties that future research in persona creation, particularly with generative AI, will need to navigate.

DOMAIN APPLICATIONS (RQ2)

Interactive personas are creating new opportunities for presenting information to development teams (J. Liu et al., 2022), automating usability testing (Holmgård et al., 2019), and enabling new experiments through behavior simulation (Godwin et al., 2024). Moreover, interactive personas are creating new opportunities to advance computing for social good, such as reducing tension around vaccination (Matias et al., 2024), training (Markel et al., 2023), and promoting awareness to protect vulnerable communities (Pillis et al., 2024). The broadening scope of persona use highlights their potential to address complex challenges and information needs across various sectors, especially when dealing with nuanced levels of diversity for representing human aspects in computing systems.

INTERACTION MECHANISMS (RQ3)

While the majority of systems deliver interaction via web applications, the landscape of human-persona interaction is moving toward a more interactive, diverse, and immersive future. While interactive persona systems designed to make aggregated user data more interpretable are becoming more sophisticated, emerging technologies, particularly VR (Maruhn et al., 2023) and LLMs (Ha et al., 2024), opened a whole new world of possibilities for developing interactive persona systems and created new use cases and directions for using personas, and indicates growing areas of research in persona science. Moreover, the literature discusses interaction with personas not just for user need-finding but also for integration into systems to deliver human-like behavior for AI, opening new avenues for human-AI collaboration (Benharraq et al., 2024). Personas are not just design artifacts; they are designed to define the behavior of AI systems, especially in agent-based systems.

TECHNOLOGY MATURITY (RQ4)

The analysis of the Technology Readiness Level (TRL) of persona systems across the primary studies reveals that the field is still in its developmental stages, with only 7.14% of systems achieving high maturity (TRL 6-8). This maturity gap presents both challenges and opportunities for advancing the field toward more robust, validated implementations.

A PRACTITIONER'S TOOLKIT FOR INTERACTIVE PERSONA SYSTEMS

It is now clear that there are underexplored areas in this domain that can be investigated through novel research approaches. Based on systematic mapping of this design space, we developed a Practitioner's Toolkit for building interactive persona systems. These design guidelines aim to guide researchers and practitioners who either seek to invest in the human dimension of information technology solutions, want to utilize this novel development to study users, or aim to build systems that behave like humans. An educator could deploy LLM-powered simulated students with distinct learning profiles, allowing trainee teachers to practice classroom management in a safe, repeatable environment (Markel et al., 2023). In communication training, a configurable simulated audience ranging from supportive to hostile enables deliberate presentation practice without coordinating live participants (J. Park & Choi, 2023). In cybersecurity education, learners can step into the social media footprints of personas with varying risk profiles to evaluate the consequences of online behavior (Az-zopardi et al., 2022). In each case, Figure 8 serves as a decision map for identifying the appropriate system type and scoping a feasible implementation. To further operationalize this framework, Table 7 presents the toolkit's decision matrix mapping each system type to key project constraints, including data availability and validation requirements, to guide researchers and practitioners in selecting the most appropriate system type for their deployment context.

