MatrAIx: Simulating the World with 8.3 Billion Persona Agents

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Abstract

Human evaluation of Artificial Intelligence (AI) systems and digital products is costly, slow, and difficult to scale. Offline evaluations are more scalable but often abstract away human diversity and interactive behavior. We therefore introduce *MatrAIx*, a population-scale simulated-user evaluation infrastructure for testing AI systems and digital products with heterogeneous users. MatrAIx has three core components: First, Persona 8B contains 8.3 billion persona records represented through a schema of 1,290 categorical dimensions. Records are either sampled from a dependency graph that preserves correlated attributes or derived from human-authored profiles. We release a quality-filtered coreset of approximately 1 million personas, comprising 599,847 human-grounded and 400,000 synthetic records. Second, the MatrAIx Playground provides four environments in which diverse users evaluate and interact with digital products: Survey, AI Chatbot, Web, and App. Third, MatrAIx provides 1,010 application tasks spanning more than 25 domains, including Commerce, Software, Finance, and Healthcare. We conducted 18,189 evaluation trials across eight representative tasks. Persona agents were powered by three large language models: Claude Opus 4.8, GPT 5.5, and Claude Haiku 4.5. The resulting feedback captures how decisions and preferences vary across persona backgrounds, including hesitation after a price increase, willingness to continue after an AI assistant fails, and latency tolerance. We conducted two main validation studies: First, a 400-trial controlled study evaluated persona adherence across ten behavioral attributes and all four environments. The declared behavior was expressed or correctly suppressed in 366 trials (91.5%). Second, human and large language model (LLM) judges evaluated the extraction quality of human-grounded personas. Overall, MatrAIx provides an end-to-end infrastructure for evaluating AI systems and digital products with diverse simulated human users.

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Code: https://github.com/MatrAIx-ai/MatrAIx-Persona-8B. Project website: https://matraix.ai.

1 Introduction

Human evaluation remains essential for understanding how AI systems and digital products perform for real users. However, its time and expense limit the breadth and frequency of studies during development. Offline benchmarks offer a scalable and reproducible alternative. However, they typically measure task outcomes without modeling how diverse users formulate requests, interact with a system (Chang et al., 2025), and judge its results (Santurkar et al., 2023; Kirk et al., 2024). For example, a coding-agent benchmark may test whether the trajectory passes all unit tests (Jimenez et al., 2024; Miserendino et al., 2025; Zan et al., 2025; Zhang et al., 2025). This establishes functional correctness, but it does not capture user needs or preferences. A novice may want explanations, small edits, and frequent confirmation. An expert may instead prefer terse responses, broader refactoring, and greater autonomy. Some users provide detailed specifications and inspect every change. Others begin with underspecified goals and expect the agent to ask clarifying questions. Such differences shape interaction trajectories, trust in the result, and willingness to continue after a failure. Offline capability benchmarks emphasize task completion (Zhou et al., 2024a; Yao et al., 2025; Xie et al., 2024b). They provide less evidence about how performance and experience vary across users (Chang et al., 2025). Aggregate scores can also hide problems encountered by particular user groups. The same limitation applies to any digital product whose outcome depends on how users interact with it, not only to AI systems.

Simulated-user evaluation can help bridge the gap between offline benchmarks and online evaluation. Persona-driven agents can interact with a system (Yoon et al., 2024), adapt their actions to its responses (Zhou et al., 2024b), and report outcomes from different user perspectives (Dou et al., 2025). This approach is increasingly practical because AI agents can now reason and plan (Liu et al., 2024; Mialon et al., 2024), browse the web (Zhou et al., 2024a), write code (Trivedi et al., 2024), call tools (Qin et al., 2024), and operate software (Xie et al., 2024b). User simulation offers several practical advantages. First, it reduces time and cost. Human studies may require weeks for recruitment, scheduling, and data collection, whereas parallel agent trials can return initial screening results within hours. Second, it supports controlled repetition. The same task, cohort, and configuration can be rerun after a system change to compare product versions. Third, it enables cohort-level analysis by holding the system and task fixed while comparing user groups. Fourth, it expands population coverage. A simulated-user pool can contain millions or billions of profiles, while each task runs only the cohort it needs (Ge et al., 2024; Yang et al., 2024; Piao et al., 2025). The approach does not require a perfect model of human behavior to be useful. Even an imperfect (Li et al., 2025a; Zhou et al., 2026) but diverse simulated population can expose corner cases, subgroup-specific friction, and failure modes before deployment (Dou et al., 2025). Putting simulated-user evaluation into practice requires two foundations: a structured persona population for sampling diverse cohorts (Zhang et al., 2018; Mazaré et al., 2018; Ge et al., 2024), and environments in which those personas can interact with systems (Park et al., 2023; Yang et al., 2024; Piao et al., 2025).

We introduce *MatrAIx*, a population-scale simulated-user evaluation infrastructure for testing AI systems and digital products with heterogeneous users. Its first core component, *Persona 8B*, represents human variation through a shared categorical schema. The schema contains 1,290 dimensions spanning background, psychology, capability, behavior, and lifestyle. Persona 8B contains 8.3 billion records built using two complementary approaches. Synthetic records are sampled from a dependency graph that combines source-informed distributions, cross-attribute correlations, and compatibility rules. For example, English-proficiency probabilities are adjusted using primary language and region, while a compatibility rule excludes a persona whose primary language is English but whose English proficiency is `None`. Human-grounded records draw from six sources: Wikipedia biographies, Amazon Reviews histories, the Stack Overflow Developer Survey, the General Social Survey (GSS), PRISM Alignment profiles, and consented MatrAIx Persona Survey responses. All are mapped into the same schema. Each populated attribute includes a natural-language description, so the result reads as a profile rather than a list of categorical values. To protect privacy, human-grounded records are de-identified by removing direct identifiers such as names and contact details while retaining only the extracted attributes and descriptions. Together, these complementary paths combine principles from synthetic-population modeling (Borysov et al., 2019; Chapuis et al., 2022) and grounded user profiling (Wang et al., 2025b). To support research use, we apply contradiction checks, deduplication, and calibration toward selected real-world demographic distributions. We then release a coreset of approximately 1 million personas, comprising 599,847 human-grounded and 400,000 synthetic records.*

The second core component is the *MatrAIx Playground*, an interactive interface for running simulated-user studies. It

*The public dataset and its card are available at https://huggingface.co/datasets/MatrAIx2026/MatrAIx_Persona_1M.

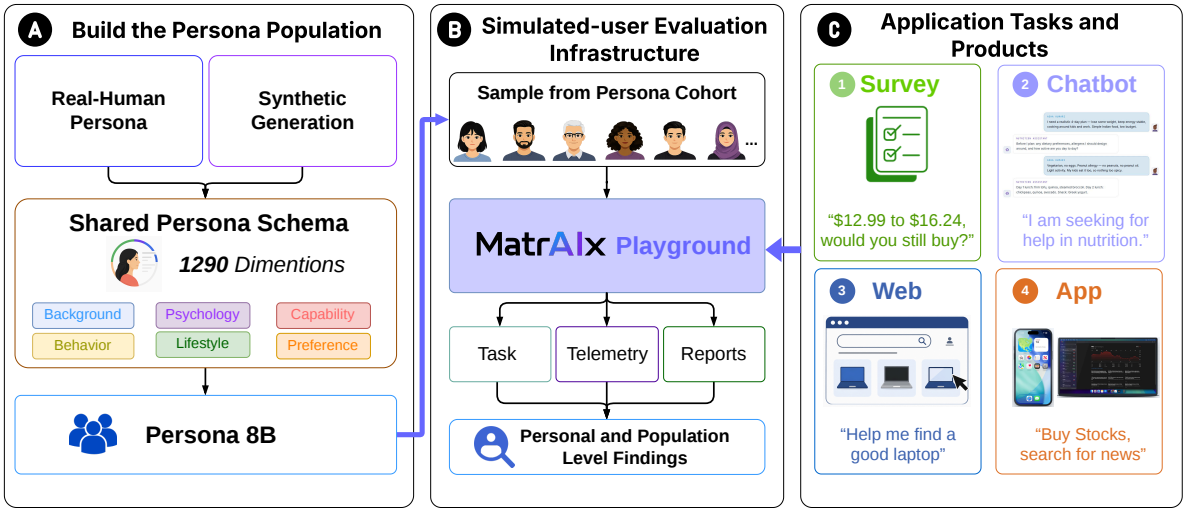


Figure 1: **Overview of the MatrAIx simulated-user evaluation framework.** Evaluators describe the target audience, and MatrAIx retrieves matching personas from Persona 8B to form an evaluation cohort. The four environments define how these persona agents interact, while MatrAIx Applications provides the task specifications they execute. Shared telemetry and task-owned verification preserve the evidence needed for subgroup and population-level reporting.

supports four types of environments: Survey, AI Chatbot, Web, and App. **Type I: Survey** asks persona agents to complete surveys and questionnaires for concept testing, market prediction, and price-sensitivity research. For example, one survey could ask how many consumers would still buy a six-pack of soda after a $2 price increase. **Type II: AI Chatbot** places persona agents in conversations with AI assistants or customer-support chatbots. For example, a study could test whether users continue a conversation after a chatbot gives a hallucinated answer and then corrects it. Another could measure how response latency affects satisfaction and willingness to continue. **Type III: Web** supports both browser automation and computer-use agents (CUAs) that browse websites. A study could ask shoppers with different needs and budgets to assess the recommendations and how easily they can find, compare, and select an option. **Type IV: App** uses CUAs as simulated users of native desktop and mobile applications. App tasks run in a Docker-based Linux desktop sandbox or through a remote macOS desktop or iOS simulator. For example, a study could test whether users can discover and use a feature, or find and change privacy and security settings. Across all four types, MatrAIx evaluates system behavior, feature usefulness, latency, user experience (UX), and privacy and security controls. It records what each persona agent thinks, says, and does, including task duration, completion status, and verifier results. These environments build on advances in task-oriented user simulation (Schatzmann et al., 2007), realistic web interaction (Zhou et al., 2024a; Koh et al., 2024), and multimodal computer use (Trivedi et al., 2024; Xie et al., 2024b).

The third component is *MatrAIx Applications*, a library of reusable tasks for evaluating AI systems and digital products. Each task specifies the target system or product, the persona cohort, and the scenario and user goal. It also defines the outcome measures and the verifier used to check each result. For example, a price-sensitivity task could present the same soda price increase to personas from different income and economic motivation groups. It would record whether they would still buy the product and why, then verify that each response includes both purchase intent and a rationale. The current MatrAIx Applications release contains 1,010 tasks: 621 Survey, 371 AI Chatbot, 12 Web, and 6 App. The library covers more than 25 domains, including Commerce, Software, Finance, and Healthcare. Each task defines a study that can be run with a selected persona cohort. The task count does not mean that all 1,010 studies have been executed. For this paper, we ran 18,189 evaluation trials across eight representative tasks. For each task, we report the persona cohort and model configuration. We also report trial-level verifier results and cohort-level analyses. Figure 1 shows how the three components form the end-to-end evaluation pipeline.

Together, these components form an operational end-to-end pipeline across all four environments. The pipeline connects population construction, cohort retrieval, persona-agent execution, task-owned verification, and population-level reporting. We evaluate three questions. Does the persona population preserve plausible distributions and dependen-

cies? Do agents follow their assigned personas in what they say and do? Do simulated-user studies reveal consistent differences across systems, models, and user groups? Our results show that the pipeline operates across all four environments. Assigned persona attributes are reflected in agent behavior at high rates, and application studies reveal differences across persona groups and user needs. These findings expose variation that aggregate scores alone can miss. We assess population coherence, persona adherence, and evaluation sensitivity separately because they capture distinct properties. This follows prior work that treats persona fidelity, behavioral consistency, population correspondence, and simulator-based system rankings as separate questions (Wang et al., 2024b; Li et al., 2025a; Dou et al., 2025; Wang et al., 2025a; Zhou et al., 2026). In addition, we conduct two validation studies. First, a 400-trial controlled study across ten behavioral attributes and all four environments finds that agents express or correctly suppress the assigned behavior in 366 trials (91.5%). Second, two LLM judges evaluate all 1,000 extracted personas, and six humans rate a source-matched subset of 100. The human mean is 4.135/5, and scores from GPT 5.5 and Claude Opus 4.8 are within one point of the human mean in 79.2% and 93.8% of comparisons, respectively.

Our main contributions are:

- **Population-scale 8.3B persona data.** Persona 8B contains 8.3 billion records under a shared 1,290-dimensional schema, with a curated coreset of one million personas released for research.
- **Complementary persona construction methods.** Synthetic records are sampled from source-informed distributions with explicit dependencies and compatibility rules. Human-grounded records map information from biographies, reviews, surveys, and consented self-reports into the same schema.
- **Four evaluation environments.** Survey, AI Chatbot, Web, and App support studies ranging from questionnaires and conversations to browser and native-application use. Each environment records persona-agent interactions, applies task-specific verifiers, and aggregates results into cohort-level reports.
- **1K tasks across 25+ domains.** MatrAIx Applications contains 1,010 reusable task specifications across more than 25 domains, including Commerce, Software, Finance, and Healthcare.
- **Validation of data, behavior, and task results.** We investigate population structure, extraction quality, persona adherence, and task outcomes.
- **End-to-end demonstrations at scale.** We demonstrate the complete pipeline through 18,189 trials across eight tasks and all four environments. A separate 400-trial controlled study finds that agents express or correctly suppress the assigned behavior in 91.5% of trials.

2 Related Work

Persona data and populations. Prior work represents personas as short dialogue-conditioning descriptions, structured profiles, persistent user states, or large synthetic collections. Some resources are crowd-authored (Zhang et al., 2018) or generated at scale (Mazaré et al., 2018; Ge et al., 2024). Others are grounded in population statistics (NVIDIA, 2025), reconstructed from documents (Park et al., 2025), or updated from interaction histories (Wang et al., 2025b; Jiang et al., 2025). Free-text profiles are flexible conditioning inputs, whereas typed schemas make missing values, contradictions, population queries, and sampling decisions easier to inspect. For a collection intended to represent a population, plausible individual profiles are not enough. The collection must also preserve relevant marginals, cross-attribute dependencies, and structural constraints. Synthetic-population research studies these questions in terms of marginal and joint fidelity (Borysov et al., 2019; Chapuis et al., 2022). Existing resources generally focus on constructing persona datasets or conditioning models. They do not cover the full evaluation process, from sampling a target population to running interactive tasks and analyzing the outcomes.

User simulation. Population- and persona-conditioned language models have been studied as survey respondents and task-oriented service users (Argyle et al., 2023; Sun et al., 2024; Park et al., 2024; Yoon et al., 2024; Schatzmann et al., 2007; Kreyssig et al., 2018; Gür et al., 2018). This approach supports controlled comparisons across user profiles and can reveal differences in preferences and failure modes. However, fluent or plausible responses do not establish that a simulator behaves like a person. Models may flatten within-group variation (Santurkar et al., 2023), amplify stereotypes (Wang et al., 2025a), ignore persona fields (Wang et al., 2024b), or otherwise depart from human behavior (Li et al., 2025a). Validation must therefore match the intended use. Survey simulations require calibrated population sampling,

while interactive simulations must also capture behaviors such as disclosure, correction, refusal, and abandonment. Recent work evaluates whether simulators adhere to assigned personas and preserve behavioral chains (Li et al., 2025a). It also measures human–simulation agreement (Xie et al., 2024a; Chang et al., 2025), ranking reliability (Dou et al., 2025), and sim-to-real transfer (Zhou et al., 2026).

Agents and evaluation. Agent benchmarks evaluate systems that plan, use tools, and act in interactive environments (Liu et al., 2024; Mialon et al., 2024; Huang et al., 2026; Kim et al., 2026). Their tasks span APIs (Qin et al., 2024; Yao et al., 2025), websites (Yao et al., 2022; Deng et al., 2023; Zhou et al., 2024a; Koh et al., 2024), applications (Trivedi et al., 2024), and operating systems (Xie et al., 2024b). Evaluation usually combines executable task outcomes with rubric-based LLM judges for open-ended outputs and interactions (Liu et al., 2023; Zheng et al., 2023). Because these scores depend on the judge and prompt and can exhibit systematic biases, they require calibration against human annotations (Wang et al., 2024a; Angelopoulos et al., 2023). A separate line of work uses agents as simulated participants rather than as the systems under test. Generative Agents (Park et al., 2023), SOTOPIA (Zhou et al., 2024b), Concordia (Vezhnevets et al., 2023), OASIS (Yang et al., 2024), and AgentSociety (Piao et al., 2025) give agents persistent identities, memories, and relationships to support social interaction. MatrAIx adopts this participant role for simulated users and uses them to evaluate a fixed target. Unlike an agent benchmark, the target need not be an agent: it may be a website, application, survey, or other digital product. MatrAIx varies the simulated-user population under a declared sampling design while holding that target fixed.

3 Persona 8B: A Population-Scale Persona Dataset

3.1 Representation and Schema

Persona 8B is the population-scale persona dataset that powers the MatrAIx simulated-user evaluation infrastructure. It is not designed to reconstruct identifiable people. Instead, it provides a shared schema for describing human variation, querying records, and sampling evaluation cohorts. Persona 8B contains 8.3 billion persona records. A record becomes a *persona agent* when it is paired with a model. Evaluations then assign sampled persona agents to an agent interface and task.

The representation is built around $d = 1{,}290$ categorical dimensions. Let

$$\mathcal{D} = \{X_1, \ldots, X_d\}, \qquad d = 1{,}290, \tag{1}$$

where dimension X_i has a finite value set $\mathcal{X}_i$. A fully specified synthetic persona is an assignment

$$x = (x_1, \ldots, x_d) \in \mathcal{X}_1 \times \cdots \times \mathcal{X}_d. \tag{2}$$

Human-grounded records use the same coordinate system but may be partial, with x_i = `null` when the available evidence does not support an assignment. For example, age bracket includes values such as 18–24, 25–34, and 35–44. English proficiency ranges from `Native` to `None`, with intermediate levels such as `Fluent (C1-C2)`, `Intermediate (B1-B2)`, and `Basic (A1-A2)`. Risk tolerance ranges from `Risk-averse` to `Risk-seeking`.

