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A new gold standard for consumer profiling: a qualitative methodology powered by AI-moderated interviews

Introduction: Rethinking how we understand consumers

For years, demographic segmentation has provided the backbone of consumer targeting. It made sense given the media and research constraints of the past. But, today, that model is starting to break down.

In this paper, we set out how AI-moderated interviews — which enable in-depth qualitative analysis at scale — will change how consumer profiling works. By moving qualitative research beyond traditional focus groups and into consumer insight platforms alongside quantitative data, researchers can connect the two in ways that were not previously possible. We describe this shift as Connected Insights.

And when qualitative insight is available at scale, it can be combined with behavioural data to build a far richer understanding of how people think and decide.

This new approach flips the starting point for profiling. Instead of grouping consumers by age or gender and adding qualitative insight as supporting colour, it begins with motivations — and shows how understanding them at scale changes how we're able to define, segment and engage audiences.

A more complex consumer reality

Moving to behavior-first profiling is not just an opportunity — it's a necessity. The media landscape has changed; it is now personalized and algorithmic. Cultural trends move across generations at speed. Peer networks, online communities and influencers shape behaviour in ways that cut across age and income.

Behavior also varies by category and context. One person can be thrifty in groceries, indulgent in skincare and adventurous in travel; another may value familiarity in finance but seek novelty in entertainment. When identity is layered and context-dependent, traditional approaches struggle to capture how people actually make decisions.

But with our five-step methodology, brands can not only access that depth of insight, they can also apply it at a scale and cadence that was previously impractical.

Todd Latham
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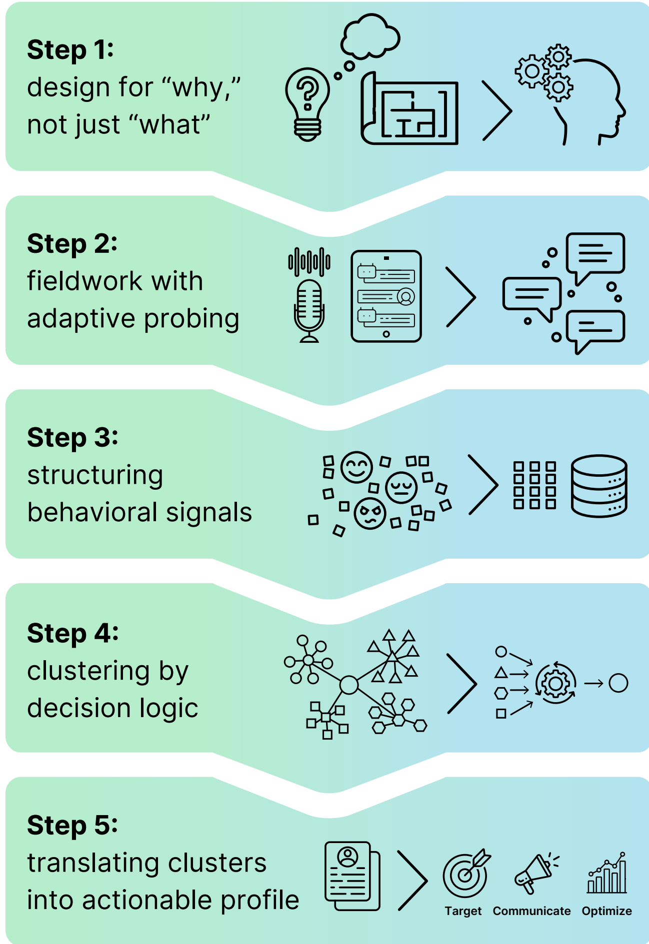
Five-step methodology for behavior-first profiling with AI-moderated interviews



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1. Three myths in consumer targeting

If demographic segmentation is increasingly limited, why does it remain so dominant? The answer is largely practical. Demographics are built into the way legacy marketing systems work.

They're also efficient. They create clean boundaries and make audiences easy to describe, while generational labels provide convenient cultural narratives. They allow teams to communicate quickly about "who the target is".