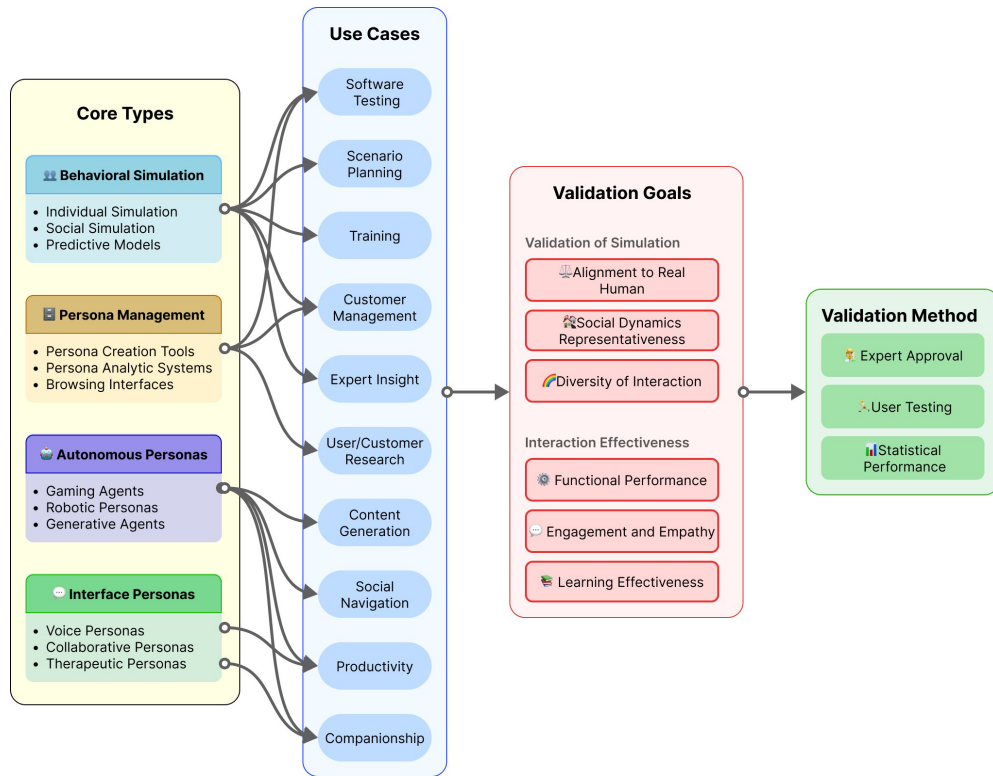


Figure 8. Design Framework for Interactive Persona Systems

The first step in building a persona system is understanding its core goal, as illustrated in Figure 8. Behavioral Simulation, Autonomous Personas, Interface Personas, and Persona Management Systems are core systems, as described:

Table 7. Decision Matrix for Selecting an Interactive Persona System

Constraint	Behavioral Simulation	Persona Management	Autonomous Personas	Interface Personas
Data Availability	Large empirical dataset required	Moderate — survey or API data	Low — LLM knowledge sufficient	Low to moderate
Validation Requirements	must align with real users	population coverage	Bias and fidelity testing	interaction quality
Primary Use Case	User/customer research, scenario planning, Social Studies	UX research, persona lifecycle management	Game testing, teacher training, simulation	Productivity, therapy
Recommended When	You need predictive or population-level insight	You need to organize and analyze existing personas	You need autonomous agents acting on behalf of users	Enhancing Human -AI Interaction, and Bridging Human-AI Alignment

Behavioral simulation personas

These systems replicate human behavior patterns for research and analysis purposes, enabling software testing, scenario planning, and user/customer research. Three main implementation approaches emerge:

Individual Simulation systems that model specific user behaviors, such as the predictive personas for target marketing (Hsu et al., 2024) that forecast individual purchase intentions, or the pilot opinion simulation system (Bouzekri et al., 2024) that replicates cognitive responses of aviation professionals to automation systems.

Social Simulation systems deliver Large-scale behavioral modeling, and support scenario planning and social navigation applications. The social simulacra system (J. S. Park et al., 2022) demonstrates this capability by generating 1,000 personas to simulate Reddit community behavior for scenario planning of design research of social computing systems. These population-level behavioral modeling efforts parallel a longer tradition of agent-based modeling in computational social science, where synthetic agents have been used to study emergent social phenomena (Axelrod, 1997; Epstein & Axtell, 1996), situating interactive persona systems within a broader lineage of computational approaches to simulating human behavior.

Predictive Persona systems enable scenario-based customer management by combining historical data with forecasting capabilities, using data augmentation (Kikuchi & Takahashi, 2021) that accounts for inflation and economic changes, enabling personas to respond to future market scenarios rather than relying solely on historical patterns.

Persona management systems

These platforms provide tools for creating, organizing, and analyzing personas throughout their lifecycle. They primarily support user/customer research and expert insight generation: Persona Creation Tools facilitate the creation of personas by following an algorithmic approach that transforms survey data into interactive personas in real time for user/customer research with minimal user input (Salminen, Jansen, & Jung, 2022).

Persona Analytics Systems supports expert insight generation by tracking interaction patterns, such as the mouse-tracking persona system (Jung et al., 2021) that analyzes how users engage with persona profiles and enables meta-analysis of persona usage patterns for research optimization.

Browsing Interfaces facilitates user/customer exploration by building empathy and providing insights, such as helping users see diverse end users and learn design recommendations for each one (Liu et al., 2022).

Autonomous personas

These systems utilize persona agents that can independently perform actions and make decisions, enabling software testing, content generation, and social navigation:

Gaming Agents can deliver software testing capabilities that play games autonomously (Holmgård et al., 2019; Mugrai et al., 2019) that simulate different player types in tile-matching and dungeon games for game balance testing.

Robotic Personas are AI agents that support social navigation by controlling physical or virtual robots, including the robot policy learning system (Andriella et al., 2019) that uses persona-behavior simulators to reduce patient fatigue during therapy sessions, and the teleoperation feedback system (Rea & Young, 2020).

Generative Agents are LLM-powered personas that enable real-time content generation and training applications that create content and respond dynamically, such as the configurable audience personas for public speaking practice (J. Park & Choi, 2023) and the GPT-based student personas for teacher training (Markel et al., 2023).