The schema groups background, psychology, capability, behavior, and lifestyle attributes under one typed interface (Table 1). It was designed to support both population queries, such as selecting by age, region, language, expertise, or accessibility needs, and model-facing persona conditioning. Public sources inform both the schema and selected priors. These sources cover demographics, economics, education, labor, health, values, and technology use. Examples include UN World Population Prospects (United Nations Department of Economic and Social Affairs, Population Division, 2026b), World Bank indicators (World Bank, 2026b), ILOSTAT (International Labour Organization, 2026), public surveys (World Values Survey Association, 2026), and developer-ecosystem statistics (Stack Overflow, 2026). Table 1 summarizes the schema at a high level. The complete three-layer taxonomy appears in Appendix B.1 (Figure 4). Appendix B.3 maps the schema groups to their grounding sources and roles. The full dependency graph appears in Appendix C.1 (Figure 5).

Top-level group	Dims.	Representative attributes	Representative grounding
Background	238	Age, region, language, education, family, career, industry	Population statistics, household surveys, education and labor taxonomies
Psychology	210	Personality, values, worldview, motivation, risk	Validated instruments, values surveys, schema design priors
Capability	331	Domain expertise, general skills, tools, programming, developer context	Occupational taxonomies, technology/developer surveys
Behavior and Interaction	124	Preferences, habits, interaction state, work practices, technology adoption	Time-use, consumer, workplace, and technology-use evidence
Lifestyle	387	Interests, media, culture, hobbies, sports, food, health, fitness	Health statistics, consumption surveys, cultural sources
Total	**1,290**		

Table 1: **Persona 8B schema overview.** Dimension counts refer to emitted categorical attributes. Sources provide different kinds and strengths of grounding; they do not imply direct population estimates for every value.

3.2 Synthetic Persona Generation with DAG Sampling

Matching marginal distributions alone does not produce a coherent population. Independent sampling can break age–education, region–language, employment–seniority, and other dependencies, producing implausible profiles despite accurate aggregate counts. We therefore use a dependency-aware probabilistic model that combines source-informed correlations with explicit compatibility constraints. Concretely, each of the 1,290 schema dimensions is a node. An edge indicates that one dimension is sampled conditionally on another. For example, a persona's education level is drawn given its age bracket, while English proficiency is drawn given its primary language and region. We add an edge when a source directly reports the conditional relationship. We do not infer edges from a joint distribution that no available dataset provides. A persona is then built one dimension at a time in an order that visits parents first, so every draw uses the context on which it depends. Appendix C.1 works through the full calculation for one dimension and describes how the edges were recovered.

Let $G = (\mathcal{D}, E)$ be a directed acyclic graph (DAG) over the persona dimensions, and let $\mathrm{Pa}(i)$ denote the parents of X_i. The proposal distribution factorizes as

$$p_\theta(x) = \prod_{i=1}^{d} p_\theta\big(x_i \mid x_{\mathrm{Pa}(i)}\big)\,. \tag{3}$$

This factorization makes local dependency assumptions explicit and conditions each dimension only on its relevant predecessors. For a root dimension, the local conditional probability distribution (CPD) is a categorical prior $\pi_i(v)$, the population-wide probability of candidate value v. For a non-root dimension, a candidate value $v \in \mathcal{X}_i$ is scored by combining the prior with parent-dependent adjustments and compatibility constraints:

$$p_\theta(X_i = v \mid x_{\mathrm{Pa}(i)}) \propto \pi_i(v)\, r_i(v; x_{\mathrm{Pa}(i)})\, m_i(v; x_{\mathrm{Pa}(i)}). \tag{4}$$

The source-informed adjustment r_i combines parent-specific likelihood ratios, while the binary mask $m_i \in \{0, 1\}$ applies compatibility rules. Consider English proficiency when primary language is English and region is North America. The prior $\pi_i(v)$ gives the population-wide probability of each proficiency value before those parent attributes are known. The adjustment r_i increases the weight of values that are common in this context, such as `Native`. It decreases the weight of values that are less common. The mask m_i handles a different question: whether a combination is allowed at all. A persona whose primary language is English cannot have English proficiency `None`, so that candidate receives a zero mask and is removed. A less typical but possible value, such as `Basic`, remains eligible rather than being treated as a contradiction. Scores are then normalized over $\mathcal{X}_i$. Separating dependency adjustment from compatibility filtering preserves rare but valid profiles while enforcing hard constraints. Appendix C.1 provides details on these definitions.

Base priors and local dependencies are derived from the sources summarized in Table 1; graph construction and review procedures are detailed in Appendix C.1. Synthetic personas are generated by forward sampling in a topological order $\tau = (\tau_1, \ldots, \tau_d)$:

$$x_{\tau_k} \sim p_\theta\big(X_{\tau_k} \mid x_{\mathrm{Pa}(\tau_k)}\big)\,, \qquad k = 1, \ldots, d. \tag{5}$$

Source	Released records
Wikipedia extraction	323,438
Amazon Review extraction	97,915
Stack Overflow survey extraction	113,120
PRISM Alignment	1,487
General Social Survey	63,532
MatrAIx volunteer survey	355
Human-grounded subtotal	**599,847**
Full-DAG synthetic	**400,000**
Total	**999,847**

Table 2: **Composition of the public Persona 1M coreset.** "Human-grounded" identifies the origin of a record, not a guarantee that every extracted field is a verified fact. These counts mirror the *Composition* table of the dataset card (footnote ∗), which is the authoritative record for the release.

Root attributes are drawn from their grounded categorical priors, while each downstream attribute is drawn from its normalized local CPD. Each evaluation loads only its selected cohort rather than the full population. Synthetic records still reflect the model's priors, dependencies, and design choices. We therefore complement them with human-grounded records from public profiles, coded surveys, and consented self-reports.

3.3 Real-Persona Extraction and Volunteer Collection

To complement synthetic coverage with observed evidence, we map biographies, behavioral histories, coded surveys, and consented self-reports into the same 1,290-dimensional schema. Human-grounded records include only source-supported assignments, while unsupported dimensions remain null.

The human-grounded population draws from six sources. *Wikipedia* provides biographies, while *Amazon Reviews* are grouped by reviewer to form review histories (Hou et al., 2024). The *Stack Overflow Developer Survey* is mapped through a deterministic crosswalk that preserves coded responses (Stack Overflow, 2026). The *General Social Survey (GSS)* responses are also mapped directly from the survey's coded answers into the persona schema (Davern et al., 2026). *PRISM Alignment* provides coded demographics and participant self-descriptions (Kirk et al., 2024). The *MatrAIx Persona Survey* contributes 355 consented self-reports collected through social-media posts and university email lists. The survey collects no names, contact details, or account identifiers, and the released records contain no direct identifiers. We use LLM-based constrained extraction for the free-text content from Wikipedia, Amazon Reviews, and PRISM Alignment. Appendix D provides extraction and instrument details, and Appendix D.5 reports missingness and cohort composition.

3.4 Quality Control and the Public 1M Coreset

Quality filtering and deduplication. Synthetic records are checked for cross-attribute conflicts, while human-grounded records are checked for unsupported assignments and provenance. Human-grounded records are deduplicated using exact hashing and MinHash-based fuzzy detection. Synthetic records are deduplicated using a set of 14 high-information attributes: records with identical values across all 14 attributes are treated as duplicates, and only one is retained. Appendix C.2 gives the full filtering rules, deduplication procedure, and record counts.

Distribution calibration and the 1M coreset. The human-grounded sources are not population-representative. We therefore select synthetic records so that the combined coreset approximates published population statistics for age bracket, region, gender identity, and urbanicity (United Nations Department of Economic and Social Affairs, Population Division, 2026b; World Bank, 2026b). Missing fields are not imputed, and the result is a best-effort match to these four marginal distributions rather than representative joint coverage over all 1,290 dimensions. The final deterministic coreset contains 599,847 human-grounded and 400,000 synthetic records. This split is a release design choice rather than an estimate of a real-world source ratio. Table 2 reports the exact composition, and Appendix C.3 provides the sampling and calibration procedure.

4 Evaluation Infrastructure

4.1 Simulation Configuration and Execution

A simulation begins with a population query and application task submitted through the MatrAIx Playground. The Playground records the eligible persona pool, sampling procedure, task version, agent, and model in a run manifest. It then launches one independent trial for each persona in the sampled cohort. Each trial is represented as $\tau = \langle \pi, \theta, \alpha, \mu, \sigma \rangle$, where persona π performs task θ through agent interface α using model μ and seed σ. Each trial produces a canonical artifact bundle $A = \alpha(\pi, \theta; \mu)$ containing its submission and, when applicable, its trajectory and environment state. A task-owned verifier maps this bundle to typed findings $V_\theta(A)$. Trials share no state and are therefore parallel by construction. The manifest retains both the requested population and realized cohort, while typed findings keep persona fidelity, product outcomes, and execution failures distinct.

4.2 Four Evaluation Environments

The four environments differ in how persona agents interact with the product being evaluated and what evidence they record:

1. **Type I: Survey.** Each persona agent completes a questionnaire. The environment records structured answers and rationales and checks that required questions have valid responses.
2. **Type II: AI Chatbot.** Each persona agent converses with the chatbot being evaluated. The environment records the full conversation, tool and service calls, and whether the user's goal was resolved.
3. **Type III: Web.** Each persona agent browses a live or task-hosted website. The environment records the pages viewed, actions taken, screenshots when used, and the agent's final submission.
4. **Type IV: App.** Each persona agent operates a Linux, macOS, or iOS application with mouse, keyboard, or touch actions. The environment records the interaction sequence, final application state, and changes such as created files or updated settings.

Implementation and deployment details for each environment are provided in Appendix E.

4.3 Execution, Verification, and Reporting

Trials can run on the local machine or on remote workers connected over HTTP. Each worker can execute multiple trials in parallel, and adding workers increases throughput without changing the task or output format. Only approved, non-secret configuration fields are sent to remote workers, and model-provider credentials remain on the worker.

For each trial, MatrAIx stores the persona, task, agent, model, and seed, along with the interaction trajectory, final environment state, verifier results, and environment-specific artifacts. Programmatic verifiers check observable outcomes such as required states, constraints, and side effects. Human or LLM judges are used when an outcome requires interpretation. Reports aggregate these results by task, cohort, and subgroup while preserving links to the underlying trials and evidence. This supports multidimensional evaluation rather than reducing system performance to a single score (Liang et al., 2023; Xing et al., 2026).

After reviewing a report, evaluators can change the cohort, scenario, or verifier and rerun the study while keeping the task version and other settings fixed. Appendix E provides details on remote execution, scaling, security, telemetry, and storage.

5 Application Tasks

5.1 Task Library

MatrAIx Applications organizes tasks by evaluation environment and domain. The environment determines how persona agents interact with a product, while the task defines the AI system or digital product under test, persona cohort, scenario, user objective, and outcome measures. The four environments are Survey, AI Chatbot, Web, and App. The

	Commerce	Software	Finance	Healthcare	Other	Total
Survey	202	138	141	139	1	**621**
AI Chatbot	3	11	17	29	311	**371**
Web	2	2	2	0	6	**12**
App	0	5	1	0	0	**6**
Total	**207**	**156**	**161**	**168**	**318**	**1,010**

Table 3: **Application-task coverage.** Counts are unique specifications on the repository's main branch together with the batch collections on its synthetic-task branches; individually contributed tasks still under review on open pull requests are not counted. "Other" aggregates more than 25 additional domains.

library uses Commerce, Software, Finance, and Healthcare as anchor domains and covers more than 25 others, including travel, legal services, insurance, education, entertainment, food, real estate, and games. The library includes two categories of tasks. Grounded tasks are based on public instruments, existing AI models or agents, real products, or live interfaces. Synthetic tasks provide controlled coverage for recurring study designs, including purchase intent, price sensitivity, retention, support resolution, and recommendation. Our current release contains 1,010 unique task specifications: 621 Survey, 371 AI Chatbot, 12 Web, and 6 App tasks (Table 3). Appendix F describes the inventory and distinguishes available, implemented, executed, and reported tasks.

5.2 Application Task Specification

Each task specifies four elements. It names the evaluation target, such as an AI model, agent, chatbot, website, or native application. It also defines the persona cohort, the user-facing scenario and objective, and the response, behavior, outcome, or final state that counts as evidence. Keeping these fields in the task contract makes tasks portable without placing product credentials or scoring rules in the persona instructions. For example, a price-sensitivity task can present the same price increase to shoppers with different economic motivations and record their purchase intent and rationale. The stored cohort query and seed support repetition with the same sample or comparison with a different population while holding the product and scenario fixed.

Each task also specifies the evidence to retain and how it will be evaluated. Survey tasks produce structured answers and rationales. AI Chatbot tasks record the conversation and post-run feedback. Web tasks preserve the pages viewed, actions taken, considered options, and final submission. App tasks can also record exported files, permission changes, final application state, and cross-application effects. These artifacts support measures such as the share of simulated users who purchase or continue using a product, mean satisfaction ratings, task-completion rates, and average completion times. For example, a task can test whether more than 60% of simulated users would continue using an AI chatbot or whether its mean satisfaction rating exceeds 4 out of 5. The interaction trajectories show how personas reached, revised, or abandoned their decisions.

A task-specific verifier converts these artifacts into structured findings. Programmatic checks evaluate directly observable outcomes, while human or LLM judges assess interpretive properties using recorded prompts and rubrics. Reports summarize completion, outcome distributions, uncertainty, and subgroup differences while retaining links to the underlying traces and evidence. Product outcomes, simulated-user behavior, and persona fidelity remain separate, so task success is not treated as evidence of human validity.

5.3 Case Study: Meal-Planning Chatbot

The meal-planning chatbot task shows how a task specification becomes an executable study. In every trial, a persona agent asks the same GPT-4o mini assistant for a multi-day meal plan tailored to its dietary needs and preferences. The assistant remains fixed across all trials, while the model powering the persona agent varies among Opus 4.8, GPT 5.5, and Haiku 4.5. This design allows us to compare how different persona agents use the same persona information when interacting with the same assistant. Figure 2 summarizes the study design and examines whether persona attributes are associated with the agent's stated likelihood of following the resulting meal plan. Appendix F.7 reports the corresponding conversation-path analysis. Together, the example shows how one task specification connects the system under test, persona cohort, interaction protocol, outcome measures, and supporting evidence.

(A) AI Chatbot task · Meal planning & nutrition

Task and protocol

- A persona agent powered by Opus 4.8, GPT 5.5, or Haiku 4.5 interacts with the same GPT-4o mini assistant
- Goal: obtain a multi-day meal plan tailored to the persona, including one substitution and one dining-out recommendation
- 7.1 turns per conversation on average (SD = 1.8)

Outcome measures

- Eight self-report questions after the conversation; two examples:
- "How likely are you to follow the meal plan from 1 to 10?" (1–10, primary outcome)
- "How well did the meal plan satisfy your core dietary constraints and health goals?": yes / partially / no

Persona cohort

- 1,000 personas per persona-agent model: 82 schema dimensions plus 42 task-specific diet and cuisine attributes
- Ages 25–54; six diet-relevant attributes are stratified
- The rest are spread evenly across their levels, not weighted to any real population
- Each persona LLM draws its own 1,000 personas from the same sampling recipe

(B) Persona deviation in the downstream outcome

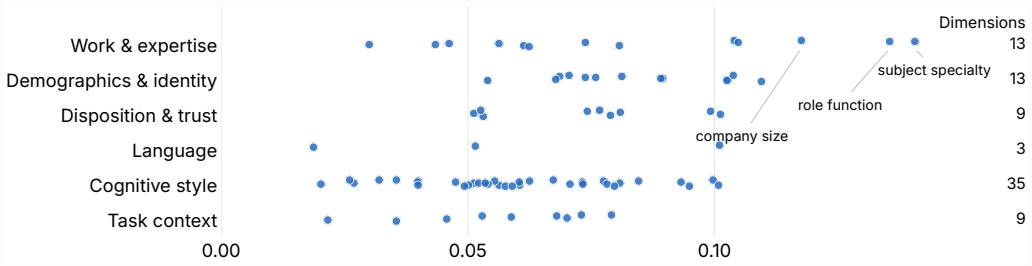


Figure 2: **Meal-planning chatbot task and persona-outcome analysis. (A)** The task protocol, outcome measures, and persona cohort. The cohort supports comparisons across its sampled subgroups and persona-agent models, but it is not weighted to represent a real population. **(B)** Association between each of 82 persona dimensions and whether the persona agent selected the modal adherence response in the GPT 5.5 condition, measured using Cramér's V. The three largest associations are labeled. Empty nesters reported a higher likelihood of following the plan than career changers (66% versus 46%), but no association remained significant after Benjamini–Hochberg correction (best $q = 0.51$). These differences are therefore descriptive rather than confirmed persona effects. Appendix F.7 reports how the same subgroups differed in their conversation paths.