These assumptions guide planning decisions, media investment and creative direction. But neat categories rarely reflect messy reality. So if targeting is going to evolve, common beliefs about consumer targeting need to be challenged.

Myth 1: Gender predicts category behavior

Many categories have historically been organized around gender. Beauty and skincare were positioned as female domains, gaming and technology as male-oriented, and financial planning often assumed male decision-makers. While biology and socialization can influence behavior, contemporary consumption patterns are far less neatly divided.

Male skincare influencers, female-led gaming communities and the growing participation of women in investment platforms reflect a broader trend. Shared digital culture exposes people to overlapping content, and algorithmic systems respond to behavior rather than identity labels. Interests and values increasingly shape consumption more than gender categories.

Psychological drivers such as status-seeking, experimentation or security orientation are not inherently male or female. Within any gender group there is wide variation in how individuals approach decisions. When segmentation begins with gender, it risks smoothing over meaningful differences in how people think.

Myth 2: Generations behave as cohesive groups

Generational labels are widely used as a way to explain cultural behavior. "Millennials," "Gen Z" and "Boomers" are often treated as unified groups assumed to share attitudes, values and consumption patterns. While people who grow up in the same period may share certain reference points, the idea that generations behave cohesively is often overstated.

Research from the Pew Research Center has repeatedly shown that attitudes and behaviors vary widely within generational groups.[1]

Cultural signals make this clear. Spotify Wrapped routinely reveals listening habits that cut across age boundaries: middle-aged professionals streaming emerging artists while younger users gravitate toward decades-old classics. TikTok trends, BookTok communities and fitness movements spread rapidly between age groups. Nostalgia is no longer rooted in lived experience, with younger consumers embracing aesthetics such as Y2K from eras they never personally experienced.

Within any generation, behavioral differences are often greater than similarities. A risk-averse Gen Z consumer focused on savings may resemble a cautious Gen X professional more than a novelty-seeking peer. Age influences life stage, but it does not reliably determine motivation.

Myth 3: Income predicts aspiration

Income segmentation feels intuitive because purchasing power matters. Budget constraints influence what is possible. But income does not consistently predict aspiration or mindset.

The rise of "dupe culture" shows that high-income consumers may choose affordable alternatives not out of necessity but preference. At the same time, lower-income consumers may invest heavily in visible categories such as fashion or technology because of their symbolic value. Buy-now-pay-later services further blur the link between income and aspiration, enabling aspirational spending across income brackets.

Luxury brands often attract customers with varied incomes who share similar motivations for symbolic consumption. Conversely, some high earners reject conspicuous spending because it conflicts with their identity. So while financial capacity shapes constraints, it does not determine how people interpret value.

2. What actually drives consumer behavior

Behavioral science has long shown that decisions are shaped by motivations, identity and situational context rather than static characteristics alone.[2] Profiling becomes far more useful when it's organized around those forces rather than around life statistics.

At a basic level, decisions are goal-driven. Consumers pursue recognition, security, belonging, novelty or efficiency depending on the situation. These motivations fluctuate with context rather than lining up neatly with demographics. The same person may look for value in one moment and indulgence in another, or choose familiarity in one situation and experimentation in the next — even within the same category. These shifts can play out across individual products and over time, meaning behavior needs to be understood as something dynamic rather than fixed and revisited repeatedly. What matters is not who they are on paper, but what they're trying to achieve in that moment.

Identity shapes how those goals are expressed. Research on Self-Concept Theory in consumer behavior shows that people often choose products that align with their self-image or with the identity they aspire to project.[3] People move between aspirational, social, private and practical identities depending on the environment.

Social Identity Theory further explains how people use consumption to signal belonging to particular groups and reinforce shared identities.[4] For example, choosing a specific sports brand, fashion style or tech product can act as a signal of membership within a cultural or social community.