Interface personas

These systems integrate personas as core interface components that mediate user system interactions. Interface personas such as vocal personas primarily support productivity and become companions of their users:

Collaborative Personas are AI partners that enhance productivity in work environments, exemplified by the temporal collaboration system (Rinott & Shaer, 2024) that considers timing aspects of human-AI interactions, and the writer assistance system (Benharrak et al., 2024) that enables authors to define AI personas representing target readers for feedback generation during writing processes.

Voice Personas are at the heart of interaction in Voice-based user interfaces (Noufi et al., 2023) as they employ different system personas tailored to user types.

Therapeutic Personas are specialized interface personas for healthcare and social contexts with distinct personalities, to deliver therapeutic goals such as the stress care voice interface (Navarro Sainz & Prabhakar, 2022).

Data foundation

Successful interactive persona systems require carefully considered data sources. High-maturity systems, such as the tourism persona analytics platform (Jung et al., 2021), demonstrate the importance of combining multiple data streams, including behavioral analytics, demographic information, and interaction patterns. For LLM-based systems, validation against real human responses is crucial, as shown in the pilot simulation study (Bouzekri et al., 2024).

Validation strategy

Among the studies that conducted validation, researchers pursued two main goals of validation of simulation and validation of interaction effectiveness.

Among the 20 studies that conducted any form of validation, only 6 addressed the alignment between simulated personas and real users — through approaches such as expert evaluation of behavioral accuracy (Bubna et al., 2020) and statistical comparison of persona-generated outputs against real human responses (Bouzekri et al., 2024; Godwin et al., 2024). The remaining 14 focused on interaction effectiveness or task performance outcomes. This distribution points to a critical gap: persona simulation validation cannot be achieved solely through conventional usability studies, as these evaluate how well users engage with a system but leave the deeper question of behavioral authenticity unexamined. Persona simulation requires dedicated methods for studying the alignment between simulated personas and real users, examining their social interactions and behavioral fidelity — a methodological challenge that the field has yet to systematically address

Interaction Effectiveness Validation evaluates how well users can engage with interactive persona systems to achieve intended outcomes. Interaction Quality validation assessed conversation effectiveness and user engagement, demonstrated by the customizable LLM persona system (Ha et al., 2024) that measured conversation diversity scores, response relevance ratings. The LGBTQIA+ advocacy training system (Pillis et al., 2024) similarly evaluated social interaction quality and the development of empathy. Learning Effectiveness validation assessed educational outcomes in training applications, as shown in the teacher training platform (Markel et al., 2023) and the career guidance system (Aragon Bartsch et al., 2022), using pre-/post-assessments and longitudinal performance tracking. Task Performance validation measured functional effectiveness through completion rates and user productivity improvements (Benharrak et al., 2024).

These unique aspects of interaction with personas suggest that persona simulation could develop into a distinct area of inquiry that draws on multiple disciplinary traditions. The unique methodological requirements of this area present a dual challenge: validating both technical functionality and behavioral authenticity. Additionally, there is a growing need for specialized theoretical frameworks that

connect computational modeling with the representation of human behavior, pointing to opportunities for dedicated research investment that future work should explore.

IMPLICATIONS

In this section, we discuss theoretical, practical, and methodological implications:

THEORETICAL IMPLICATIONS

The patterns observed across the 42 reviewed studies suggest that persona simulation may be consolidating into a distinct area of inquiry within human-centered computing, capitalizing on its interdisciplinary nature. While HCI researchers have long embraced cross-disciplinary approaches, the unique methodological requirements—validating both technical functionality and behavioral authenticity—necessitate specialized theoretical frameworks to simulate personas, effectively bridging computational modeling and human behavior representation. Integrating personas into HCI studies can enhance the analytical depth of research and yield new insights, as these simulations (Godwin et al., 2024) provide access to diverse human perspectives that may be difficult to engage with consistently in real time. This approach represents a novel method for user experience researchers, enabling more dynamic and inclusive explorations of user interactions.