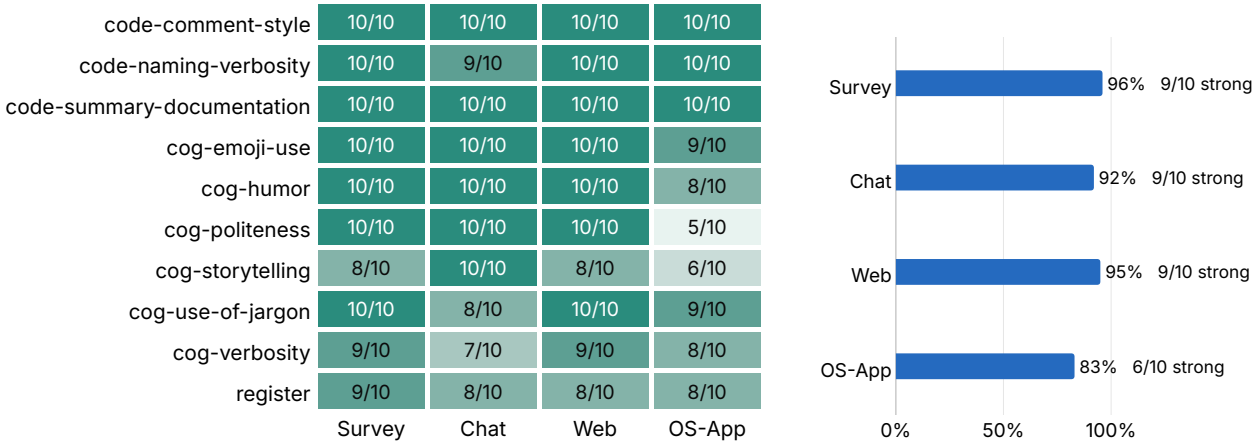
6 Validation of Simulated-User Evaluation

We evaluate four properties of the infrastructure: whether tasks execute as specified, whether task-relevant persona effects can be recovered across models, whether assigned persona attributes affect observable behavior, and whether human-grounded records are supported by their source material. Together, these studies test end-to-end execution, application-level consistency, behavioral adherence, and source grounding.

Execution coverage. We ran eight representative tasks, two from each environment type, with OpenAI GPT 5.5, Claude Opus 4.8, and Claude Haiku 4.5. Survey, AI Chatbot, and Web tasks used approximately 1,000 personas per model. The two App tasks used 24 and 20 because native interaction is substantially more expensive. All analyses report actual completion denominators and apply Benjamini–Hochberg correction (Benjamini and Hochberg, 1995) across the eight declared primary outcomes. Appendix G provides complete run accounting, statistical procedures, and artifact-integrity exceptions.

Application-level consistency. Persona effects are clearest when the assigned attribute is directly relevant to the task. In the OpenBB task, trust level separates subgroups under all three persona-agent models (Cramér's $V = 0.228$–0.363, all $q < 10^{-8}$), and all three models order the four trust groups identically. This result shows that MatrAIx can recover a consistent subgroup pattern across models when the task provides a clear behavioral channel for the persona attribute. We report the persona-agent model as part of every evaluation configuration, consistent with prior work showing model-dependent differences in reflected opinions (Santurkar et al., 2023), user-simulation behavior (Yoon et al., 2024), and persona fidelity (Wang et al., 2024b). Appendix H reports the complete model- and task-level comparisons.

Controlled behavioral adherence. Ten behavioral attributes are each evaluated in Survey, Chatbot, Web, and App, with five personas declaring one pole and five declaring the opposite, for 400 trials. The declared behavior is expressed or correctly suppressed in 366 trials (91.5%). Of the 40 attribute-by-environment cells, 33 achieve at least four of five successes in both arms. Survey, AI Chatbot, and Web each meet this threshold for 9 of 10 attributes, compared with 6 of 10 for App. Figure 3 summarizes the results; Appendices I and I.2 provide the design, judge evidence, and per-cell breakdown.



(a) Attribute-level adherence.

(b) Environment summary.

Figure 3: **Controlled behavioral adherence across four environments. (a)** Each cell pools five personas declaring one pole of an attribute and five declaring the opposite pole; 10/10 means that all five positive personas expressed the target and all five negative personas expressed the opposite value. **(b)** Overall successful-trial share by environment and the number of strong attributes, defined as at least four of five successes in both arms. An LLM judge evaluates the recorded trajectory or artifact. Overall, 366 of 400 trials succeed.

Extraction quality. We also test whether human-grounded persona records are supported by their source material. Two LLM judges score 1,000 extracted personas, with 89.1% of paired metric scores within one point. On a source-matched subset of 100 personas rated by six humans, the mean quality score is 4.135/5. GPT 5.5 and Claude Opus 4.8 are within one point of the human mean in 79.2% and 93.8% of comparisons, respectively. These results support source-grounded extraction quality. Appendix J gives the rubric, sampling procedure, and full results.

Interpretation. The persona-agent model is part of the evaluation configuration and should be reported with each result. Important findings should be checked with more than one model before they guide product decisions. The present studies validate execution, persona adherence, and source-grounded extraction quality; Appendix M discusses the remaining validation scope.

7 Conclusion

AI systems and digital products serve people with different goals, capabilities, preferences, and constraints, yet many evaluations represent only a generic user. MatrAIx provides an end-to-end infrastructure built from three components: Persona 8B, with approximately 8.3 billion records under a shared schema; the MatrAIx Playground, which runs persona agents in Survey, AI Chatbot, Web, and App environments; and MatrAIx Applications, a library of 1,010 versioned tasks across more than 25 domains. In this paper, we completed 18,189 trials over eight representative application tasks using three persona-agent models. In the controlled adherence study, assigned behaviors were expressed or correctly suppressed in 366 of 400 trials (91.5%). The extraction study also found strong support for human-grounded persona records: six human raters assigned a mean quality score of 4.135 out of 5 on the source-matched subset. These results support using MatrAIx for pre-deployment screening, subgroup analysis, stress testing, and comparison across product versions. Important findings should be checked across persona-agent models and traced back to the underlying interactions. Human studies remain necessary before applying conclusions to real populations or consequential decisions. Before release, simulate diverse users, then validate against reality.

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Appendix Table of Contents

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A.3 Author Contributions

X.L. and Y.H. contributed equally across all stages of the work. They conceived and coordinated the project; designed the persona schema, population construction methods, and simulated-user evaluation infrastructure; and participated directly in implementation and execution across synthetic persona generation and post-processing, human-grounded persona extraction and data curation, the four Playground environments, application-task and verifier development, evaluation runs, extraction-quality and persona-adherence validation, statistical analysis, and figure preparation. They jointly interpreted the results and wrote and revised the manuscript.

The contributor group built and operated the system reported here: the dependency-aware generation pipeline and its post-processing, the human-persona extraction engine and its source-specific adapters, the four evaluation environments and the shared trial, telemetry, and reporting interfaces, the application-task library and its verifiers, and the statistical analyses and figures. Contributors also ran the evaluation jobs behind the reported results and carried out the extraction-quality and persona-adherence validation studies.

The advisory committee advised on research design, evaluation methodology, measurement validity, and responsible release, and reviewed the manuscript.

All authors reviewed the manuscript and approved the submitted version.

A.4 Competing Interests

This work was supported by research funding, compute resources, model access, and program mentorship from OpenAI, Anthropic, Microsoft Azure, Amazon Web Services, Meta, the MIT CSAIL Alliance, and the MIT Sandbox Innovation Fund.

OpenAI and Anthropic, both listed above as supporters of this work, produce agent models evaluated in section 6 and Appendix G. We disclose this relationship for transparency. All model conditions follow the reported evaluation procedures; the per-trial records underlying each aggregate are retained; and the analysis code and task definitions are released to support independent verification.

The supporting organizations had no role in the design of the study, the selection of tasks or models, the analysis or interpretation of results, or the decision to submit this work for publication. The views and conclusions expressed here are those of the authors and do not necessarily reflect the positions of the supporting organizations.

B Persona Schema

B.1 Three-Layer Persona Taxonomy

The 1,290 attributes are organized at two related levels. The conceptual taxonomy assigns every attribute to one of five groups, 16 subgroups, and 55 fine-grained categories. The storage and questionnaire schema uses 43 categories. Most conceptual categories correspond directly to one schema category; selected broad schema categories, such as domain expertise and cultural interests, are split into more informative conceptual categories. Every attribute has exactly one assignment at each taxonomy layer, and all counts in Figure 4 sum to 1,290.

Provenance of the taxonomy. The two levels have different origins. Selected dimensions and value sets follow measurement conventions from the source families catalogued in Table 5. Census and labor instruments inform categories for education, occupation, and household structure; public-opinion surveys inform response scales for values and attitudes; and developer-ecosystem surveys inform the technology-use vocabulary. These sources play different roles and do not directly determine every schema field or value.

The three-layer organization above them is ours. The five groups, 16 subgroups, 55 conceptual categories, and separate 43-category storage schema are design choices made for this dataset. The conceptual layers allow a cohort to be selected by an idea (*accessibility needs*, *domain expertise*) rather than by enumerating fields. The storage layer keeps the questionnaire and record format stable when the conceptual grouping is revised. We are not aware of a published persona taxonomy at this granularity that we could have adopted, and we do not claim the grouping is the only defensible one. It is auditable instead: every attribute has exactly one assignment at each layer, the counts in Figure 4 sum to 1,290, and the complete attribute-level mapping ships with the release so that a reader who prefers a different organization can regroup from the same fields.

B.2 Complete Schema Category Index

Table 4 indexes all 43 schema categories used by the dimension catalog and questionnaire interface. The complete attribute-level mapping, including stable index, field identifier, label, schema category, and all three conceptual taxonomy assignments, is supplied as `supp_material/persona_taxonomy_mapping.csv`. The 1,290-item questionnaire supplement additionally records every field's prompt and allowed values.

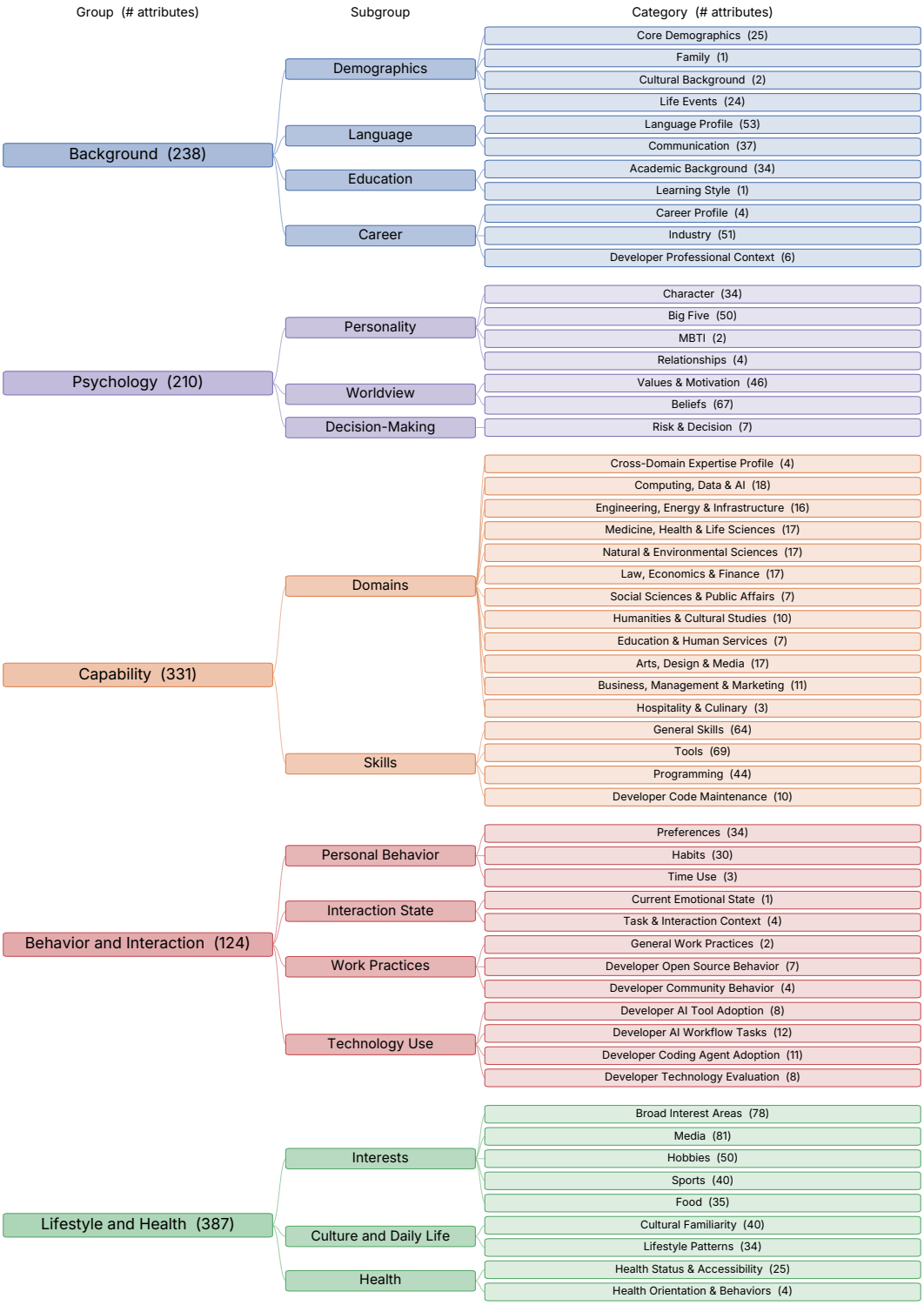


Figure 4: **Complete three-layer taxonomy of the Persona 8B schema.** The left column gives the five top-level groups and their attribute totals; the middle column gives 16 subgroups; and the right column gives all 55 conceptual categories with counts. The hierarchy covers exactly 1,290 attributes and excludes latent or helper variables used only by the generation graph.

Table 4: **Complete index of the 43 schema categories.** Counts sum to 1,290 attributes. Examples are labels from the authoritative dimension catalog; the complete attribute-level mapping is supplied as `supp_material/persona_taxonomy_mapping.csv`.

Group	Subgroup	Schema category	Count	Representative attributes
Background	Demographics	Demographic: Core	25	Age bracket; region; gender identity
Background	Demographics	Demographic: Cultural	2	Cultural background; attitude toward immigration
Background	Demographics	Demographic: Family	1	Household size
Background	Demographics	Demographic: Life Events	24	Life stage; major life events; childhood environment
Background	Language	Linguistic: Language	53	Primary language; English proficiency; multilingualism
Background	Language	Linguistic: Communication	37	Expected tone; verbosity; communication preferences
Background	Education	Learning: Academic	34	Highest education; academic field; institution tier
Background	Education	Learning: Style	1	Learning style
Background	Career	Professional: Career	4	Research output; seniority; years of experience
Background	Career	Professional: Industry	51	Company size; role function; industry
Background	Career	Developer: Professional Context	6	Professional status; role archetype; contribution context
Psychology	Personality	Personality: Character	34	Domain stance; dominant trait; curiosity
Psychology	Personality	Personality: Big Five	50	Imagination; artistic interest; emotionality
Psychology	Personality	Personality: MBTI	2	Neurotype; Myers-Briggs type
Psychology	Personality	Personality: Relationships	4	Attachment anxiety; attachment avoidance; interpersonal agency
Psychology	Worldview	Values & Motivation	46	Core value; religiosity; economic motivation
Psychology	Worldview	Worldview: Beliefs	67	Political leaning; trust level; safety sensitivity
Psychology	Decision-Making	Risk & Decision	7	Risk tolerance; decision style; need for closure
Capability	Domains	Expertise: Domains	144	Domain; subject specialty; technology savviness
Capability	Skills	Expertise: Skills	64	Writing; copywriting; editing
Capability	Skills	Skills: Tools	69	Excel; Google Sheets; Python
Capability	Skills	Skills: Programming	44	Comment style; summary documentation; naming verbosity
Capability	Skills	Developer: Code Maintenance	10	Complexity tolerance; modularity preference; type-system orientation
Behavior and Interaction	Personal Behavior	Behavior: Preferences	34	Modality preference; accessibility needs; media diet
Behavior and Interaction	Personal Behavior	Behavior: Habits	30	Journaling; meditation; use of to-do lists
Behavior and Interaction	Personal Behavior	Behavior: Time	3	Time pressure; sleep schedule; micromanagement aversion
Behavior and Interaction	Interaction State	State: Emotional	5	Emotional state; intent; query complexity
Behavior and Interaction	Work Practices	Behavior: Work	2	Work schedule; office versus remote work
Behavior and Interaction	Work Practices	Developer: Open Source Behavior	7	Open-source activity; GitHub contribution mode; pull-request style
Behavior and Interaction	Work Practices	Developer: Community Behavior	4	Stack Overflow use; participation style; help-seeking preference
Behavior and Interaction	Technology Use	Developer: AI Adoption	8	Coding-AI use frequency; sentiment; output trust
Behavior and Interaction	Technology Use	Developer: AI Workflow Tasks	12	AI fit for code generation; debugging; testing
Behavior and Interaction	Technology Use	Developer: Agent Adoption	11	Agent use frequency; autonomy preference; workflow impact
Behavior and Interaction	Technology Use	Developer: Technology Evaluation	8	AI capability; API completeness; reliability and latency
Lifestyle and Health	Interests	Interests: Topics	78	Politics; sports; travel
Lifestyle and Health	Interests	Interests: Media	81	Pop music; rock music; hip-hop
Lifestyle and Health	Interests	Interests: Hobbies	50	Knitting; crocheting; pottery
Lifestyle and Health	Interests	Interests: Sports	40	Soccer; basketball; American football
Lifestyle and Health	Interests	Interests: Food	35	Italian; French; Spanish cuisine
Lifestyle and Health	Culture and Daily Life	Interests: Culture	74	Familiarity with national and regional cultures
Lifestyle and Health	Health	Health: Physical	25	General health; chronic condition; mobility
Lifestyle and Health	Health	Health: Fitness	2	Interest in fitness; exercise frequency
Lifestyle and Health	Health	Health: Lifestyle	2	Diet type; alcohol use

B.3 Detailed Schema-to-Source Grounding Map

Table 5 expands the high-level schema summary in Table 1. The sources play different roles. Some define categories or measurement conventions, some provide population priors, some support selected conditional dependencies, and others serve primarily as validation references. Listing a source does not imply that every dimension in the corresponding group is directly estimated from it.

Table 5: **Detailed schema-to-source grounding map.** The mapping records source families and their roles in schema design, prior estimation, dependency construction, compatibility rules, or downstream validation.