The role of context and category mindset

Context adds another layer. Economic pressure, time constraints and social visibility all influence how motivations play out. A consumer who experiments freely when stakes are low may default to familiarity when risk increases. behavior is not fixed; it adjusts to circumstance. Research on brand loyalty shows that consumer behavior varies across situations and categories, rather than remaining stable over time.[5]

Consumers also apply different rules in different categories. Research in consumer psychology shows that people construct their preferences depending on context and category, rather than applying a single fixed decision rule across purchases.[6] What signals value in skincare may not signal value in groceries or technology. In one domain, higher price may imply quality. In another, value may dominate. These internal rules frequently matter more than shared demographics.

When motivation, identity, context and category mindset are considered together, you can anticipate how different groups will respond. People cluster around shared ways of thinking about trade-offs, risk and value rather than around shared age or income. If profiling is meant to inform targeting and strategy, it needs to reflect those patterns of reasoning rather than treat them as afterthoughts.

Until recently, uncovering these behavioral drivers required intensive qualitative work with limited scale. The insight was rich but hard to operationalize. Advances in AI remove that bottleneck. The same depth that once lived in interview rooms can now be captured, structured and applied across entire markets.

3. The structural shift: when depth becomes scalable

The barrier to behavior-first profiling has never been uncertainty about what drives decisions. Researchers have long understood that motivation, identity and context matter. What we've struggled with is how to capture those forces consistently across audiences without losing nuance.

Traditional qualitative research is excellent at uncovering meaning. In-depth interviews and moderated discussions allow researchers to move beyond initial answers, explore contradictions and surface identity cues. But that depth comes with limits. Samples are small – typically just 6-10 people in a focus group – moderation varies and synthesis takes time. Scaling those insights beyond exploratory work has historically been expensive and slow.

As a result, qualitative research is often run as a one-off exercise, rather than something that can be revisited regularly. Consumer profiling becomes a large, infrequent project, rather than an ongoing source of insight. This means profiling is often out of date by the time it is used.

Quantitative research offers the opposite strength. It scales easily and supports comparison across markets. Yet it depends on predefined variables and structured response formats. Motivations are reduced to agreement scores, identity becomes a set of statements and context is simplified into fixed options. The reasoning behind decisions often disappears in the process.

From constrained depth to scalable exploration

AI-moderated interviews change that equation. During fieldwork, adaptive one-to-one interviews can now be conducted across larger samples. Unlike quantitative surveys, questioning isn't restricted to a static list – the system responds to what participants say. If someone describes feeling "proud" of a purchase, the interview can explore what that pride represents. If a participant explains that they behave differently in different situations, the system can unpack the triggers behind those variations.

This probing is guided by structured logic built into the design. What once depended on the time and skill of a single moderator can now happen consistently across scores of interviews, meaning depth is no longer confined to small groups.

Turning language into structured behavioral signals

The shift continues after fieldwork. Traditionally, qualitative responses were analyzed manually, with researchers reading transcripts and pulling out illustrative quotes. This made it difficult to work with large volumes of responses and meant insights often remained descriptive rather than structured.

Advances in AI-assisted qualitative analysis are changing that. Research from MIT Sloan Management Review shows that natural language tools can detect patterns across large volumes of responses that would previously have required extensive manual coding.[7] Instead of relying on verbatim comments as illustration, researchers can now identify recurring patterns in how people frame trade-offs, describe value and express identity. Language that signals reward, security, belonging or control can be detected across large datasets and organized into meaningful variables.

While AI increases analytical capacity, interpretation remains human-led. As researchers, you still define constructs, validate clusters and assess relevance. The difference is that you're working with far richer and more consistent data.

Even a small number of qualitative interviews can generate a large volume of verbatim responses, making it difficult to review everything systematically and without bias. Analysis often relies on what stands out or what is remembered. AI-assisted analysis changes that by ensuring all responses are considered consistently, rather than selectively.

Instead of extrapolating from small samples and partial recall, you can observe behavioral patterns across larger audiences with a more complete and consistent view of the data.