A primary theoretical contribution of this review is extending the scope of Human-AI alignment to address these methodological requirements. Traditionally viewed as a unidirectional process focused on task execution and preventing negative side effects (Shen et al., 2025), we propose that alignment should also encompass representational alignment. Rather than merely performing tasks for a user, AI in this paradigm should authentically simulate a user’s cognitive, emotional, and behavioral models through continuous, evolving engagement (Shen et al., 2025). This extension broadens the ethical landscape of human-centered computing. As personas become more autonomous and lifelike, theoretical frameworks will need to address new questions of agency, trust, and moral responsibility. For instance, measuring the disparity between persona simulations and stereotypes requires robust metrics to evaluate how closely simulations align with authentic human populations rather than perpetuating oversimplified or biased representations. We propose that TRL maturity in persona systems should be understood as alignment-dependent. A system cannot meaningfully progress beyond early developmental stages without demonstrating representational fidelity to real human behavior. We therefore call on researchers deploying LLMs in persona systems to treat Human-AI Alignment not as a parallel evaluation concern but as a precondition for claiming system maturity — and to incorporate alignment validation explicitly into their TRL assessments.

PRACTICAL IMPLICATIONS FOR PRACTITIONERS

Personas for human AI collaboration

Personas are being used in two directions within human-AI collaboration: (a) To give personality and context to AI systems, making them more relatable and understandable to human users; (b) To represent human users or user types to AI systems, allowing for more tailored responses. By using personas to represent human users, AI systems can be designed to better understand and respond to different user types, needs, and contexts. This humanization role is evident in studies like Rinott and Shaer’s (2024) work on temporal aspects of human-AI collaborations. Personas are being used to humanize AI systems’ interactions. This is seen in voice user interfaces for stress care (Navarro Sainz & Prabhakar, 2022), empathetic AI coaches (Alazraki et al., 2021), and intelligent knowledge agents (Zhao et al., 2024) where personas help create more engaging and productive interactions. As discussed in the analysis, these new avenues of research are at an early stage of maturity, and there could be an unprecedented potential in this domain. One major emerging direction is the exploration of personas as a fundamental bridge for human-AI cognitive alignment. While current work uses personas to either humanize AI or represent users, future research could investigate how a pool of personas might serve as a shared cognitive framework between humans and AI systems.

Educational personas

Educational personas simulate human behavior to develop educational systems (J. Park & Choi, 2023) and enhance training in contexts such as public speaking and teacher training (Markel et al., 2023). Azzopardi et al. (2022) employed personas to create educational material for privacy decision awareness.

The application of personas in education offers a powerful tool for creating immersive and personalized learning experiences. Personas enable educators and instructional designers to develop scenarios that simulate real-world interactions, allowing learners to practice and refine their skills in controlled environments.

While our review identified separate advances in educational personas and gaming personas, we explored the integration of LLM-driven personas in educational game systems. This integration can create more intelligent, human-like non-player characters, thereby increasing training opportunities.

Furthermore, educational personas can represent diverse student profiles, enabling the creation of adaptive and inclusive learning systems for different learning goals and needs, but employing these novel systems requires conducting research to define rigorous persona frameworks for educational and pedagogical objectives.

Interface integration

The emergence of LLMs has created opportunities for proactive integration of personas in interactive systems, where personas are not just guiding interface design but becoming integrated components of the systems themselves. By allowing users to create and customize their own personas as system inputs, designers can enhance user productivity (Benharrak et al., 2024; J. Park & Choi, 2023), representing a promising future direction for Computer-Supported Cooperative Work. This innovation opens up a new research area: exploring the potential of personas as user interface components. Future studies could focus on designing effective interfaces for presenting and interacting with these personas across various systems, aiming to further enhance user productivity through personalized AI collaboration.

Living personas

Immersive environments such as virtual reality enhance user studies, as designers can experience users' needs and pain points by living their experience through this medium (Wang et al., 2021). Exploring machine learning aspects for delivering simulated user experiences in immersive environments can be a new area of research. The convergence of AI and virtual reality can bring an unprecedented level of empathy-building in user experience design. Future research could develop systems that enable designers to experience software across various workspaces alongside users with different physical and mental abilities through virtual reality, thereby enhancing the accessibility and inclusivity of information technology systems. This immersive approach can significantly advance the understanding of diverse user needs by creating virtual environments that represent personas with different cultural backgrounds (Lachner et al., 2015) and disabilities (Schulz & Skeide Fuglerud, 2012). Architecturally, Asadi (2021) offers a concrete realization of this direction, proposing modular Cognitive Digital Twin systems that continuously convert user activity into reusable knowledge objects, pointing toward a future where interactive persona systems maintain persistent, self-updating user models.

Dynamic and predictive personas

While personas used to rely on retrospective data, the emerging area of research is developing updated dynamic personas (Matias et al., 2024), which can react to future events (Kikuchi & Takahashi, 2021), and predict the future behavior of target demography (Hsu et al., 2024). This approach not only enhances the relevancy of personas over time but also provides invaluable insights for strategic planning and product development. Furthermore, integrating predictive analytics enables organizations to anticipate user needs and behaviors. It can potentially revolutionize how products and services are conceptualized and delivered. While no one can accurately predict the future, these methods

require a novel validation approach that assesses the importance, soundness, and relevance of personas.