Schema group	Facets	Grounding roles	Sources
Background	Demographics (52); language (90); education (35); career (61)	Category definitions; population priors; household, language, education, and labor dependencies	UN World Population Prospects and Population Data (United Nations Department of Economic and Social Affairs, Population Division, 2026b;a); World Bank WDI and WorldPop (World Bank, 2026b; WorldPop, 2026); Eurostat, ACS PUMS, and IPUMS (Eurostat, 2026; U.S. Census Bureau, 2026; IPUMS, 2026); DHS, UNICEF MICS, and OECD Family Database (The DHS Program, 2026; UNICEF, 2026; Organisation for Economic Co-operation and Development, 2026a); Pew and World Values Survey (Pew Research Center, 2026b; World Values Survey Association, 2026); UNESCO UIS, World Bank Education Statistics, OECD INES, and OECD PISA (UNESCO Institute for Statistics, 2026b; World Bank, 2026a; Organisation for Economic Co-operation and Development, 2026b;c); ILOSTAT, BLS OEWS, and O*NET (International Labour Organization, 2026; U.S. Bureau of Labor Statistics, 2026b; O*NET Resource Center, 2026); Stack Overflow Survey, GitHub Octoverse, and JetBrains Developer Ecosystem (Stack Overflow, 2026; GitHub, 2026; JetBrains, 2025).
Psychology	Personality (90); worldview (113); decision-making (7)	Instrument and value-set design; selected prevalence estimates; validation	IPIP and MIDUS (International Personality Item Pool, 2026; Midlife in the United States, 2026); Pew and World Values Survey (Pew Research Center, 2026b; World Values Survey Association, 2026); GSS, European Social Survey, ISSP, and Gallup World Poll (NORC at the University of Chicago, 2026; European Social Survey, 2026; International Social Survey Programme, 2026; Gallup, 2026); Afrobarometer, Arab Barometer, Asian Barometer, Latinobarometro, and Eurobarometer (Afrobarometer, 2026; Arab Barometer, 2026; Asian Barometer Survey, 2026; Latinobarómetro Corporation, 2026; European Commission, 2026); ARDA (Association of Religion Data Archives, 2026).
Capability	Domain expertise (144); general skills (64); tools (69); programming (44); developer context (10)	Occupational and skill taxonomies; technology access and adoption; developer-tool prevalence	ITU Statistics, World Bank WDI, DataReportal, and Pew Internet (International Telecommunication Union, 2026; World Bank, 2026b; DataReportal, 2026; Pew Research Center, 2026a); Stack Overflow Survey, GitHub Octoverse, and JetBrains Developer Ecosystem (Stack Overflow, 2026; GitHub, 2026; JetBrains, 2025); O*NET (O*NET Resource Center, 2026).
Behavior and Interaction	Personal behavior (67); interaction state (5); work practices (13); technology use (39)	Time-use and consumer priors; workplace behavior; technology and AI adoption	American Time Use Survey, Consumer Expenditure Surveys, and OECD Time Use (U.S. Bureau of Labor Statistics, 2026a;c; Organisation for Economic Co-operation and Development, 2026d); ITU, DataReportal, and Pew Internet (International Telecommunication Union, 2026; DataReportal, 2026; Pew Research Center, 2026a); Stack Overflow Survey, GitHub Octoverse, JetBrains Developer Ecosystem, and O*NET (Stack Overflow, 2026; GitHub, 2026; JetBrains, 2025; O*NET Resource Center, 2026).
Lifestyle	Interests (358); physical health (25); fitness (2); health lifestyle (2)	Health and disability priors; consumption and time use; cultural and interest category design	WHO GHO and IHME GBD (World Health Organization, 2026; Institute for Health Metrics and Evaluation, 2026); ACS PUMS, NHIS, BRFSS, DHS, and UNICEF MICS (U.S. Census Bureau, 2026; Centers for Disease Control and Prevention, 2026b;a; The DHS Program, 2026; UNICEF, 2026); ATUS, CEX, and OECD Time Use (U.S. Bureau of Labor Statistics, 2026a;c; Organisation for Economic Co-operation and Development, 2026d); FAOSTAT and UNESCO Culture Statistics (Food and Agriculture Organization of the United Nations, 2026; UNESCO Institute for Statistics, 2026a); Eurobarometer, Pew, DataReportal, WVS, and Gallup World Poll (European Commission, 2026; Pew Research Center, 2026b;a; DataReportal, 2026; World Values Survey Association, 2026; Gallup, 2026).

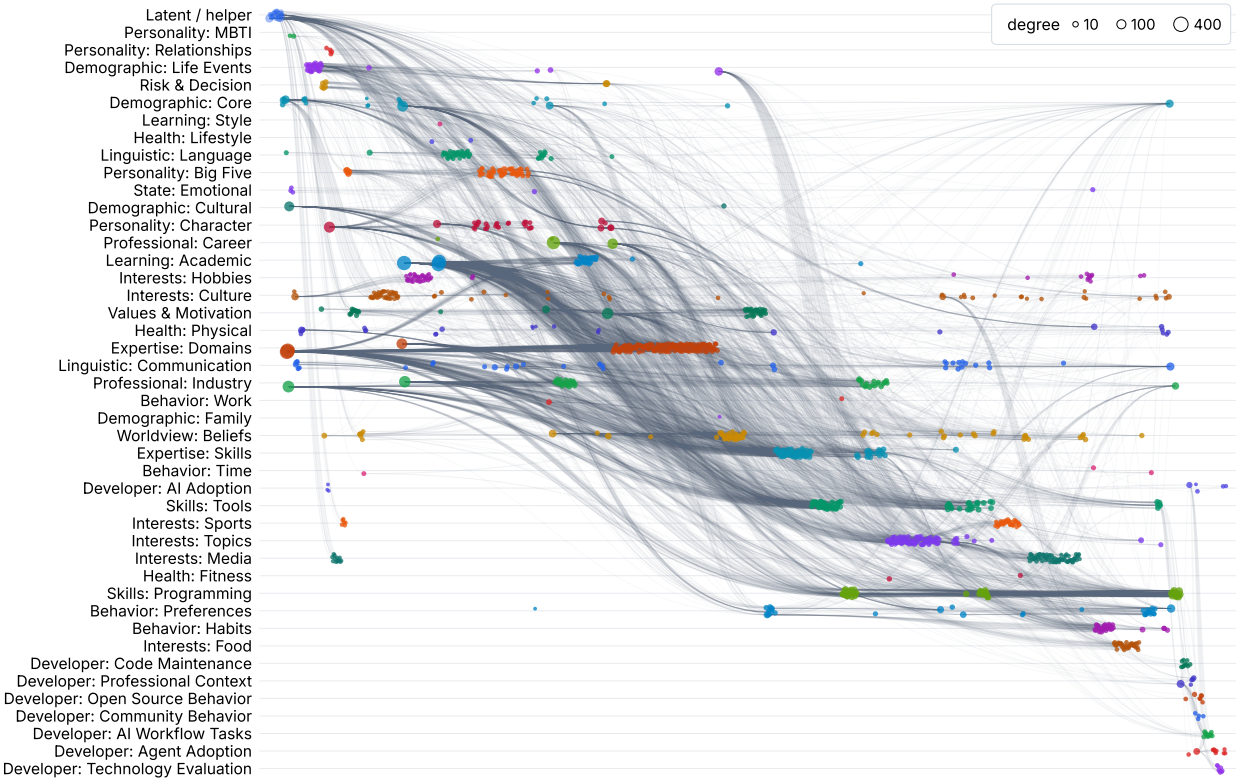


Figure 5: **The full persona DAG.** All 1,308 graph nodes and 6,999 directed edges. Nodes are placed left to right by the topological order used in Equation 5 and grouped vertically into one lane per schema category, with lanes ordered by their mean topological position; marker area scales with a node's directed degree. Edges are drawn as translucent curves, so darker bands mark the dependency bundles that connect demographic and educational roots to downstream expertise, interest, and behavior dimensions.

C Population Model and Post-Processing

C.1 DAG Construction and Sampling Details

For each non-root dimension, the adjustment term in Equation 4 aggregates source-informed dependency factors:

$$r_i(v; x_{\mathrm{Pa}(i)}) = \prod_{a \in \mathcal{A}_i} \left(\frac{q_{a,i}(v \mid x_{S_a}) + \epsilon}{\pi_i(v) + \epsilon} \right)^{\lambda_{a,i}}, \qquad S_a \subseteq \mathrm{Pa}(i). \tag{6}$$

Here $\mathcal{A}_i$ is the set of dependency factors for X_i, S_a is the parent subset used by factor a, and $q_{a,i}(\cdot \mid x_{S_a})$ is the corresponding conditional distribution. The ratio upweights values that become more likely in the parent context and downweights those that become less likely. The exponent $\lambda_{a,i}$ controls factor strength, and $\epsilon > 0$ provides smoothing.

The compatibility term combines local hard constraints:

$$m_i(v; x_{\mathrm{Pa}(i)}) = \prod_{b \in \mathcal{B}_i} \mu_{b,i}(v; x_{T_b}), \qquad T_b \subseteq \mathrm{Pa}(i), \tag{7}$$

where $\mathcal{B}_i$ is the rule set for X_i and each $\mu_{b,i}(v; x_{T_b}) \in \{0, 1\}$ is a binary mask multiplier. Zero excludes an invalid assignment and one leaves an admissible assignment unchanged. Statistical rarity is represented only by r_i, so a rare but admissible combination is not penalized again by the mask. Representative rules exclude adult work histories for young children, reconcile primary language with proficiency, and align accessibility states with relevant health attributes.

Graph construction begins with the demographic, socioeconomic, educational, health, behavioral, and technology priors summarized in Table 1 and Appendix B.3. Directed edges and local CPDs identify the parent context for each child dimension. Compatibility rules remain separate from empirical dependency factors so that statistical association and logical validity can be audited independently. Source review, schema review, and LLM-assisted coverage review identify missing dependencies and candidate conflicts. The graph

is checked for cycles before its topological order is produced.

Forward sampling applies Equation 5 to each persona. Repeating the procedure yields

$$\mathcal{P}_N = \{x^{(1)}, \ldots, x^{(N)}\}, \qquad x^{(n)} \sim p_\theta(x). \tag{8}$$

Deterministic seeds make each shard reproducible. Independent shards and append-only outputs permit parallel generation at population scale, while downstream evaluation jobs instantiate only sampled cohorts.

A node is one schema dimension together with its finite value set, and an edge records that a source supports conditioning one dimension on another. Of the 1,308 nodes in Figure 5, 1,290 are exactly the attributes a persona record contains. The remaining 18 are latent root factors such as `latent_digital_engagement` and `latent_financial_security`: each has a small ordinal value set and no parents, so it is sampled before everything else, and its outgoing edges fan out to the observable dimensions it coordinates. A family of attributes that should move together, for example the dimensions that all reflect financial security, then inherits its correlation from one shared cause rather than from many pairwise edges. Latent factors are never emitted, so a persona record still contains exactly the 1,290 schema attributes. Consider `english_proficiency`, whose value set here is {`None`, `Basic`, `Fluent`, `Native`}, with parents `primary_language` and `region`. Two of the terms in Equation 4 attach to those parents. A dependency factor $q_{a,i}$ says how the proficiency distribution shifts once the parent is known, and it is estimated from a source. A compatibility rule $\mu_{b,i}$ says which combinations are not admissible at all, and it is asserted rather than estimated: a persona whose primary language is English cannot also have no English proficiency.

A worked example. Table 6 runs one child dimension through Equation 4 for the parent context `primary_language` = `English`, `region` = `North America`, with both factor exponents $\lambda_{a,i} = 1$ and ϵ small enough to ignore. *The values are illustrative and are chosen to show the arithmetic; they are not the deployed parameters.* Reading across: the prior π_i is the population-wide distribution; each factor contributes the ratio $q_{a,i}/\pi_i$, which exceeds one where the parent context makes a value more likely; the mask zeroes the one combination a rule forbids; and the product is renormalized over the surviving values.

v	$\pi_i(v)$	q_{lang}	q_{region}	$r_i(v)$	$m_i(v)$	$\pi_i r_i m_i$	$p_\theta(v \mid x_{\text{Pa}(i)})$
`None`	0.30	0.02	0.10	0.022	0	0.000	0.000
`Basic`	0.30	0.08	0.20	0.178	1	0.053	0.028
`Fluent`	0.25	0.30	0.35	1.680	1	0.420	0.224
`Native`	0.15	0.60	0.35	9.333	1	1.400	0.747
sum	1.00	1.00	1.00			1.873	1.000

Table 6: **One child dimension through the local CPD (illustrative).** `english_proficiency` conditioned on `primary_language` = `English` and `region` = `North America`. The prior alone would give `Native` a 15% share; the two dependency factors raise it to 75%, and the compatibility mask removes `None` outright rather than merely making it unlikely. Numbers illustrate Equation 4 and are not the deployed parameter values.

Two things in the example generalize. First, a single factor with $\lambda = 1$ would reproduce that factor's conditional exactly, since $\pi_i \cdot (q_{a,i}/\pi_i) = q_{a,i}$; the machinery earns its keep when several factors condition on *different* parent subsets S_a, as here, and no single source supplies the joint. Second, separating r_i from m_i is what lets a rare-but-valid profile survive. A low-probability combination is downweighted by the factors and can still be sampled, whereas a combination that is not admissible is removed by the mask and can never be, so statistical rarity and logical invalidity never get confused with each other.

How the edges are recovered. Edges are not learned from a fitted joint over 1,290 dimensions, which no available source would identify. They are added where a source reports a conditional. Construction proceeds in three passes over the catalogue in Table 5. First, a source review adds an edge wherever a dataset reports one attribute broken down by another and records the supporting table. Second, a schema review checks that each added parent is meaningful for the child's value set rather than merely correlated in the source population. Third, an LLM-assisted coverage review proposes pairs that a human pass may have missed; each candidate is then accepted or rejected by hand. Compatibility rules are collected separately in the same passes so that an association and a prohibition are never entered as the same object. The result is checked for cycles, and the topological order used by Equation 5 is produced from the acyclic graph.

C.2 Detailed Persona Post-Processing Pipeline

Post-processing is non-destructive: each source shard produces a rejection bitmap and a report with source, rule, and row-count provenance. The quality filter evaluates 21 hard contradiction rules over packed synthetic codes and populated human fields. Across 10,002,288,277 original records, it rejected 239,310. Missing or unsupported human fields do not trigger a conflict.

Human deduplication canonicalizes populated `field=value` tokens. Exact 128-bit hashes merge identical records; near-duplicates use 64-permutation MinHash signatures, eight bands of eight rows, and an estimated Jaccard threshold of 0.95. Synthetic records instead use a 14-field projection chosen by graph-prior entropy across schema categories. Records sharing a projection signature form a bucket, and deterministic priorities select one survivor per bucket. A final deterministic cutoff sets the desired synthetic corpus size.

Stage	Rejected	Remaining
Original corpus	–	10,002,288,277
Contradiction filter	239,310	10,002,048,967
Human exact/MinHash deduplication	41,597	2,222,496 human
Synthetic projection deduplication	252,936,392	9,746,848,482 synthetic
Synthetic deterministic cutoff	1,349,070,978	8,397,777,504 synthetic
Audited baseline		**8,400,000,000**

Table 7: Detailed post-processing accounting for the audited baseline. Human and synthetic remaining counts have different scopes until the final row.

Accepted records are materialized into a unified Arrow/Parquet schema. The 1,290 attributes occupy a 645-byte vector with two four-bit codes per byte; a 162-byte null bitmap preserves missing values, and sparse overrides preserve legacy values outside the current codebook. Descriptions, grounding, confidence, assignment types, and source metadata remain attached where available. Every output file is checked against the unified schema and listed in a SHA-256 manifest. The accepted snapshot contains 8,399,989,719 rows, 10,281 below the intended materialized target because one incomplete Wikipedia conversion task was excluded.

C.3 Coreset Candidate Selection and Calibration

All retained records from Amazon, Stack Overflow, PRISM, GSS, and the volunteer survey enter the human component; Wikipedia is calibrated to 323,438 rows. For the synthetic component, seed `20260720` selects 40 of 100 shards and one Parquet file and row group from each, yielding 2,187,354 candidates before selecting 400,000.

Let h_{dv} be the human count for value v of dimension d, H_d the number of human records where d is known, and p_{dv} the target share. The desired synthetic residual is

$$r_{dv} = p_{dv}(H_d + 400{,}000) - h_{dv}. \tag{9}$$

Missing fields are not imputed to satisfy a target, and infeasible residuals are retained in the release audit.

Calibration iteratively updates a positive weight w_i shared across the four target dimensions. Fixed-size inclusion probabilities are

$$\pi_i^{\text{inc}} = 1 - e^{-tw_i}, \qquad \sum_i \pi_i^{\text{inc}} = n, \tag{10}$$

where t is solved for sample size n. Deterministic sampling without replacement assigns

$$q_i = \frac{-\log U_i}{w_i}, \tag{11}$$

with U_i derived from the seed and stable row identifier, and selects the n smallest priorities. This yields an exact-size, order-independent sample.

The release consists of ten 100K-row Zstandard-compressed Parquet files. `manifest.json` records source counts, file sizes, and hashes; `audit.json` records targets, achieved shares, known and missing counts, infeasible residuals, and synthetic candidate provenance; and `RESULTS.md` summarizes the completed build.

D Human-Grounded Persona Construction

D.1 Extraction Engine and Output Contract

The current free-text extraction engine uses two parallel signals. A regex matcher finds literal aliases and values, while regex and embedding retrievers jointly propose semantically relevant dimensions to an LLM judge. The judge sees only the retrieved dimensions, their questions, and closed allowed-value sets; it may assign a value or abstain. Regex and judge outputs are retained separately and merged by dimension, with disagreements preserved for audit. Literal matches receive confidence 0.7; judged assignments retain their model confidence and quoted evidence.

Production source pipelines normalize extracted attributes to records of the form

$$\mathcal{E}(s) = \{(i, \hat{x}_i, c_i, e_i, a_i, d_i)\}_{i=1}^{1,290}, \tag{12}$$

where $\hat{x}_i$ is a schema value or null, c_i is confidence, e_i is evidence, a_i records assignment provenance, and d_i is a field-level description. Model-extracted fields distinguish direct evidence, structured claims, summary inferences, and unsupported fields.