As qualitative depth becomes scalable, profiling moves beyond broad description and into something far more precise. Motivations and identity cues can be treated as measurable inputs rather than interpretive afterthoughts, making behavior-first segmentation workable at scale without sacrificing quality. AI does not replace quantitative validation, but it strengthens it by providing a clearer behavioral foundation.

The challenge is making this repeatable: creating a system for organizing behavioral signals into segments. We outline that framework in the next section.

How AI-moderated interviews upgrade consumer profiling

Traditional persona

- Point-in-time snapshot
- Quant-led with illustrative qual
- Describes behavior

Behavior-first profile

- Continuously updated
- Qual depth at scale
- Explains decision logic

4. The model: from snapshot personas to behavior-first profiling

If AI-moderated interviews make it possible to capture behavioral reasoning at scale, the next step is to organize those insights. A behavior-first model moves the starting point. Instead of defining people by demographic attributes and layering behavior on afterward, it begins with how people decide.

Traditional personas are often built using a combination of quantitative behavioral data and small-scale qualitative insight. While this provides useful context, the output is typically a point-in-time view, supported by illustrative quotes rather than deeply explored reasoning.

By contrast, behavior-first profiling uses qualitative depth at scale to uncover the motivations and context behind behavior. This allows profiles to be updated, refined and applied continuously rather than treated as static outputs.

The four layers of behavior-first profiling

Behavior-first profiles are organized across four connected layers: motivational drivers, identity expression, contextual triggers and category-specific mindsets. Each layer captures a different aspect of how people approach decisions. The model draws on established insights from behavioral science and identity theory, bringing them together in a practical way to structure segmentation.

Motivational drivers

Motivational drivers reflect the goals behind decisions. Some consumers consistently orient toward reward and recognition, while others prioritize stability, efficiency or exploration. These patterns cut across age and income because they reflect how people think. When dominant motivations are identified, segments can be defined by what people are trying to achieve rather than by surface characteristics.

Identity expression

Identity expression captures how those motivations are framed. Consumers describe purchases in ways that reveal how they see themselves — or how they want to be seen. One group may link choices to aspiration and visibility; another may emphasise authenticity and continuity; a third may prioritize belonging. These identity narratives help distinguish groups that might look similar demographically but operate according to different self-concepts.

Contextual triggers

Contextual triggers recognize that behavior shifts depending on circumstance. The same person may experiment freely in one situation but default to familiarity in another — for example, when they are short on time or have just been paid. Accounting for context prevents profiling from assuming consistency where it does not exist.

Category-specific mindsets

Category-specific mindsets reflect the internal rules consumers apply within a domain. For example, in fitness subscriptions, community and accountability may define value. While in fashion, visibility and differentiation may matter more than durability. These category logics explain why consumers behave differently across markets.

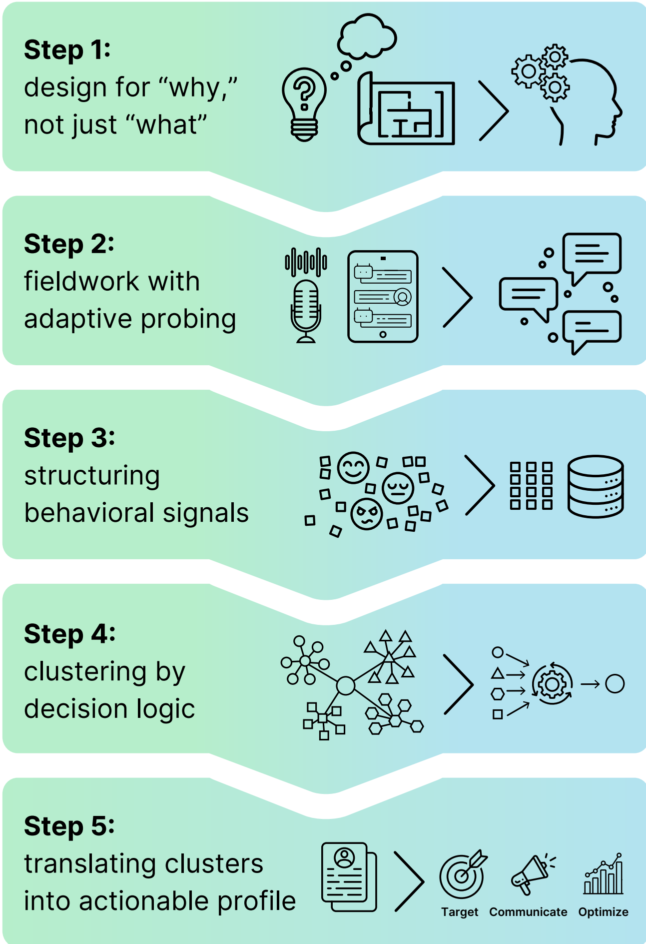
When these four layers are considered together, coherent behavioral clusters emerge. These clusters often span age and income boundaries because they are unified by shared reasoning rather than shared demographics. Instead of a snapshot persona, you get a clear picture of how a group thinks, decides and behaves.