Datasets for addressing simulation shortness

Systematically identifying gaps in persona simulation can lay the groundwork for developing data-collection strategies that augment simulations with real-world evidence. Precise data collection and the development of public datasets for simulation could transform how researchers gather and use empirical evidence for persona creation, maximize representativeness, and maintain cost-effectiveness.

METHODOLOGICAL IMPLICATIONS

Gaming environments as data collection tools

Another notable development is the use of user interaction data for creating personas, particularly in gaming contexts (Mugrai et al., 2019). Unlike traditional methods that rely on self-reported data from interviews or surveys, capturing actual player behaviors and decisions during gameplay is an interesting and novel way to create personas. While it is similar to social media interaction data (An et al., 2018) in its merits of collecting data without leading subjects toward an attitude, as well as providing opportunities for real-time data collection, player interaction data offers deeper and richer insights into user decision-making processes. Where social media data might show preferences, gaming data captures how users solve problems, plan, and react to changing scenarios in a controlled environment. Generating personas based on player interactions opens up new possibilities for moving toward dynamic behavior-based personas. Moreover, this methodological innovation could transform both persona creation practices and behavioral research methodologies across domains, as it reveals how the gaming environment can be used as a data-collection tool.

AI-mediated human representation

Personas that behave like users have been employed to test games in different scenarios (Fernandes et al., 2021; Holmgård et al., 2019; Mugrai et al., 2019), and the emergence of LLM-powered personas introduces a distinct methodological challenge: using AI systems trained on human-generated content to represent human behavior. LLM simulation fidelity has been shown to be conditional on the strength of persona variable grounding which means representational accuracy must be demonstrated empirically rather than assumed (Argyle et al., 2023; Dillion et al., 2023; Hu & Collier, 2024). This creates unique considerations:

- **Representational Validity.** Unlike traditional AI applications, where accuracy is measured against objective outcomes, AI-generated personas must be validated against subjective human experience and cultural authenticity. Empirical work supports this concern:

Bias amplification and ethical challenges

Recent literature on large language models (LLMs) has documented a significant risk: these models often perpetuate and amplify harmful social biases related to demographics such as gender, ethnicity, and socioeconomic class (Gallegos et al., 2024). In particular, “persona-steered generation” tends to reveal deep-seated stereotypical biases, as models frequently default to stereotypical views instead of accurately reflecting the characteristics associated with assigned personas (A. Liu et al., 2024). This underscores the need to incorporate bias auditing into any persona-validation framework.

- **Dynamic Authenticity:** AI personas must remain behaviorally consistent while adjusting to new contexts—this is a challenge unique to human-like adaptability. It involves maintaining authenticity in human behavior.

Privacy-preserving social research

Persona creation anonymizes connections to smaller target audiences without revealing individual identities (Alvertis et al., 2016; Vandenberghe, 2017). When personas are created to represent social

dynamics of a society (J. S. Park et al., 2022), researchers interact with data rather than directly with people (Alvertis et al., 2016). This methodological approach allows for the exploration of user needs and behaviors while maintaining privacy and ethical considerations.

This approach extends the scope of using personas in serving social good by creating opportunities to address complex societal issues without compromising individual privacy. By leveraging these anonymized models, researchers and policymakers can gain valuable insights into community dynamics, social trends, and potential interventions while safeguarding the identities of the individuals they represent.

Persona validation as a methodological research gap

The effectiveness of all discussed applications hinges on a critical missing component: validating persona simulation and interactivity. While usability studies have established robust methods for validating IT systems, persona simulation validation requires new measures. This challenge extends beyond interactive personas to the broader field of behavioral simulation, where J. S. Park et al. (2022) noted the difficulty of moving beyond subjective “believability” assessments to objective validation of human behavior replication.

Research urgently needs standardized frameworks to assess persona alignment with real users. The gap between simulated and actual human responses represents both a limitation and an opportunity to advance data-collection methodologies. With limited resources, researchers need validated approaches to extract precise behavioral insights from smaller datasets and determine which data types are most critical for creating authentic persona representations. Effective human-AI alignment requires a shift from viewing simulations as static outputs to understanding them as part of a dynamic, reciprocal process. As Amershi et al. (2019) established, the reliability of AI systems depends on adhering to interaction guidelines such as “mitigating social biases” and “learning from user behavior” to ensure the system remains consistent with human expectations. Persona researchers should consider adapting evaluation principles from AI literature, including structured approaches to documenting model behavior and limitations (Mitchell et al., 2019).