D.2 Source-Specific Preprocessing

One Wikipedia source row defines one persona and retains its global index, Wikidata identifier, title, URL, text hash, and source-row provenance. The source database contains 2,125,897 profiles. Amazon instead defines one persona per reviewer: reviews are sorted chronologically and rendered with category, product, rating, verified-purchase status, title, and text. The production cohort contains 100,000 reviewers selected for sufficiently long and repeated histories (Hou et al., 2024).

The production batch extractor partitions the 1,290 dimensions by semantic category into 53 chunks of at most 50 dimensions. Wikipedia and Amazon use Qwen3.6-35B-A3B through vLLM; PRISM uses Qwen3-235B-A22B through an OpenAI-compatible endpoint. Wikipedia is divided into 200 contiguous index shards and Amazon into 256 deterministic user buckets. Outputs are append-only, and completed identifiers are skipped on restart, making runs resumable and idempotent.

D.3 Observed, Hybrid, and Direct Modes

The General Social Survey uses a deterministic crosswalk from 18 coded source variables; all other dimensions remain null. Afrobarometer uses a comparable rule-based crosswalk, and ConvAI2 uses conservative phrase matching. PRISM is hybrid: nine coded demographic fields are mapped exactly and override the LLM, while self-description and stated AI preferences support extraction of additional fields. Direct volunteer submissions preserve self-reported values and unanswered fields without inference.

The complete instrument is reproduced as supplementary material. That document, `supp_material/matraix_persona_survey_instrument.pdf`, lists all 1,290 items grouped by their 43 interface categories and records, for each item, the schema index, the field identifier used in the exported record, the prompt text shown to the participant, the full closed set of selectable options, and the neutral default applied when a participant skips the surrounding category. The document is generated directly from the schema the live questionnaire loads, so item order, wording, and options match what a volunteer sees at `https://matraix.ai/play.html`.

Two properties of that instrument govern how missingness is recorded. Of the 1,290 items, 434 already carry a native `None` or `N/A` option, which is a substantive answer and is exported verbatim; the remaining 856 receive a synthetic opt-out rendered as "Skip / not applicable," and choosing it or leaving the item untouched exports the field as null. A participant may also declare an entire category unfamiliar, in which case the interface fills that category with the neutral defaults listed in the supplement and marks it skipped, leaving individual items open to override. Responses are held in the browser and submitted only when the participant exports and returns the resulting file, so submission is an act separate from answering.

The consent notice and recruitment materials are reproduced in full as supplementary material. They document the recruitment method and its platform-specific variants, open eligibility, unverified responses, and the return of an exported file as the act of consent. They also state the data-handling terms: three-year retention on MIT-managed storage, release under CC BY 4.0, and an instrument that requests no name, contact detail, or account identifier and collects no address, fingerprint, or analytics. Sensitive attributes follow the same opt-out semantics as every other item, with a native or synthetic decline option on all 1,290. Completion and missingness for the released cohort are reported in section D.5.

D.4 Normalization and Validation

Post-processing restores schema order, nulls values outside the allowed set, demotes evidence that is not grounded in the source text, and detects phrases that argue from absence (for example, "not mentioned"). Exact observed values override inferred values with direct provenance and confidence 1.0. Validation checks JSON structure, unique record IDs, all 1,290 field IDs, duplicates, allowed values, assignment types, confidence ranges, null semantics, and, when source profiles are available, quotation grounding. These checks are designed to make unsupported inference visible rather than silently filling missing human attributes.

D.5 Volunteer Survey Cohort

This subsection reports the full composition of the volunteer subset that section 3.3 summarizes. Everything is computed from the 355 released `real_human_survey` records and matches the public dataset.

figure 6 shows how much of the instrument the records exercise. The median item is answered by 91.3% of records, and no item falls below 87.3% or rises above 95.8%. Aggregated to the 43 interface categories the range is narrower still, 89.3% to 92.4%. Of the 355 records, 272 carry an answer for every one of the 1,290 items and the remaining 83 answer between 520 and 1,186 of them.

Table 8 states the declared composition on six dimensions, and figure 7 is its graphical form; the numbers are stated once, here.

Dimension	Answered	Share of those answering
Age bracket	321	25–34 22.1%, 55–64 19.0%, 35–44 15.9%, 18–24 13.7%, 45–54 13.4%, 65–74 8.4%, 75–84 4.0%, 85+ 3.4%
Gender identity	322	Woman 47.5%, Man 42.9%, Non-binary 3.7%, Self-described 3.4%, Prefer not to say 2.5%
Region	329	South Asia 20.4%, Sub-Saharan Africa 19.1%, East Asia 13.4%, Southeast Asia 10.9%, Latin America 9.7%, Western Europe 7.0%, MENA 6.7%, North America 5.8%, Eastern Europe 4.6%, Oceania 2.4%
Urbanicity	328	Rural 33.2%, Dense urban 22.3%, Small town 21.0%, Suburban 20.4%, Nomadic / remote 3.0%
Socioeconomic band	340	Low 31.8%, Lower-middle 30.0%, Middle 20.3%, Upper-middle 12.6%, High 5.3%
Employment	330	Full-time 25.8%, Retired 16.1%, Homemaker 14.2%, Self-employed 11.8%, Part-time 9.1%, Student 8.2%, Unemployed 7.6%, Gig / freelance 7.3%

Table 8: **Declared composition of the 355 released volunteer records.** Shares are of the records answering each dimension, so the denominator differs by row. Computed from the public release, so the table matches what a reader downloading the dataset obtains.

The consent notice and recruitment text shown to participants are reproduced in the supplementary material. The released cohort is an opt-in sample, with 5.8% based in North America, 39.5% in South Asia or Sub-Saharan Africa, 61.8% in the low or lower-middle socioeconomic bands, and 33.2% in rural settings. Recruitment-channel composition and response propensities are not available, so population weights cannot be justified. We therefore report the cohort as released, without reweighting, and do not treat it as a probability sample of any population.

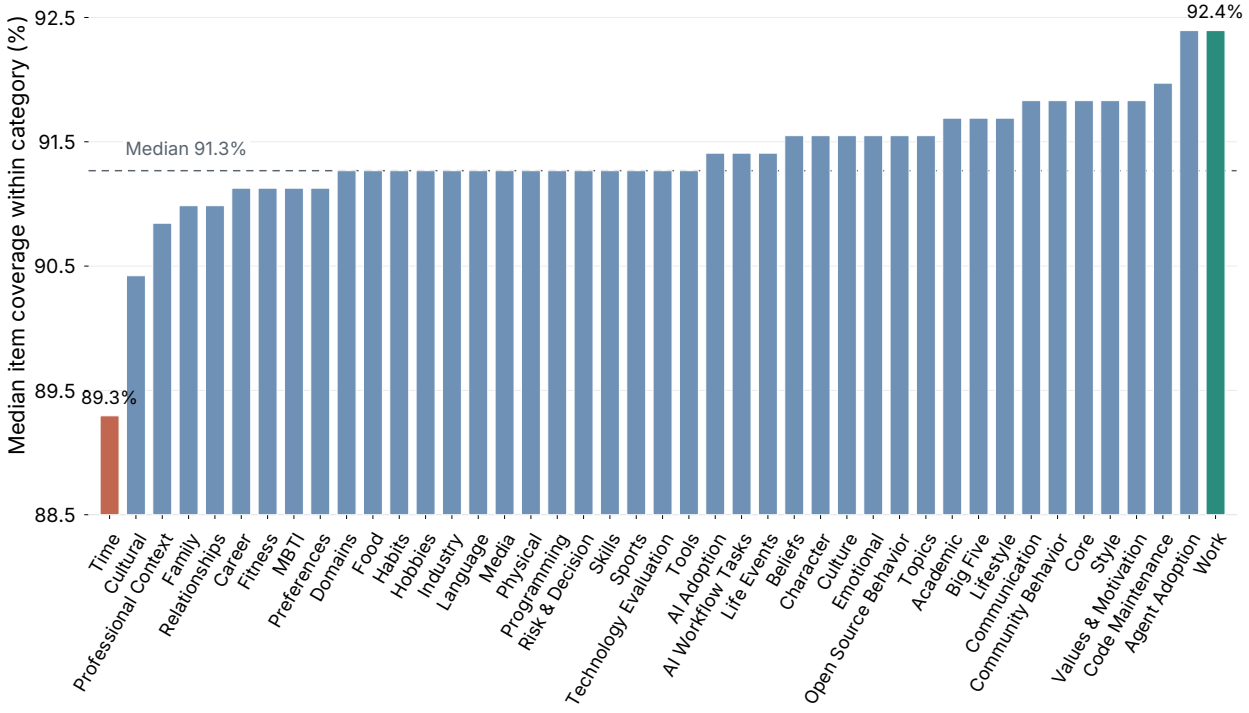
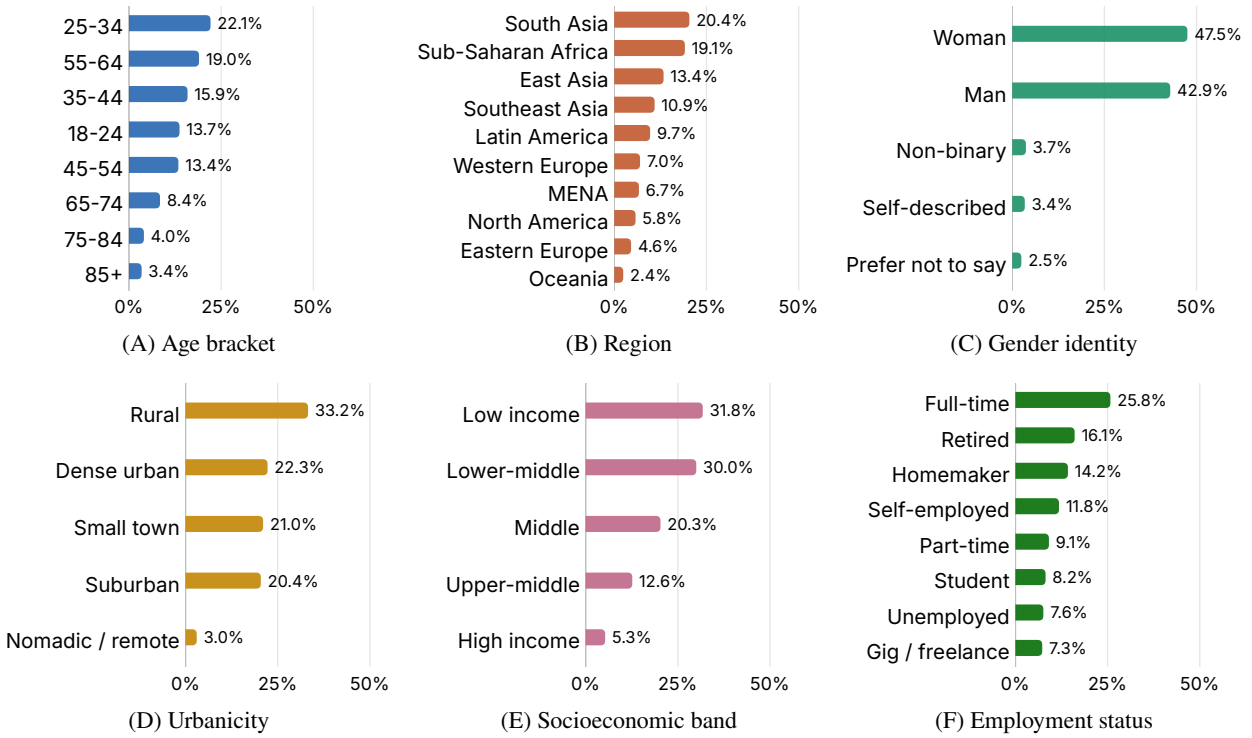


Figure 6: **How much of the 1,290-item instrument the volunteer subset exercises.** Each vertical bar is the median coverage of one interface category's items, sorted, for all 43 categories. Labels carry the category's leaf name, dropping the group prefix (*Interests*, *Behavior*, and so on) that would otherwise repeat under every bar. The vertical axis starts at 88.5% rather than zero because the finding is how narrow the range is, from 89.3% (*Time*, under *Behavior*) to 92.4% (*Agent Adoption*, under *Developer*; both extremes are named on their bars), which a zero-based axis would render as 43 nearly identical bars. The dashed line marks the 91.3% category median. The narrow range indicates that missingness is not concentrated in a small set of categories. Separately, 272 of the 355 records answer every one of the 1,290 items and the remaining 83 answer between 520 and 1,186.



(A) Age bracket (B) Region (C) Gender identity

(D) Urbanicity (E) Socioeconomic band (F) Employment status

Figure 7: **Declared composition of the volunteer subset on six core dimensions.** Shares are computed among records answering each item, so each panel's denominator differs; unanswered items remain null and are never imputed. The plotted values correspond to Table 8.

E Runtime and Environments

The execution harness builds on Harbor, an open-source framework for evaluating and optimizing agents and models in container environments (Harbor Framework Team, 2026). MatrAIx extends this substrate with persona-conditioned cohort sampling, four product-facing environment adapters, task-owned verification, and population-level reporting.

E.1 Trial, Job, and Cohort Formalization

The atomic execution unit is a trial

$$\tau = \langle \pi, \theta, \alpha, \mu, \sigma \rangle, \tag{13}$$

where persona π performs task θ through agent interface α, using model μ under seed σ. The agent determines the observation and action interface; the model supplies the policy. A trial produces an artifact bundle

$$A = \alpha(\pi, \theta; \mu), \tag{14}$$

which the task-owned verifier maps to one or more outcomes $V_\theta(A)$. Keeping persona, agent, model, and task independently configurable supports controlled comparisons in which one factor changes and the others remain fixed.

A job replicates this primitive over a seeded cohort

$$\{\pi_i = \mathcal{S}(\mathcal{P}, \sigma, i)\}_{i=1}^{N}, \tag{15}$$

where $\mathcal{P}$ is the eligible persona pool and $\mathcal{S}$ is the declared sampling procedure. The job retains everything needed to rerun it, down to the seed. Trials do not share state, so cohort execution is parallel by construction.

E.2 Launch Surfaces and Application Attachment

The same resolved recipe can be launched from an interactive playground, a command-line interface, or a REST API. These surfaces share the same task and artifact contract, allowing an exploratory run to be reproduced in scripts, continuous integration, or an external

evaluation service. Applications follow a bring-your-own-product model: a survey is supplied as a stimulus and questionnaire; an AI chatbot is attached as a sidecar over REST or the Model Context Protocol; a web target is supplied through a browser or container; and a native desktop or mobile app is supplied through a platform backend. The application remains the system under test and need not be reimplemented inside the runtime.

E.3 Execution Lifecycle and Environment Routing

Each trial follows four stages. First, the runtime binds one persona to the resolved task, agent, model, and seed. Second, it materializes the structured persona into model-facing instructions while retaining source fields for later analysis. Third, the agent observes and acts through the interface declared by the task and writes its submission to a canonical artifact location. Finally, the verifier reads the submission and, where applicable, the trajectory or environment state, and the runtime persists the scored trial record. State is isolated between trials.

Execution mode and execution location are independent. In the default mode, Survey and AI Chatbot generally run host-natively, Web uses a browser or container backend, and App routes to a native desktop or mobile backend, including Linux, macOS, and iOS. A container-forcing mode strengthens isolation, and a smoke mode validates the recipe without issuing a model call. Separately, the execution plane places the same trial locally or on a remote worker over HTTP without changing task definitions or artifact layout.

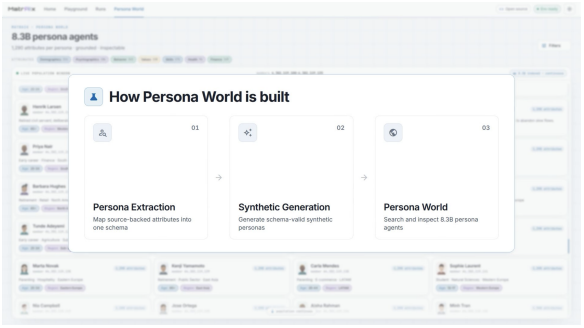
E.4 Scaling and Reproducibility

Scaling a job replicates its independent trial work units. A configurable concurrency bound controls trials on one machine, while remote dispatch fans them out across stateless workers. Adding workers changes throughput, not the trial contract. Seeded sampling makes the cohort redrawable; strict reproducibility of model behavior still depends on provider versions and backend determinism, which are recorded with the run.

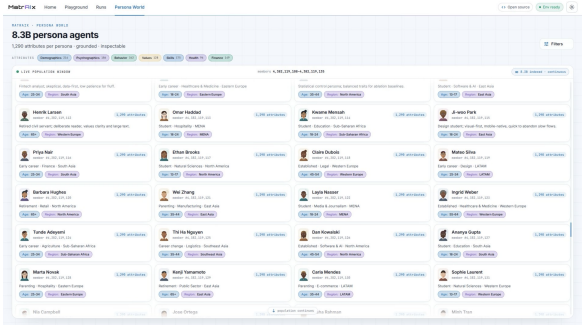
Remote dispatch transmits only allow-listed, non-secret execution parameters. Provider credentials remain on workers and are excluded from payloads and artifacts. Containers and desktop backends isolate higher-risk interactive tasks, and sensitive fields are minimized or redacted before telemetry crosses an execution boundary.

E.5 The MatrAIx Playground

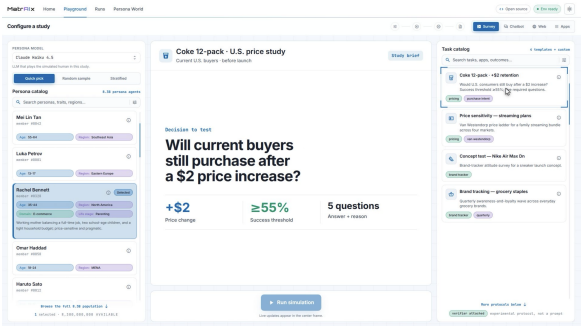
The Playground is the interactive front end to MatrAIx: it lets a user browse the persona population, assemble a cohort, configure a study, watch simulated users act, and read the aggregated population report without writing code. This appendix walks through the interface in the order a user would meet it, from the persona corpus to a final population-level report.