5. The method: how to build behavior-first profiles in practice

The model explains what behavior-first profiling is. The five-step method shows how to make it work. You don't need a team of data scientists to do this. AI-moderated qualitative systems take on much of the analytical workload, while interpretation and strategic judgement remain human.

In practice, this approach works best alongside quantitative research rather than replacing it. Surveys and behavioral data often reveal patterns in what people buy, how often they purchase and which brands they choose. These signals help identify the behaviors worth exploring further. AI-moderated interviews can then probe those behaviors in depth, uncovering the motivations, identity cues and contextual factors behind them.

Five-step methodology for behavior-first profiling with AI-moderated interviews



Step 1: design for "why," not just "what"

The process begins with research design. Traditional quantitative studies often focus on behavioral facts — what was bought, how often, at what price. A behavior-first approach looks beneath that surface. It asks why a choice felt right, what alternatives were considered, how options were weighed and how the decision connects to identity.

Interview prompts are built to draw out explanation rather than confirmation. Respondents are encouraged to describe situations in which they would switch brands, trade up or down, or behave differently under specific conditions. These stories reveal motivations and identity cues that structured surveys rarely capture. Clear definitions of the concepts being explored — such as status orientation or convenience prioritization — help ensure the analysis stays consistent.

Designing for "what"

Typical survey questions

- Which brand did you buy most recently?
- How often do you purchase this category?
- How much do you typically spend in this category?
- How satisfied are you with your current brand?

This captures behavior but rarely reveals why people made that decision.

Designing for "why"

Behavior-first interview prompts

- Tell us why you choose that brand?
- Explain your decision process when choosing between two similar products.
- Describe the value you got from the purchase.
- What advice would you give to a brand to persuade you to choose differently?

This approach surfaces motivations, identity signals and decision logic.

Step 2: fieldwork with adaptive probing

During fieldwork, AI moderation enables probing at scale. Instead of following a fixed script, the system responds to participants' responses. If someone mentions "treating myself," the interview can explore what makes that purchase feel earned. If a respondent expresses hesitation, the system can probe what is driving it. If behavior changes depending on who they are with, the interview can unpack why.

This adaptive logic is embedded in the design and applied consistently across large samples. What once required extensive moderator time can now happen simultaneously across scores of interviews, without sacrificing depth. These conversations help explain the behavioral patterns first identified in quantitative data, revealing the motivations and context behind them in far greater detail than static survey questions allow.

Example of a behavioral question in a static survey

Why did you choose that product?
(Select all that apply)

- ☐ It was the best value for money
- ☐ I trust the brand
- ☐ It was recommended to me
- ☐ It looked like good quality
- ☐ It was convenient or easy to buy
- ☐ It was the most familiar option
- ☐ I had used it before
- ☐ It was the most attractive option available
- ☐ It was on promotion
- ☐ It matched my needs at the time
- ☐ Other (please specify)

The output shows reported reasons for purchase, but not the decision logic behind them.