A RESEARCH ROADMAP FOR INTERACTIVE PERSONA SYSTEMS

The systematic mapping reveals that while interactive persona systems have immense potential, the field remains primarily in early developmental stages (TRL 1-5). To advance this domain into a rigorous engineering discipline with fully operational systems (TRL 8-9), we identify three research challenges that emerge:

1) Validating Behavioral Authenticity: Because 52% of current systems lack empirical validation, and standard usability studies only measure interface engagement, new validation paradigms are required. *How can we design standardized, empirical frameworks to objectively measure the behavioral authenticity and representational fidelity of AI-simulated personas against real-world populations?*

2) The Data-Cost-Fidelity Trilemma: There is a severe trade-off between the high resource cost of gathering large-scale empirical data and the hallucination risks of using low-cost LLMs. *What hybrid architectural models can optimally balance the high resource costs of empirical data collection with the adaptability of generative AI, without sacrificing representational fidelity?*

3) Mitigating Algorithmic Stereotyping: LLM-powered systems run a well-documented risk of defaulting to deep-seated stereotypes rather than accurately reflecting nuanced human characteristics. *To what extent can structured interaction constraints and continuous empirical grounding interventions mitigate demographic stereotyping and bias amplification in AI-generated personas?*

LIMITATIONS AND FUTURE WORK

As with any study, this research has limitations that should be acknowledged. To begin with, the initial screening was conducted by a single researcher rather than multiple independent reviewers. To

mitigate potential bias, we implemented a temporal separation strategy whereby the same researcher re-screened articles after an extended period to improve consistency. While this approach does not fully substitute for dual screening, it provides a practical balance between resource constraints and methodological rigor.

Furthermore, our focus on peer-reviewed HCI literature was intended to ensure quality and relevance to the field, though this excluded potentially valuable preprints from repositories like arXiv. This decision prioritized methodological rigor and the peer-review process over absolute comprehensiveness. Future work could incorporate a systematic approach to including high-quality preprints, perhaps by utilizing specific citation metrics. Additionally, this review is bounded to peer-reviewed academic literature; grey literature and technical reports from commercial AI laboratories — including OpenAI, Anthropic, and Google DeepMind — were excluded. As these organizations are active deployers of large-scale persona-based systems, a dedicated grey literature review would provide a more complete picture of how interactive persona systems are being developed and validated in commercial settings.

Regarding the scope of the corpus, the restriction to English-language publications reflects both practical constraints and the predominance of English in HCI literature; however, this may have excluded valuable perspectives from non-English-speaking research communities. Future work should adopt a multilingual search strategy incorporating regional repositories to capture persona systems research outside the Anglo-centric venues indexed here.

Lastly, while the ACM Digital Library and IEEE Xplore provide comprehensive coverage of core HCI venues, studies published exclusively in Springer, Elsevier, or Sage outlets may be underrepresented. To partially mitigate this risk, we employed a Google Scholar hand-search of the top 20 HCI publications and forward snowball sampling from four recognized SLRs. Future work should explore broader search strategies, including indexing databases such as Scopus or Web of Science, to extend data collection and further validate the comprehensiveness of the corpus.

CONCLUSION

Our systematic literature review provides one of the earliest comprehensive analyses of interactive persona systems, addressing the identified research gap in understanding how personas have evolved from static design artifacts into dynamic, interactive systems. Treating the system rather than the persona as the object of inquiry opens a research space that is still largely unmapped. The maturity gap, the validation deficit, and the four system archetypes are all visible only from that vantage point. Future work building on this framework has the opportunity to move persona research from descriptive taxonomy toward an engineering discipline with defined validation standards. The gap between technological capability and validated implementation is crucial as personas evolve from mere design artifacts into active participants in digital experiences, influencing healthcare decisions, educational outcomes, and social interactions. Their growing importance suggests the need for sustained attention to validation frameworks, ethical standards, and methodological rigor. The next decade will determine whether interactive personas fulfill their potential as bridges to human-centered AI or become another source of algorithmic bias and misrepresentation. The field stands at a pivotal moment where establishing robust validation methods is not just a research priority but an ethical imperative.