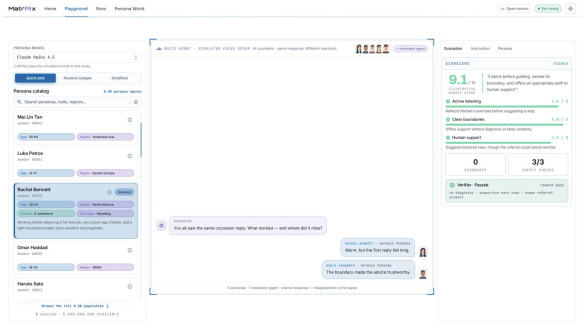
(a) **Persona World overview.** The entry point represents the Persona 8B population through source-backed attribute extraction, schema-valid synthetic generation, and searchable inspection of the corpus.



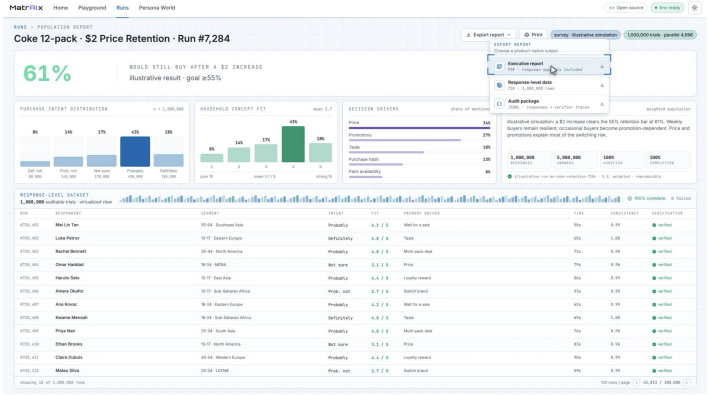
(b) **Persona browser.** Individual records are shown as cards carrying their grounded attributes (age, career, region, and further schema dimensions), and can be filtered to assemble an evaluation cohort.



(c) **Study setup.** A study is specified as a decision to test (here, a $2 price increase), with the persona cohort on the left and the task catalog on the right, before launching the simulation.



(d) **Interactive evaluation.** A persona-conditioned agent converses with the system under test in a live transcript, scored in real time against a task-owned rubric (here, an AI counselor).



(e) **Population report.** Trials aggregate into a population-level outcome (here, 61% projected retention) with response distributions, decision reasons, and the per-persona response-level dataset backing the headline number.

Figure 8: **The MatrAIx Playground.** A user browses the persona population a, inspects and filters individual persona records b, configures a study over a persona cohort c, runs an interactive evaluation of the system under test d, and reads the aggregated population-level report e, all without writing code.

Collection	Tasks	Environment	Composition
Synthetic persona surveys	405	Survey	135 Finance, 135 Healthcare, and 135 Software questionnaires, generally sharing a common survey and reporting template.
Product surveys	200	Survey	Twenty product-research archetypes, including purchase intent, price sensitivity, recommendation, and retention, crossed with ten retail products.
Synthetic chatbots	351	AI Chatbot	Scenario families across 27 domains, including travel, legal, healthcare, telecommunications, real estate, insurance, finance, and education.

Table 9: **Large template-based task collections.** Members of a collection are separate task specifications but reuse a common contract and verifier pattern.

E.6 Telemetry, Verification, and Reporting Schema

The persisted trial schema includes persona, scenario, task, agent, model, and seed identifiers; the resolved recipe; observations and prompts; responses, actions, and tool calls; timestamps and latency; state transitions; terminal status; verifier findings; and final artifacts. Environment adapters may add page histories, screenshots, exported files, database state, permission changes, or cross-application side effects while preserving the common core. Computer-use trajectories can also be analyzed to extract reusable skills (Hao and Li, 2026).

Verification is task-owned and rules-first. Objective final states, exact payloads, required tool calls, policy constraints, and side effects are checked programmatically where possible. Subjective properties such as clarity, empathy, plausibility, or persona adherence may use calibrated human or LLM judges. Cohort reports aggregate trial outcomes under the declared sampling design and preserve links back to the underlying verifier traces and artifacts.

F Application Task Details

This appendix documents the task artifacts underlying Section 5. A task is a versioned, self-contained evaluation recipe rather than an execution result. Its files declare the intended population, persona-facing goal, product attachment, runtime requirements, verifier, and aggregation policy. The runtime resolves that recipe into trials; the generated run manifest records which parts were actually executed.

F.1 Library Accounting and Status Definitions

Section 5 reports the task inventory by environment and domain. This appendix records how that inventory is assembled and how its count differs from implementation or execution coverage. The accounting combines the curated tasks on the repository's main branch with three template-based collections on synthetic-task branches. Duplicate task identifiers are resolved before counting, and individually contributed tasks still under review on open pull requests are excluded. The resulting total is the 1,010 unique specifications reported in Table 3; Table 9 below exposes the batch contribution behind that total without repeating the environment-by-domain inventory.

Library membership is tracked separately from implementation and execution. An *available* task has a discoverable specification; an *implemented* task additionally resolves its referenced artifacts, environment, and verifier; an *executed* task has at least one persisted trial; and an *empirically reported* task has a frozen cohort run whose findings appear in the paper. This report uses 1,010 only for the first of these states. Release manifests should record the latter three counts and the commit or branch from which each status was determined.

F.2 Declarative Task Contract

A task directory contains a small set of typed artifacts. The exact filenames vary by environment, but the logical contract is stable:

Environment metadata also records resource and attachment requirements. For example, an AI Chatbot task can reference the shared persona-chat environment and attach a product-specific REST or Model Context Protocol sidecar, while declaring independent verifier and agent timeouts. Web and App tasks similarly name a browser, container, Linux, macOS, or iOS backend without placing those details inside the user scenario. This separation permits the same task semantics to be exercised through a different compatible agent interface.

Contract component	Declared content	Audit purpose
Task metadata	Stable name and version, environment type, product domain, difficulty, tags, artifact paths, and runtime budgets	Identifies the recipe and prevents results from silently moving between task versions.
Persona-facing scenario	Context, user goal, constraints, disclosure policy, and required submission	Defines what every sampled persona is asked to do without exposing verifier internals.
Cohort strategy	Persona-schema filters, sampling mode, stratification fields, sample size, weights, and seed policy	Makes the target audience explicit and permits the cohort to be redrawn.
Product attachment	Questionnaire or stimulus, chat endpoint or sidecar, website target, or native application backend	Identifies the system under test and how the runtime reaches it.
Verifier	Required artifacts, structured finding schema, objective checks, timeouts, and failure conditions	Converts a trial into reproducible outcomes with supporting evidence.
Reporting policy	Aggregations, subgroup facets, summaries, optional judge directives, and disclosure rules	Defines how trial findings become a cohort-level report.

Table 10: **Logical components of an application-task contract.**

Environment	Task-owned inputs	Primary trial artifacts
Survey	Stimulus, questionnaire schema, response constraints, and optional rationale prompts	Typed responses, missing or invalid items, rationales, confidence, and completion summary.
AI Chatbot	Product endpoint or sidecar, user goal, staged-disclosure policy, turn and safety limits	Full transcript, tool or service events, resolution state, termination reason, and post-run feedback.
Web	URL or hosted site, browser backend, exploration requirements, and submission schema	Page and action trace, considered options, screenshots where enabled, final submission, and terminal page or site state.
App	Native target, platform backend, initial state, permissions, and terminal-state checks	Screenshot and action trace, exported files, application state, permission changes, and cross-application side effects.

Table 11: **Environment-specific inputs and artifacts.** App covers desktop and mobile native applications, including Linux, macOS, and iOS.

F.3 Cohort Selection Contract

The cohort strategy is a query over the shared Persona 8B schema. It may list admissible values for relevant dimensions, choose a default sampling mode, and identify fields over which the cohort should be stratified. A developer-survey task, for example, can admit adult age brackets, span several technology savviness and economic-motivation values, and stratify over the latter two. The strategy does not alter persona records or fill unknown fields; a persona is eligible only when it satisfies the query under the declared null policy.

At launch time, the runtime stores both the requested strategy and its resolved form: eligible population snapshot, filter values, sample size, strata and allocations, sampling weights, seed, and selected persona identifiers. This distinguishes the population the task is intended to address from the cohort actually executed. Failed or missing trials remain in the job accounting and are not silently replaced after results are observed.

F.4 Environment-Specific Artifacts

All environments emit a common trial envelope containing task, persona, model, agent, seed, timestamps, status, and verifier findings, but their primary artifacts differ:

Task families may share fixtures while retaining separate identifiers. The product-survey collection, for example, crosses recurring questionnaire archetypes with product stimuli; the synthetic-chat collection reuses a chat contract across domain-specific scenarios. Shared fixtures reduce mechanical duplication, but each emitted task retains its own scenario, product metadata, cohort query, and manifest entry. More broadly, the library draws on prior work in domain-grounded evaluation, controlled task variation, robustness testing, and fine-grained scoring (Li et al., 2025b; Gourabathina et al., 2025; Chen et al., 2025; Li et al., 2025c; 2026).

F.5 Verification and Reporting Contract

Verifiers emit typed findings rather than one undifferentiated score. The shared vocabulary separates what the run achieved from how it got there and what it cost, with environment-specific additions such as per-question Survey findings. Each finding includes a

numeric, categorical, Boolean, or text value and references the artifact that supports it.

Verification is rules-first. Deterministic checks cover output-schema conformance, exact values and payloads, required exploration or tool use, terminal database or application state, permission changes, and other observable side effects. When a property cannot be reduced to an objective condition, the reporting policy may declare a summary or judge directive. Such a directive names the source facet, prompt, rubric, output signals, model, and grouping field. Judge-derived signals remain labeled as such and preserve the text from which they were inferred.

Batch aggregation first runs without a language model. It reports launched, completed, failed, and valid-finding counts; summarizes numeric findings with counts and distribution statistics; ranks categorical and Boolean findings; and groups text samples by their associated outcomes. Optional summaries and judge scans run only after this deterministic layer. The resulting report stores the task version, the cohort as queried and as realized, the model and agent configuration, the verifier version, and links to every trial artifact. These fields support subgroup comparisons while keeping the population claim traceable to its sampling and execution record.

F.6 Case Study: Candy Land Price Sensitivity

The declared outcome separates the model arms more than any other task: 98.3% of the GPT 5.5 cohort answers `hesitate`, compared with 27.0% under Claude Opus 4.8 and 83.3% under Claude Haiku 4.5. Under Opus, the modal answer is `fair_buy`, selected by 73.0%. The same brief and cohort therefore support opposite product conclusions under different agent models.

Observed response support is narrower than the five-option instrument. `cheap_stock_up` and `walk_away` are never selected, and GPT and Opus each use only two options. The price-versus-quality item is nearly degenerate: 100% of GPT and Opus and 98.4% of Haiku select `balance`. Under Opus, every persona also gives the midpoint response to `q_price_matters`. These fields have nearly degenerate response distributions despite the large cohort.

The declared stratification dimension does not produce a detectable outcome difference. Under Opus, Cost-sensitive personas are least likely to hesitate at 18.4%, below Premium-seeking personas at 32.4%; the four segments span 80.4% to 86.0% under Haiku and 97.2% to 99.2% under GPT. Economic motivation is not significant under any arm after correction, and its subgroup rank correlations are −0.40, −0.20, and +0.80, none distinguishable from chance over four groups. Thus a large cohort does not guarantee a detectable persona effect.

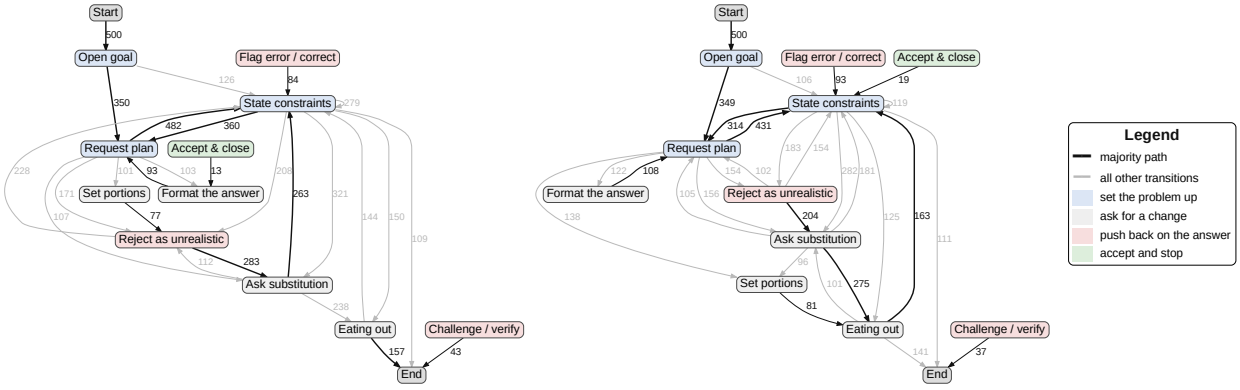
F.7 Case Study: Meal-Planning Interaction Telemetry

Figure 9 draws the full move-transition graphs of the meal-planning chat study of Figure 2: the 1,000 GPT-5.5 conversations, split by economic motivation, the persona dimension the route scan ranks first (Cramér's $V = 0.149$). Each node is a conversational move, labeled from the message text by the task's documented lexical patterns; a message can carry several moves, so a turn contributes several transitions. The moves:

- **Open goal** — states the health goal and cooking routine; the scripted opening of every conversation.
- **State constraints** — names a constraint: allergy or intolerance, diet type, religious rule, budget, activity level.
- **Request plan** — asks for the multi-day meal plan, or for it to be rebuilt.
- **Reject as unrealistic** — pushes back that a suggestion is too expensive, unavailable where the persona shops, or impractical.
- **Ask substitution** — asks to swap or replace an ingredient.
- **Set portions** — asks about portion sizes, grams, calories, or macros.
- **Eating out** — asks for a restaurant, takeaway, or menu-ordering strategy.
- **Format the answer** — asks for a table, list, or one compact final version.
- **Flag error / correct** — points out something dropped, missing, or contradicting an earlier commitment.
- **Challenge / verify** — questions whether a claim is safe, true, or evidence-backed; asks for sources or flags crash-diet risk.
- **Accept & close** — accepting or thanking language. In practice, this is often the "great, but one more thing" move: it appears mid-conversation and almost never ends a chat.
- **Start / End** — pseudo-nodes marking each conversation's first and last move.

A conversation is not one pass from Start to End. The average conversation runs six exchanges and makes about fourteen moves, so it circles through this graph: every edge count aggregates all the times that hand-off happened at any point in any conversation, and the edges curving back up the page are the returns. This loop is the task's core dynamic: personas continue revealing constraints after seeing a draft plan. In the 500 cost-sensitive conversations, Request plan returns to State constraints 482 times, and State constraints transitions to itself 279 times. More than one thousand constraint moves occur after the fourth move of a conversation.

Three further patterns stand out. First, every conversation opens by stating a goal, as the protocol scripts. Second, conversations end either at the dining-out request, the protocol's last deliverable (157 and 141), or at the exchange cap while still refining the plan (109 and 111 directly from State constraints). Third, the strata differ in how they push back: cost-sensitive personas route more transitions from Reject as unrealistic to Ask substitution (283 versus 204), while premium-seeking personas spend more of the conversation on Eating out and Format the answer.



(A) Cost-sensitive (500 conversations) (B) Premium-seeking (500 conversations)

Figure 9: **Move-transition graphs for the meal-planning chat study, by economic motivation.** 1,000 GPT-5.5 persona conversations, 500 per stratum, one fixed assistant; 13,120 move transitions in total. A conversation averages six exchanges and fourteen moves, so it traverses the graph in loops rather than one pass; edges curving back up the page are those returns. Each panel draws only its own moves and transitions and lays itself out, so shape differences reflect the data. Black edges trace each step's most frequent successor; every drawn edge carries its transition count, and a pair of moves with no edge between them co-occurred fewer than the panel's count floor of about 90 transitions.

F.8 Case Study: News+ Subscription Decision

The Candy Land analysis in Appendix F.6 runs a thousand personas against a static brief. At the other end of the execution cost range, each News+ trial boots an iPhone-17 simulator on iOS 26.4, drives the real Apple News app through a multi-step browse, and returns a structured decision for a cohort of 24. figure 10 states the task and its submission contract, then asks the same question as the meal-planning study in Figure 2: does any persona dimension affect the downstream answer?

The environment does what it claims. All 72 trials returned a schema-valid submission, all 72 listed at least one publication seen on the page, and every arm read the same live price: $12.99 per month, recorded in phrasings that differ only in how much of the auto-renewal text each persona copied. That is the load-bearing result for an OS-app environment, because it is the part that can fail invisibly. Nothing here was mocked, and no arm hallucinated a price.

The declared outcome, however, is too sparse for a precise rate estimate. One GPT 5.5 persona subscribed, five under Claude Opus 4.8 and none under Claude Haiku 4.5, so the 95% Wilson intervals are $[0.7, 20.2]$, $[9.2, 40.5]$ and $[0.0, 13.8]$ percent. The omnibus test clears correction ($q = 0.025$), but the intervals remain wide and no single-arm rate is estimated precisely. This is also why the News+ row of Table 14 carries no usable rank correlation: Haiku 4.5 subscribed nobody in any of the six segments, so there is no ordering for another arm to agree with. At this cohort size, the binary conversion rate has limited value for subgroup analysis.

What the same trials show in free text is a different matter, and it is the reason to keep the task. In every arm, 23 of 24 reasons cite something specific about the persona rather than about the product in general, and the specificity is not generic hedging. A GPT 5.5 persona declined because the catalog offered "not enough Portuguese/Sub-Saharan news or electrical/engineering titles I would read often"; an Opus 4.8 persona because there was "almost nothing in my agronomy/natural-sciences field and no Spanish-language coverage for my primary language"; a Haiku 4.5 persona because the catalog was "heavily Western-focused with limited representation of MENA or Indigenous perspectives relevant to my background." Each names the persona's own field, language or region against the catalog it actually browsed. Price appears in 24, 23 and 24 of the reasons respectively, so price salience separates nothing: it is named by subscribers and decliners alike, and catalog fit is what the declines turn on.