Example of AI probing

Initial question:
Why did you choose that product?

Respondent:
"It just feels like good quality."

AI follow-up:
"What signals quality to you in this category?"

Respondent:
"The packaging and the price."

AI follow-up:
"Would you still choose it if it were cheaper?"

Respondent:
"No – if it was cheaper I'd probably think it wasn't as good."

Insight surfaced: ***Price as a quality signal.***

This shows how AI uncovers the decision logic behind behavior.

Step 3: structuring behavioral signals

Once interviews are complete, the platform analyzes how participants describe their decisions. Rather than manually reading transcripts for themes, the system detects recurring patterns in language — signals of reward, security, belonging, efficiency or risk sensitivity. These patterns are then translated into clear indicators of how people judge value and make decisions.

Unlike behavioral outputs from quantitative surveys, which typically show what people did or which option they chose, this analysis surfaces the reasoning behind those behaviors. At this stage, the aim isn't complex modeling. It's making the patterns clear and usable. The output remains grounded in how consumers explain their decisions, so teams can trace insights directly back to real language.

Behavioral outputs from quantitative research

Quantitative surveys often produce themes such as:

"Price matters"

"Brand trust"

"Convenience"

"Quality perception"

These are useful but remain broad observations.

Behavioral outputs from AI-moderated interviews

AI analysis identifies patterns in language and reasoning:

Behavioral signal	Evidence in responses
Status orientation	"It feels premium" "I deserve something better"
Security seeking	"I stick with what I know" "I don't want to risk it"
Convenience prioritization	"It just saves time" "It's the easiest option"
Belonging cues	"Everyone I know uses it"

These signals become structured inputs for segmentation.

Step 4: clustering by decision logic

With behavioral signals defined, respondents are grouped according to shared patterns. Clustering is based on motivations, identity expression and how context changes their behavior rather than demographic similarity. People who articulate similar decision logic are grouped together, even if they differ in age or income.

Only after clusters are formed are demographic overlays applied. This sequence ensures behavior defines the segment, while demographics provide scale and context.

Step 5: translating clusters into actionable profiles

The final step is interpretation and application, carried out by the researcher using their knowledge of the brand and customer base. The clusters and behavioral signals provide a structured foundation, which researchers can then translate into behavior-first profiles — clearly outlining what drives the group, how they approach decisions, what triggers shifts in behavior and which messaging angles are most likely to resonate. These profiles are written for practical use, enabling creative, product and media teams to move from insight to action.

They should be treated as starting points rather than fixed truths. As campaigns are tested and performance data builds, profiles can be refined. The approach is repeatable and adaptable, allowing behavioral insight to evolve alongside consumer language and context. This makes profiling something that can be updated regularly, rather than revisited every few years.

Example of a traditional snapshot persona

Emma, 32

Urban professional, high disposable income
Shops online frequently
Interested in fashion and beauty

Insight summary

- Prefers premium brands
- Influenced by social media
- Values quality

Describes who she is, but not how she decides

Example of a behavior-first profile

The strategic indulger

Core motivation Selective reward

Decision pattern Trades down in essentials, trades up in visible categories

Context sensitivity More likely to spend after payday or in social settings

Category mindset Uses price as a signal of quality in identity-driven purchases

Messaging response Responds to language that frames premium choices as earned rather than impulsive

Explains how decisions are made, and when behavior shifts

6. What this evolution means for brands

When behavior-first profiling becomes scalable and repeatable, it changes where strategy begins and how advantage is built.

For creative teams, this shifts the central question. Instead of asking, “Who are we targeting?” the focus becomes, “How does this group think?” Messaging can align with identity states rather than demographic assumptions. A campaign aimed at consumers who see a purchase as a reward will look very different from one designed for those who prioritize reliability and control, even if both groups span similar age ranges.