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APPENDIX A. THE LIST OF INCLUDED ARTICLES

ID	Title	Year	Context	Reference
P1	Building a National E-Service using Sentire experience report on the use of Sentire	2014	E-government service design	Porter et al., 2014
P2	Using Crowdsourced and Anonymized Personas in the Requirements Elicitation and Software Development Phases of Software Engineering	2016	Crowdsourced software requirements	Alvertis et al., 2016
P3	Bot Personas as Off-The-Shelf Users	2017	AI-based user simulation	Venberghes, 2017
P4	Exploring personal data futures trading with design fiction based hybrid simulation	2017	Data privacy and future scenarios	Bell, 2017
P5	Imaginary People Representing Real Numbers: Generating Personas from Online Social Media Data	2018	Social media-based persona generation	An et al., 2018
P6	Automatic Persona Generation (APG): A Rationale and Demonstration	2018	Automated persona creation	S.-g. Jung et al., 2018
P7	Learning Robot Policies Using a High-Level Abstraction Persona-Behaviour Simulator	2019	Robotics and AI behavior modeling	Andriella et al., 2019
P8	Automated Playtesting With Procedural Personas Through MCTS With Evolved Heuristics	2019	AI-driven game testing	Holmgård et al., 2019
P9	Automated Playtesting of Matching Tile Games	2019	AI game testing for specific genres	Mugrai et al., 2019
P10	Designing Prototype Player Personas from a Game Preference Survey	2020	Game design and player modeling	Salminen, Vahlo, et al., 2020
P11	Backseat teleoperator: affective feedback with on-screen agents to influence teleoperation	2020	Human-robot interaction	Rea & Young, 2020
P12	Enhancing collaborative creativity with virtual dynamic personas	2020	Creative process enhancement	Bonnardel & Pichot, 2020
P13	Persona Analytics: Implementing Mouse-Tracking for an Interactive Persona System	2021	User interaction analysis with personas	S.-G. Jung et al., 2021
P14	Virtual Reality Enabled Human-Centric Requirements Engineering	2021	VR in software engineering	Wang et al., 2021
P15	An Empathetic AI Coach for Self-Attachment Therapy	2021	Mental health AI applications	Alazraki et al., 2021
P16	Persona Design Method Based on Data Augmentation by Social Simulation	2021	Data-augmented persona creation	Kikuchi & Takahashi, 2021
P17	Adapting Procedural Content Generation to Player Personas Through Evolution	2021	Adaptive game design	Fernandes et al., 2021
P18	Survey2Persona: Rendering Survey Responses as Personas	2022	Data-driven persona creation	Salminen, Jansen, & Jung, 2022
P19	Caring through Conversations: Voice User Interfaces For Everyday Stress Care	2022	Health-focused conversational AI	Navarro Sainz & Prabhakar, 2022

ID	Title	Year	Context	Reference
P20	Generative Personas That Behave and Experience Like Humans	2022	AI-generated realistic personas	Barthet et al., 2022
P21	Training lay counselors with virtual agents to promote vaccination	2022	Healthcare training simulations	Murali et al., 2022
P22	A Day in the Life: Exploring the Use of Scheduled Mobile Chat Messages for Career Guidance	2022	Career counseling via mobile apps	Aragon Bartsch et al., 2022
P23	Are Taylor’s Posts Risky? Evaluating Cumulative Revelations in Online Personal Data	2022	Online privacy awareness	Azzopardi et al., 2022
P24	Social Simulacra: Creating Populated Prototypes for Social Computing Systems	2022	Social computing prototyping	J.S. Park et al., 2022
P25	Toward Designer Modeling Through Design Style Clustering	2022	AI-assisted design processes	Alvarez et al., 2022
P26	AudiLens: Configurable siAudiences for Public Speech Practice	2023	Public speaking training	J. Park & Choi, 2023
P27	GPTeach: Interactive TA Training with GPT-based Students	2023	AI-assisted teacher training	Markel et al., 2023
P28	Introducing VR personas: an immersive and easy-to-use tool for understanding users	2023	VR-based user research	Maruhn et al., 2023
P29	CloChat: Understanding How People Customize, Interact, and Experience Personas in Large Language Models	2024	LLM-based persona customization	Ha et al., 2024
P30	Writer-Defined AI Personas for On-Demand Feedback Generation	2024	AI writing assistance	Benharrak et al., 2024
P31	Modeling Users for User Modeling: Dynamic Personas for Improved Personalisation in Digital Behaviour Change	2024	Personalized behavior changes interventions	Matias et al., 2024
P32	Temporal Aspects of Human-AI Collaborations for Work	2024	Workplace AI integration	Rinott & Shaer, 2024
P33	ChatGPT, tell me more about pilots’ opinion on automation	2024	AI in aviation research	Bouzekri et al., 2024
P34	Creating and validating predictive personas for target marketing	2024	Marketing strategy and persona validation	Hsu et al., 2024
P35	To Split or Not to Split? Evaluating IA Roles Providing Knowledge and Emotional Support	2024	AI roles in emotional support	Zhao et al., 2024
P36	Putting a Face on Algorithms: Personas for Modeling Artificial Intelligence	2021	Persona agent design and modeling	Karahasanović et al., 2021
P37	Auto-Generated Personas: Enhancing User-centered Design Practices among University Students	2024	Automated persona Generation, and Curation System	Zhang et al., 2024
P38	Service design simulation using fine grained agents	2020	User experience simulation for service design	Bubna et al., 2020
P39	AI Comes Out of the Closet: Using AI-Generated Virtual Characters to Help Individuals Practice LGBTQIA+ Advocacy	2024	Awareness and Social Justice Advocacy	Pillis et al., 2024