The two case studies have complementary limitations. Candy Land uses a thousand personas stratified on economic motivation but finds no detectable segment structure in the result. News+ shows persona-specific reasons in free text but lacks the cohort size to test modest behavioral differences. For expensive OS-App studies, structured free-text facets may therefore be more informative than a binary conversion flag alone.

(A) OS-App task · News+ subscription decision

Task and protocol

- Persona LLM plays the user (Opus 4.8, GPT 5.5, or Haiku 4.5) in the real Apple News app on an iOS 26.4 simulator; nothing is mocked
- Goal: read the full News+ offer, check price and features, then decide; **Get Started** subscribes, payment never completes
- Declared outcome: `clicked_get_started = true`

Instrument

- Scored on the returned JSON, not the screenshots
- Required: the decision, two browse flags, the on-screen price, at least one noticed title, and a reason
- Skipping the browse fails the flags; after deciding, the persona rates experience, trust, and effort

Persona cohort

- 24 personas, 124 dimensions; the same 24 under all three LLMs, 72 trials
- `economic_motivation` (3) × `media_diet` (2), four per cell; the rest unconstrained
- 1,800 s per trial, twice the chat budget: hence 24 personas here against 1,000 in Figure 2

(B) Persona deviation in the downstream outcome

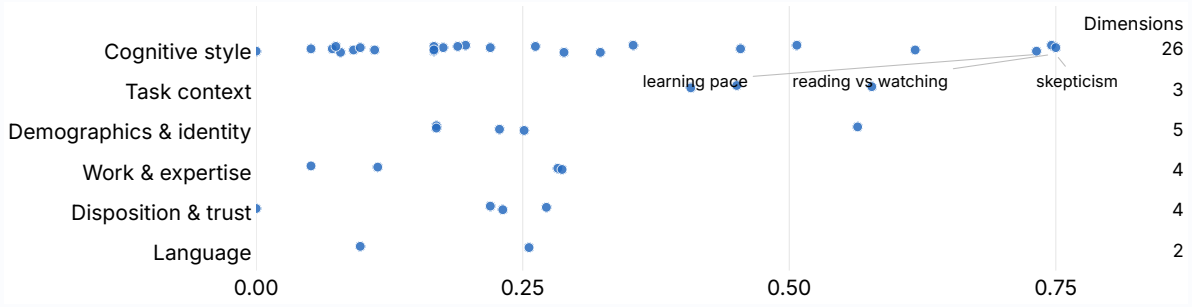


Figure 10: **The News+ subscription task: the contract, and whether personas deviate downstream.** **(A)** The executable contract: a live iOS app the persona must actually browse, the submission the verifier enforces (the price as read from the screen and a non-empty list of noticed titles, so a trial cannot pass by guessing about a product it never opened), and the cohort, which crosses two persona dimensions fully and leaves the rest unconstrained. **(B)** The same panel as Figure 2, at the opposite end of the cost gradient: each schema dimension as one dot, grouped into the same six families and placed by its association (Cramér's V) with whether the persona gave the modal experience rating (GPT-5.5 arm; the declared outcome, one subscription in 24, cannot carry a per-dimension test). At this cohort size, only 44 of the 82 dimensions have two levels with six or more personas to test. The descriptive gradients run in plausible directions: personas who strongly prefer reading over watching give the modal rating more often than those with no preference (89 versus 14 percent). However, none survives Benjamini–Hochberg correction (best $q = 0.11$): the free text, not the binary, is where this run's persona signal lives.

G Experimental Setup

G.1 Tasks, Models, and Cohorts

Each of the eight tasks was intended to run once with GPT 5.5, Claude Opus 4.8, and Claude Haiku 4.5 on a shared sampled cohort. Survey, Chatbot, and Web tasks use approximately one thousand personas per model; the two App tasks use 24 and 20. Table 12 gives each task's declared primary outcome and the observed three-arm result. The cohort-integrity exception for the meal-planning GPT 5.5 arm is reported below.

Response coverage is retained as part of each report. For example, the OpenBB run returns 980 usable trials of 1,000 under Claude Opus 4.8, and downstream rates use the field-specific answered denominator. MIT OpenCourseWare is tested at course level because no individual course is modal enough across arms. The App cohorts are too small to resolve modest subgroup effects and are interpreted accordingly.

G.2 Statistical Tests and Artifact Integrity

Categorical primary outcomes use one omnibus χ^2 test across all three models rather than selecting a pair after observing the data. Numeric outcomes use the corresponding three-arm test on the mean. Reported intervals are exact 95% Wilson intervals for proportions, and multiplicity is controlled with the Benjamini–Hochberg procedure within each declared family of tests. Subgroup ordering analyses use Spearman's ρ with exact permutation p-values.

Two integrity exceptions remain explicit. The meal-planning GPT 5.5 arm agrees with the shared cohort manifest on only 43 of 370

Task	Env.	Primary outcome	Share giving that answer			Range	q
			GPT	Opus	Haiku	(pt)	
Annual checkup	Survey	`q31` = e	50.5%	41.4%	29.7%	20.8	$< 0.001^{***}$
Candy Land price	Survey	`q_threshold` = hesitate	98.3%	27.0%	83.3%	71.3	$< 0.001^{***}$
OpenBB honesty	Chat	`wouldStillContinueUse` = unsure	81.3%	85.5%	28.1%	57.4	$< 0.001^{***}$
Meal planning[†]	Chat	`adherenceLikelihood` = 7	50.6%	0.2%	40.0%	50.4	$< 0.001^{***}$
Notion plans	Web	`decision_subject_id` = plus	63.5%	21.5%	75.7%	54.2	$< 0.001^{***}$
MIT OCW course	Web	`task_course_level` = Graduate	40.0%	34.5%	47.5%	13.0	$< 0.001^{***}$
News+ subscription	App	`clicked_get_started` = true	4.2%	20.8%	0.0%	20.8	0.025^{*}
Stocks sentiment	App	`sentiment` = hold	60.0%	30.0%	50.0%	30.0	0.153 ns

Table 12: **Complete primary-outcome results for the eight validation tasks.** Range is the largest minus smallest model share in percentage points. The q column reports a three-arm χ^2 test after Benjamini–Hochberg correction across the eight tasks ($^{***}q < 0.001$, $^{*}q < 0.05$; ns otherwise).

matched identifiers, whereas the Opus and Haiku arms match completely; its cross-model result is therefore not interpreted. For the Stocks task, two artifacts write `sentiment` and disagree on 1, 2, and 4 trials across the three arms; reported primary outcomes use the task's declared decision file. These exceptions remain in the run record rather than being silently repaired after inspection.

H Application-Level Validation Results

H.1 Complete Product-Level Outcomes

Table 13 reports one product-facing measure for each task and exposes the numerator and answered denominator behind every rate.

Task	Product-level measure	GPT 5.5	Opus 4.8	Haiku 4.5
Annual checkup	Very likely to schedule in time	50.5% (505/1,000)	41.4% (414/1,000)	29.7% (297/1,000)
Candy Land price	Hesitates or worse at new price	98.3% (983/1,000)	27.0% (270/1,000)	83.3% (833/1,000)
OpenBB honesty	Would not continue using	18.5% (185/1,000)	14.5% (132/909)	71.9% (719/1,000)
Meal planning[†]	Stated need fully satisfied	46.2% (462/1,000)	0.2% (2/1,000)	28.1% (281/1,000)
Notion plans	Selected a paid plan	75.8% (776/1,024)	23.2% (237/1,022)	93.9% (958/1,020)
MIT OCW course	Chose a graduate-level course	40.0% (403/1,008)	34.5% (347/1,007)	47.5% (473/996)
News+ subscription	Subscribed	4.2% (1/24)	20.8% (5/24)	0.0% (0/24)
Stocks sentiment	Buy opinion	40.0% (8/20)	70.0% (14/20)	47.4% (9/19)

Table 13: **Product-level conclusions under three agent models on identical cohorts.** Denominators are trials in which the field was answered. Notion aggregates its three paid tiers against the free tier. [†]The meal-planning GPT 5.5 arm did not run the declared cohort and is not comparable with the other two arms.

H.2 Cross-Model Persona-Effect Consistency

Within each task, persona subgroups are ranked by their outcome rate separately under each model and the rankings are compared with Spearman's ρ. This permits different outcome levels while testing whether a persona effect points in the same direction. Table 14 reports every defined comparison.

Trust level in OpenBB is the only dimension significant under all three models, and all three order its four groups identically. Three independent random orderings of four groups coincide with probability $(1/4!)^2 = 0.0017$. Across all 22 defined pair-by-task comparisons, 14 point in the same direction and the median ρ is +0.29; correlations without a detected subgroup effect are not interpreted as evidence.

H.3 Persona-Fidelity Statistics

Table 15 reports the complete paired-agreement counts and age-band self-report result.

Task	Persona dimension	Groups	Sig.	Spearman ρ, exact p		
				GPT/Opus	GPT/Haiku	Opus/Haiku
Annual checkup	age bracket	6	○ ○ ●	+0.26 p=0.329	−0.43 p=0.822	−0.77 p=0.971
Candy Land price	economic motivation	4	○ ○ ○	−0.40 p=0.792	−0.20 p=0.625	+0.80 p=0.167
OpenBB honesty	trust level	4	● ● ●	**+1.00** p=0.042	**+1.00** p=0.042	**+1.00** p=0.042
Meal planning†	life stage	4	○ ○ ○	+0.95 p=0.083	+0.32 p=0.500	+0.33 p=0.417
Notion plans	company size	8	○ ○ ○	+0.44 p=0.138	+0.60 p=0.059	−0.24 p=0.725
MIT OCW course	academic field	8	○ ○ ○	+0.93 p=0.001	+0.09 p=0.420	+0.06 p=0.452
News+ subscr.‡	economic motivation	3	○ ○ ○	+0.00 p=0.667	flat	flat
Stocks sentiment‡	risk tolerance	5	○ ○ ○	+0.47 p=0.267	−0.92 p=1.000	−0.67 p=0.933

Table 14: **Rank correlation between model arms' orderings of the same persona subgroups.** Significance marks are ordered GPT / Opus / Haiku (● significant after correction, ○ not). A flat arm has no ordering to compare. †The GPT arm has a cohort-integrity exception. ‡App rows contain only three to eight personas per subgroup.

	GPT × Opus	GPT × Haiku	Opus × Haiku
Paired agreement over 88 joinable fields			
Median Cohen's κ	0.000	0.000	+0.001
Fields at $\kappa \leq 0$	59 of 88	50 of 88	40 of 88
Fields reaching $\kappa \geq 0.2$	7 of 88	8 of 88	7 of 88
Fields at $\geq 50\%$ agreement, $\kappa < 0.1$	48 of 56	25 of 34	24 of 34
Self-report fidelity: age band matches the persona			
GPT 5.5 16.3% (ns) Opus 4.8 16.9% (ns) Haiku 4.5 **100.0%**			chance 16.7%

Table 15: **Persona fidelity across all three model pairs.** Cohen's κ corrects raw agreement for each model's answer distribution. GPT and Opus age-band matches are indistinguishable from uniform guessing ($q = 0.84$ and $q = 0.85$); Haiku matches 1,000 of 1,000 trials.

I Persona Adherence Validation

This appendix backs the attribute-level adherence probe reported in section 6: the matched-cohort design, the full per-cell results, and the verbatim evidence the judge cited.

I.1 Probe Design

The probe follows a minimal input–output contract: the input is a persona, the output is a behavioral signal, and the judgment is whether one drives the other. We select ten behavioral attributes that are observable in a short agent trajectory and diagnostic of the persona schema's stylistic dimensions. Seven are cognitive or register attributes (`cog-emoji-use`, `cog-humor`, `cog-politeness`, `cog-storytelling`, `cog-use-of-jargon`, `cog-verbosity`, and `register`); three are coding attributes that only surface when the agent writes code (`code-comment-style`, `code-naming-verbosity`, `code-summary-documentation`).

Each attribute is probed in all four evaluation environments (Survey, AI Chatbot, Web, and OS-App on Linux), so that adherence is measured both where text is produced directly (Survey) and where it must survive an execution layer (Web, OS-App). For every (attribute, environment) cell we construct a matched pair of cohorts: a *positive* cohort of five personas declaring one pole of the attribute (e.g. *Extensive inline comments*) and a *negative* cohort of five declaring the opposite pole (e.g. *No comments*). Cohorts are drawn by stratified sampling on the single attribute under test, holding all other persona fields to the population distribution, so the only systematic difference between the two arms is the probed attribute. This gives $10 \times 4 \times (5 + 5) = 400$ trials in total.

Each trial runs one persona through its environment's task to completion and records the full agent trajectory and any produced artifact. An LLM judge (Claude Opus 4.8, served through the same gateway used elsewhere in the pipeline) reads that trajectory together with the persona's target attribute value and returns a single binary verdict: was the target value expressed in the agent's actual behavior? The judge sees whatever trajectory or artifact text is present, so one protocol applies uniformly across environments that differ in output modality. For a positive persona a verdict of *expressed* is a success; for a negative persona, success is the judge finding the *opposite* value expressed, meaning that the target style was correctly suppressed. Each cell therefore reports two counts out of five in the same "higher is better" direction.

I.2 Per-Attribute Results and Backbone Sensitivity

Table 16 reports per-attribute adherence for two acting agents side by side—**Opus 4.8** and **GPT-5.6-sol**—under an otherwise identical 400-trial protocol (same personas, tasks, environments, and the same Opus 4.8 judge). This design changes the acting model while holding the persona representation and judge fixed, subject to the Chat adapter exception below.[‡]

With Opus 4.8 the agent expressed the declared value in 185/200 positive trials and suppressed it in 181/200 negative trials, for 366/400 = 91.5%; 33 of 40 cells are strong (pos $\geq$ 4 and neg $\geq$ 4), with strong-cell counts Survey 9/10, Chat 9/10, Web 9/10, and OS-App 6/10. With GPT-5.6-sol the same protocol yields 154/200 positive and 163/200 negative, for 317/400 = 79.2%—a $\sim$12-point drop—with per-environment scores Survey 91, Chat 82, Web 68, and OS-App 76.

Table 16: **Persona adherence per attribute and environment, both acting agents.** Each environment is split into two sub-columns: **Opus 4.8** (left) and **GPT-5.6-sol** (right), under the same Opus 4.8 judge. Each cell shows two groups of five persona icons—the left group the *positive* cohort, the right group the *negative* cohort. A filled icon (🧍) marks a persona whose behavior expressed the declared value (for the negative cohort, correctly expressed the *opposite* value—target suppressed); a faint icon (🧍) marks one that did not. More filled icons is better in both groups. Overall Opus 366/400 = 91.5% (33/40 cells strong, $\geq$ 4 filled per group) vs. GPT-5.6-sol 317/400 = 79.2%.

	Survey		Chat		Web		OS-App	
Attribute	Opus 4.8	GPT-5.6-sol	Opus 4.8	GPT-5.6-sol	Opus 4.8	GPT-5.6-sol	Opus 4.8	GPT-5.6-sol
code-comment-style	5/5 5/5	5/5 5/5	5/5 5/5	4/5 5/5	5/5 5/5	2/5 5/5	5/5 5/5	5/5 5/5
code-naming-verbosity	5/5 5/5	5/5 5/5	4/5 5/5	5/5 4/5	5/5 5/5	5/5 1/5	5/5 5/5	5/5 5/5
code-summary-documentation	5/5 5/5	5/5 5/5	5/5 5/5	5/5 5/5	5/5 5/5	5/5 5/5	5/5 5/5	5/5 5/5
cog-emoji-use	5/5 5/5	5/5 5/5	5/5 5/5	4/5 5/5	5/5 5/5	5/5 5/5	4/5 5/5	1/5 5/5
cog-humor	5/5 5/5	5/5 4/5	5/5 5/5	5/5 5/5	5/5 5/5	4/5 5/5	3/5 5/5	4/5 5/5
cog-politeness	5/5 5/5	5/5 5/5	5/5 5/5	5/5 4/5	5/5 5/5	5/5 2/5	5/5 1/5	5/5 1/5
cog-storytelling	5/5 3/5	5/5 5/5	5/5 5/5	1/5 5/5	5/5 3/5	1/5 5/5	5/5 1/5	5/5 2/5
cog-use-of-jargon	5/5 5/5	5/5 5/5	4/5 4/5	3/5 5/5	5/5 5/5	3/5 5/5	5/5 4/5	4/5 2/5
cog-verbosity	4/5 5/5	1/5 5/5	2/5 5/5	1/5 3/5	5/5 4/5	1/5 2/5	3/5 5/5	1/5 4/5
register	4/5 5/5	5/5 2/5	4/5 4/5	5/5 5/5	4/5 4/5	5/5 1/5	4/5 4/5	5/5 3/5

Where the Opus 4.8 failures fall. The failures are concentrated rather than spread evenly, which is what makes them diagnosable. By environment, out of 100 trials each: Survey 96, Chat 92, Web 95, and OS-App 83. Half of all failures (17 of 34) are in OS-App alone. By cell, 20 of the 34 come from the seven non-strong cells and the remaining 14 are isolated single misses in cells that are otherwise perfect. The OS-App negative arms alone account for 11 failures, nine of them in two cells: `cog-politeness` at 0/5, where no persona instructed to drop politeness did so, and `cog-storytelling` at 1/5. The asymmetry between the arms points the same way: agents expressed a declared value in 185/200 positive trials but suppressed it in only 181/200 negative ones, so most of what fails is suppression, not expression.