For product and innovation teams, scalable behavioral insight reveals needs that demographic analysis often misses. If a segment consistently expresses tension between aspiration and budget, that insight can shape pricing or product design. If another group prioritizes simplicity above all else, reducing friction may matter more than adding features.

Media strategy also benefits. Digital platforms increasingly optimize around behavior and interest rather than age or gender filters. Segments defined by decision logic map more naturally onto these systems, allowing targeting to reflect patterns of engagement and mindset rather than inferred characteristics.

The strategic advantage

More fundamentally, when behavior-first profiling becomes continuous, it reduces strategic blind spots. People are messy and rarely fit neatly into predefined categories, which means meaningful groups can remain hidden when segmentation is infrequent and relies too heavily on demographics.

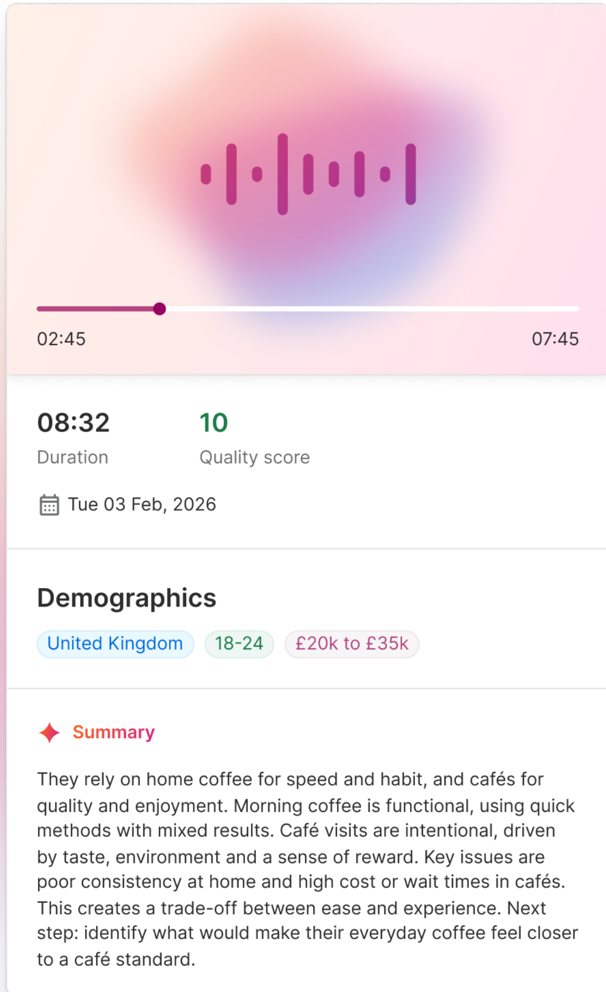
When behavioral intelligence is updated regularly, those groups come into view, creating space for clearer differentiation. You’re better equipped to design products, messages and experiences that reflect how people actually make choices. As markets become increasingly shaped by personalization and fluid identity, that alignment becomes essential.

7. Introducing AI-moderated interviews with Attest

Attest's AI-moderated interviews let you run in-depth qualitative research at greater scale. You can explore motivations, identity and decision logic across scores of participants without losing the probing depth of one-to-one conversations.

Our AI co-pilot helps you design your interview, upload stimulus such as images or video, and build tailored follow-up prompts so you capture the detail that matters. The system adapts in real time, asking clarifying questions based on what respondents actually say.

As interviews complete, thematic, sentiment and behavioral analysis surface patterns automatically. You can then use the conversational interface to interrogate the data, explore emerging segments and test hypotheses.



Flexibility built in

Finding the right respondents for your research is straightforward, with the ability to set qualifying questions alongside a range of demographic filters. You can define exactly who you want to interview, and choose between audio-only responses or full video recordings.

You can recruit from your own audience or launch to Attest's diverse US and UK panels, giving you flexibility in how and where you run research.

Discover AI-moderated interviews and get started with behavior-first profiling

Get started

Sources and further reading

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