ID	Title	Year	Context	Reference
P40	The Role of Vocal Persona in Natural and Synthesized Speech	2023	Vocal persona framework for synthesized voice	Noufi et al., 2023
P41	Advancing Privacy Research: A Novel Realistic Persona-Based Dataset	2024	Simulating human web-searching behaviors in privacy research	Godwin et al., 2024
P42	A Curated Personas and Design Guidelines Tool for Better Supporting Diverse End-users	2022	Prompting Accessibility	Liu et al., 2022

Appendix B. TOP 20 HCI PUBLICATIONS AT TIME OF DATA COLLECTION

Publication Title	Library
Computer Human Interaction (CHI)	ACM Library
Proceedings of the ACM on Human-Computer Interaction	ACM Library
Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies	ACM
IEEE Transactions on Affective Computing	IEEE
International Journal of Human-Computer Studies	Science Direct
Behaviour & Information Technology	Taylor & Francis
ACM/IEEE International Conference on Human Robot Interaction	ACM/IEEE
International Journal of Human-Computer Interaction	Taylor & Francis
Virtual Reality	SpringerLink
International Conference on Intelligent User Interfaces (IUI)	ACM
International Journal of Interactive Mobile Technologies	IAOE
Designing Interactive Systems Conference	ACM
ACM Symposium on User Interface Software and Technology	ACM
IEEE Virtual Reality Conference	IEEE
IEEE Transactions on Human-Machine Systems	IEEE
Universal Access in the Information Society	SpringerLink
ACM Transactions on Computer-Human Interaction (TOCHI)	ACM
HCI International	SpringerLink
International Journal of Child-Computer Interaction	Science Direct
Multimodal Technologies and Interaction	MDPI

APPENDIX C. CODING GUIDE

Variable	Definition	Coded Values	Source
System Type	The primary architectural role of the persona system	<i>Behavioral Simulation; Persona Management; Autonomous Personas; Interface Personas</i>	Derived from system description and use case in primary study
Creation Method	The approach used to generate or define personas	<i>Algorithm-based; Survey-based; Qualitative (interview/ diary); Expert-defined; Crowdsourcing; Predictive modeling; LLM-assisted; Secondary/ not discussed</i>	Methods section of primary study
Empirical Data Source	The type and scale of data used to build the persona	<i>Free text description of dataset, scale, and origin (e.g., social media API, survey respondents, play data, expert-defined, none/ conceptual)</i>	Data collection section of primary study
Interaction Type	The modality through which users interact with the persona system	<i>Web application; VR/ 3D environment; Voice user interface; Game-based; Robot/ physical agent; Mobile app; Chatbot; Not discussed</i>	System description in primary study
Use Case	The intended application or purpose of the persona system	<i>Free text (e.g., UX research, game testing, teacher training, marketing, therapy, social simulation)</i>	Introduction and contribution sections of primary study
Domain	The industry or research field in which the system is applied	<i>Game design; Education; Marketing; Health; Robotics; Social simulation; Cybersecurity; Career guidance; Aerospace; etc. (see Table 5)</i>	Context of primary study
Validation Goal	The specific outcome the authors sought to validate	<i>Human Alignment; Population Coverage; Representativeness; Social Dynamics; Persona Management; Interaction Quality; Learning Effectiveness; Task Performance; None</i>	Evaluation/results section of primary study
Validation Method	The procedure used to conduct validation	<i>Expert evaluation; User study (lab); Field study; Statistical performance metrics; Predictive accuracy testing; Field deployment</i>	Evaluation/results section of primary study
TRL Score	Technology Readiness Level — a nine-point scale assessing system maturity (Martinez Plumed et al., 2020)	<i>1 to 9</i>	Assessed by first author based on development stage, evaluation type

TRL	Deployment Context	Validation Method	User Population
1–2	Conceptual / design fiction	None	Not applicable
3	Lab prototype	Proof of concept	Researcher-defined
4–5	Controlled lab study	User study, limited scale	Small sample
6–7	Relevant operational context	Field study or real-world test	Target population

8–9	Deployed system	Longitudinal or real-world validation	Operational users
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AUTHORS



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