The seven non-strong cells cluster around two identifiable causes rather than random judge disagreement. First, the Web environment tends to *under-produce*: the agent frequently stops early or emits a truncated artifact, so an attribute that would have surfaced in a longer trajectory is never given the chance to surface. This is an execution-layer limit of the environment, not a failure of persona conditioning. Second, some attributes are intrinsically asymmetric to suppress: agents default to concrete examples, so a persona instructed to *avoid* storytelling (`cog-storytelling` negative) is fighting the base policy of the model, which is why that negative arm is weakest across environments (3/5 in Survey and Web, 1/5 in OS-App).

Politeness is the sharpest instance of the second cause and worth stating plainly: an agent asked to behave impolitely is being asked to act against alignment training that is not persona-conditioned, and in OS-App it declined in all five trials. We read that cell as a boundary of persona conditioning rather than as a measurement artifact. It marks where a declared attribute stops competing with the model's own policy and simply loses, and it is the reason we report the negative arm separately instead of folding both arms into one adherence rate.

The GPT-5.6 gap is structured, not uniform. GPT-5.6-sol trails Opus 4.8 by roughly 12 points overall, but the deficit is concentrated along interpretable axes rather than spread evenly. The coding attributes—comment style, naming, summary documentation—remain near parity (91% vs 100%): a structured, executable style directive transfers to the GPT backbone almost as well as to Opus. The soft-style cognitive attributes lag further (73% vs 88%). The two arms fall together (positive 154/200 = 77%, negative 163/200 = 82%), so this is a general steerability deficit rather than a one-directional bias.

[‡]GPT-5.6 is served on our gateway only through the Responses API; the Chat environment, whose reference agent speaks only the Anthropic Messages protocol, is driven for the GPT run through the same general agent used by the Web environment. The framework thus differs from the Opus Chat column, which we flag where the two are compared.

The single largest hole is `cog-verbosity` positive, which is 0/5 in *all four* environments: GPT-5.6-sol does not produce the "rambling, long-winded" persona, and its concise, well-structured prior overrides the declared attribute regardless of environment. Removing that one attribute lifts the three text-native environments to roughly 85%. Additional probes suggest this is model-specific rather than an artifact of the original prompt: opening the task prompt to invite elaboration made the model write only marginally more, and swapping in personas whose correlated dimensions align with verbosity (rather than the antagonistic blunt/low-detail combination) did not change the outcome. The remaining misses are the same boundary Opus exhibits more mildly—agents decline to *degrade* their own output (rude tone, single-letter names, colloquial register for the negative personas)—plus the Web under-production effect already noted, which is more pronounced under the GPT backbone because its default replies are terser.

Reading the two agents together. The comparison indicates that persona adherence is backbone-dependent and that the dependence is structured. Executable style conditioning is robust across models; soft stylistic conditioning, and in particular any attribute that asks the model to be more verbose or less polished than its own prior, degrades with a backbone whose prior is strongly concise. The persona representation and judge are held fixed across the two runs, while the Chat comparison also reflects the adapter difference noted above.

I.3 Cited Judge Evidence

Every verdict in the 400-trial probe is produced by the single LLM judge of Appendix I.1 (Claude Opus 4.8); no human label enters the top-line 91.5%. The judge is therefore audited rather than taken on trust. The first audit is the judge's own evidence: the protocol requires each verdict to cite verbatim behavior from the trajectory, and Table 17 reproduces that evidence for the Survey environment, where the signal is cleanest. For each attribute it pairs the behavior the judge read off a positive persona against that off its matched negative persona. The contrasts are behavioral, such as inline comments versus none, verbose descriptive identifiers versus single letters, or a narrated scene versus an abstract value statement, rather than the persona restating its own attribute, which is the distinction the probe is built to enforce.

Where the human labels are. The human labeling in this paper's validation suite belongs to the companion extraction-quality study of Appendix J, not to this probe. There, six raters each completed the same four 25-persona packets, so every persona in the source-matched 100-persona subset carries six independent human ratings: 600 persona-level records with an overall mean of 4.135/5, 97.2% of rater–rater comparisons within one point, and the two LLM judges within one point of the six-rater mean in 93.8% (Claude) and 79.2% (GPT-5.5) of comparisons. That study rates extraction quality on a five-metric rubric, which is a different task from the binary behavioral verdict here, so we cite it as the paper's human-validation evidence rather than as a calibration of this judge; the direct grounding of the 400 verdicts is the cited evidence of Table 17.

Table 17: **Cited judge evidence, Survey environment.** For each attribute, the behavior the judge identified in a positive persona (declared value) versus its matched negative persona (opposite value). Excerpts are quoted from the trial trajectories.

Attribute	Positive (declared)	Negative (opposite)
code-comment-style	Nearly every line carries an inline comment (`# Iterate over every integer`, `# Check divisibility`)	Code contains no comments whatsoever
code-naming-verbosity	`calculate_average_of_passing_scores`, `number_of_passing_scores`	Variables `s`, `t`, `a`, `c`, `x`, all single-letter
code-summary-documentation	Every function opens with a `tldr:` docstring	Prose plus code, no TLDR/summary header
cog-emoji-use	Many emoji across a short paragraph	No emoji despite a casual app-store prompt
cog-humor	Playful, witty asides ("the boxes may yet win")	Measured, earnest tone, no jokes
cog-politeness	"Might I kindly ask that you resend the document at your earliest convenience"	"Hey, you forgot the attachment. Again.": blunt and sarcastic
cog-storytelling	A narrated scene ("a storm came through, half the lodge went dark")	Abstract, value-driven, no concrete scene
cog-use-of-jargon	Dense technical jargon ("TCP three-way handshake, SYN-ACK")	Plain terms ("translate the name into a numerical address")
cog-verbosity	Rambling, multi-paragraph, tangential answer	Short clipped fragments, no elaboration
register	Standard/formal phrasing	Colloquial ("cuppa and the papers", "the wife's doing a roast")

J Extraction Quality Validation

This appendix documents two complementary evaluations of extraction quality: (i) a paired, dual-LLM evaluation of all 1,000 persona extractions, and (ii) a six-rater human evaluation of a 100-persona subset. Both evaluations use five quality dimensions on a 1–5

scale. They share the same five conceptual dimensions, but not an identical interface: the LLM judges received the full quantitative rubric, whereas human raters received concise metric descriptions and a filtered field view. We therefore analyze the two evaluation streams separately and use the human results to calibrate, rather than replace, the LLM judgments.

J.1 Extraction-Quality Rubric

Table 18: **Extraction-quality metrics.** Higher scores indicate better extraction quality.

Metric	Name	Definition
M1	Claim validity	Does each populated claim remain defensible when its value, cited evidence, and free-text description are considered jointly? A field is problematic if its value is indefensible, its evidence is plainly unrelated or non-supporting, or its description adds implausible unsupported specifics.
M2	No over-claiming	Has an attribute been populated without any plausible basis? Clearly unsupported assignments count as problems, while a plausible, appropriately labeled inference does not.
M3	Coverage	Did the extraction omit an important attribute that was clearly available in the source?
M4	Internal consistency	Do extracted fields contradict one another, especially on core identity, role, region, life stage, language, or technology-use information?
M5	Overall fidelity and plausibility	Is the extracted record usable for faithfully role-playing the source person, and are its inferred psychological, interest, and communication traits plausible and coherent?

J.2 LLM-Judge Evaluation

The full evaluation set contains 1,000 extractions: 500 from Wikipedia, 250 from Stack Overflow, 200 from Amazon, and 50 from PRISM. GPT-5.5 and Claude independently scored every extraction, yielding 1,000 paired records and 5,000 paired metric scores.

Both judges received byte-identical prompt text. Each prompt contained the complete extracted card—field, value, evidence, description, and assignment type—together with the rubric. Records were paired by `custom_id`; all 1,000 outputs from each judge parsed successfully.

Table 19: **Paired LLM-judge results on all 1,000 extractions.** Δ is GPT minus Claude; ≤ 1 is the proportion of paired scores that differ by at most one point.

Metric	GPT	Claude	Δ	≤ 1
M1 Claim validity	3.433	3.937	−0.504	81.4%
M2 No over-claiming	3.532	3.646	−0.114	82.3%
M3 Coverage	4.465	4.031	+0.434	99.2%
M4 Internal consistency	3.606	3.932	−0.326	85.0%
M5 Fidelity and plausibility	3.829	4.109	−0.280	97.8%
Overall	3.773	3.931	−0.158	89.1%

The two judges assigned generally high scores, with overall means of 3.773 for GPT and 3.931 for Claude. Across all 5,000 paired metric scores, 89.1% differed by at most one point. Agreement was strongest for coverage (M3: 99.2% within one point) and overall fidelity and plausibility (M5: 97.8% within one point).

J.3 Human Evaluation on the 100-Persona Subset

The human evaluation uses 100 personas whose source composition exactly matches the full set: 50 Wikipedia, 25 Stack Overflow, 20 Amazon, and 5 PRISM. The items were divided into four 25-persona packets. Six raters completed all four packets, so every persona has six human ratings. This produced 600 persona-level rating records and 3,000 individual metric scores.

Each human-evaluation page displayed a compact identity card and a filtered field table containing values, evidence, descriptions, and assignment types; original source text was shown where available. The interface presented concise descriptions of M1–M5 and

asked for one 1–5 score per metric, with an optional comment. For each persona and metric, the six human scores were averaged to form the human reference. We report this mean together with the proportion of comparisons that differ by at most one point.

Table 20: **Human evaluation and within-one agreement on the 100-persona subset.** H–H compares all 15 pairs of human raters; GPT–H and Claude–H compare each LLM judge with the six-rater human mean.

Metric	Human mean	H–H ≤ 1	GPT–H ≤ 1	Claude–H ≤ 1
M1	4.105	99.1%	69.0%	92.0%
M2	3.770	92.2%	81.0%	88.0%
M3	4.223	97.1%	95.0%	100.0%
M4	4.537	98.6%	55.0%	92.0%
M5	4.040	99.1%	96.0%	97.0%
Overall	4.135	97.2%	79.2%	93.8%

Human ratings were favorable overall: the mean was 4.135/5, and 84.7% of the 3,000 scores were 4 or 5. Across all metrics, 97.2% of human-rater comparisons differed by at most one point. Compared with the six-rater human mean, GPT was within one point in 79.2% of cases and Claude in 93.8%.

K System Capability Comparison

Table 21 places MatrAIx against representative agent benchmarks, simulation systems, and synthetic-sampling methods on the capabilities that decide whether a system can evaluate a product against a modelled population. The comparison is drawn from what each system states in its own publication, so a cross records an unstated capability rather than a demonstrated absence, and the matrix positions the systems rather than ranking them.

	Agent Bench	GAIA	Web Arena	Web Shop	Mind2 Web	App World	Tool LLM	Bench Flow	τ-bench	Generative Agents	SOTOPIA	OASIS	Silicon sampling	MatrAIx
Product-as-SUT evaluation	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✗	✗	✓
Persona conditioning	✗	✗	✗	✗	✗	✓	✗	✓	✓	✓	✓	✓	✓	✓
Behavioral grounding	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	✓	✓
Native-device execution	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✓
Reproducible reporting	✗	✗	✓	✓	✗	✓	✗	✓	✓	✗	✗	✓	✓	✓
Trajectory inspection	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✓
End-to-end validation	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	✓	✓	✓
Silicon sampling	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✗	✗	✓	✓
Reproducible cohorts	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓
Multi-agent simulation	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗	✗

Table 21: **Capability comparison across representative agent benchmarks, simulation systems, and synthetic-sampling methods.** Systems, left to right: AgentBench (Liu et al., 2024), GAIA (Mialon et al., 2024), WebArena (Zhou et al., 2024a), WebShop (Yao et al., 2022), Mind2Web (Deng et al., 2023), AppWorld (Trivedi et al., 2024), ToolLLM (Qin et al., 2024), BenchFlow (BenchFlow, 2025), τ-bench (Yao et al., 2025), Generative Agents (Park et al., 2023), SOTOPIA (Zhou et al., 2024b), OASIS (Yang et al., 2024), and Silicon sampling (Argyle et al., 2023). A check (✓) indicates explicit support in the published system; a cross (✗) indicates the capability is not stated. Dimensions read as follows: *product-as-SUT evaluation* treats the product, not the agent, as the subject under test; *persona conditioning* instantiates a user from a sampled population profile; *behavioral grounding* verifies that behavior tracks a target attribute rather than confounders; *native-device execution* covers real mobile/desktop apps beyond API demos; *reproducible reporting* separates verifier facts from reporting policy; *trajectory inspection* exposes per-trial traces; *end-to-end validation* closes the persona–task–product loop; *silicon sampling* substitutes simulated respondents for survey/UX pre-studies; *reproducible cohorts* deterministically re-instantiate the same cohort; and *multi-agent simulation* denotes persistent multi-agent social worlds (a deliberate non-goal for MatrAIx). The matrix compares capability coverage rather than providing an overall ranking.

L Future Directions

Future work can extend both the evaluation framework and the persona models. User-centered benchmarks could evaluate satisfaction, trust, retention, and recovery from failure alongside task completion in interactive and long-horizon settings. Persona 8B could also support automated generation of diverse, realistic tasks and robustness tests in which users express the same goal in different ways. Expanding the open-source Survey, AI Chatbot, Web, and App environments would make these evaluations easier to reproduce and extend across products and domains.

Methodological work could improve persona selection, fidelity, and consistency across models and repeated runs; develop dynamic personas with long-term memory; and compare prompting with steering, parameter-efficient adaptation, or training-based simulation. Interpretability tools could help identify how persona attributes affect model behavior. Broader applications include user-simulation-based red teaming, user-controlled personalized assistants, and studies in psychology, economics, policy, social science, multimodal interaction, and embodied systems. These extensions require stronger validation against longitudinal human data, especially before simulated behavior is used for personalization, safety assessment, or decisions about real populations.

M Responsible Use, Release, and Limitations

MatrAIx personas are simulation instruments rather than people, and a cohort of them is not a probability sample of a real population. The population conditions on attributes including age, region, income, employment, and health, so it can be turned to uses the release does not sanction: impersonating a named individual, attributing opinions or behavior to a real person or an identifiable community, assembling profiles that target individuals, or scripting persuasion, exclusion, or price discrimination aimed at a protected group. None of these are supported uses. Nor does running a simulated cohort discharge the obligation to consult the people a product actually affects, particularly where a decision carries consequences for them in health, finance, employment, or other regulated settings. The volunteer instrument that grounds part of the population asks for no name, contact detail, or account identifier and carries a decline option on all 1,290 items. Work built on the release is expected to preserve that posture rather than attempt re-identification. Human-referenced deployment studies remain the appropriate standard for consequential claims, including evaluations of patient-facing, EHR-integrated agents (Hao et al., 2025).

The public artifact is the Persona 1M coreset rather than the full internal population. Records enter the coreset only after the filtering, provenance, and deduplication checks of section 3.4. Its synthetic component is calibrated toward four supported marginals, and the release ships with a manifest, an audit of achieved shares and infeasible residuals, and per-file hashes. Corpus size is distinct from execution scale: a record becomes a persona agent only when paired with a model, interface, and task, and an evaluation instantiates only its sampled cohort.

Every reported result is therefore a persona-agent result, not a direct claim about how a person would behave. Results can also depend substantially on the persona-agent model; for example, the paid-plan share on one product page spans 23.2% to 93.9% across three models on identical cohorts. MatrAIx runs should therefore be treated as hypothesis-generating when the target claim concerns people. Such claims require human validation on the same task and instrument, following a design such as the 100-record study in Appendix J.

One configuration deserves its own warning, because it is the configuration a user of this infrastructure is most likely to reach for. When the model playing the persona and the model behind the system under test share a backbone, a favorable result is ambiguous. Agreement may mean the system served the user well, or it may mean a model recognized and preferred its own output, and the run cannot tell those apart. The direction of the bias is not obviously benign either: a persona may accept an answer a person would have pushed back on, which inflates satisfaction and suppresses exactly the friction the evaluation exists to surface.

The present experiments do not isolate that effect. They vary the persona model across three frontier systems, but each task holds one application fixed, so persona model and system backbone are never crossed and the self-preference term cannot be separated from ordinary model-to-model variation. What the results do establish is that the persona model is a first-order factor rather than an implementation detail: the paid-plan share spans 23.2% to 93.9% across three models on identical cohorts, and median pairwise Cohen's κ across 88 joinable fields is approximately zero. An outcome that moves that much with the acting persona model could also be sensitive to a shared backbone.

Two practices follow, and MatrAIx supports both. The agent model is recorded as part of the evaluation configuration rather than left implicit, so a shared backbone is visible in the report instead of hidden in it. And an evaluation whose conclusion matters should also run the same cohort under at least one persona model that does not share a backbone with the system under test, treating agreement between matched models as a hypothesis to check rather than a result to report. Isolating the effect properly requires crossing persona model with system model on one task, which we have not run and consider the natural next experiment.

A second gap is one of scope rather than configuration. section 2 argues that support-style simulation requires realistic disclosure, correction, refusal, and abandonment. The present experiments do not directly measure these behaviors. The adherence probe asks

whether a declared style appears in a trajectory, which is a question about conditioning, not about whether the resulting user resembles a real one. Nothing here establishes that a MatrAIx persona withholds context, pushes back, or gives up the way people do.

Two designs could address this gap using logs that already exist (Zhao et al., 2024; Zheng et al., 2024; Kirk et al., 2024; Paruchuri et al., 2025) and telemetry MatrAIx already stores. At the population level, simulated user turns can be compared against matched slices of real logs on turn length, question type, volunteered versus withheld context, correction and abandonment rates, and response-option entropy. A real-versus-simulated classifier can summarize these differences, with an AUC near 0.5 as the target. At the individual level, a persona can be extracted from the first half of a held-out real conversation, the next user turns simulated, and the result scored against what the person actually wrote, with shuffled-persona and no-persona baselines separating persona information from conversational momentum. The second is the behavior-chain test of Li et al. (2025a) applied to in-the-wild data rather than to a constructed benchmark. Both would have to be reported per agent model given the model dependence in section 6, and public logs would need screening for memorization, since a model may have seen the very conversation it is asked to continue. We consider this a priority for future validation.