# Mapping Mindset: AI-based Psychographic Segmentation Using the Value Map Approach


## Abstract

Segmentation based on psychographic criteria, such as values and lifestyles, is critical for effective market development but often remains costly and complex. This article presents an AI based approach to overcome these barriers. We introduce the *Value Map*, an innovative framework containing nearly 500 human values. The Value Map combines large language models (LLMs) and established psychological theories to enable customer segmentation based on intrinsic values. We show how the Value Map was developed and validated. We also present several use cases that go beyond the scope of customer segmentation. Our findings advance both the theoretical foundation of psychographic segmentation and the practical application of AI in market research.



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## 1. Introduction

Marketing has developed numerous criteria according to which markets and customers can be segmented (Madzík et al., 2021; Dibb, 1999). Among these criteria, psychographic characteristics play a special role (Sarli and Tat, 2011). These criteria, such as lifestyles or human values, are at least as important as other criteria, such as (socio-)demographic and behavioral criteria, and, when combined, can lead to better segmentation results (Lin, 2002). Some consider psychographic criteria as superior to other criteria (Vyncke, 2002), as they may be more stable over longer periods of time and in many cases directly influence preferences and purchasing behavior. However, while demographic and behavioral data are typically observable and readily available in customer databases, it is generally relatively complex and costly to collect psychographic data on target groups (Dunlop et al., 2020). Psychographic data reflect people's innermost thoughts and feelings, which they are often not even aware of themselves. Capturing these attitudes requires complex methods and for many companies, this is technically challenging and economically expensive.

The rise of artificial intelligence has the potential to fundamentally change this dynamic, particularly when combined with human intelligence (Baumgarth and Schmidt, 2024). The use of AI is highly debated in many areas of marketing (Vlačić et al., 2021; Chintalapati and Pandey, 2022). Currently, practitioners see great potential in content creation, creative performance, and market research in particular. Research is also contributing to a better understanding of the use of AI and assessing its impact on relationships with consumers and customers. In the context of customer segmentation, however, AI-supported methods are still in the trial phase at best (Salminen et al., 2023). To our knowledge, innovative and validated approaches to refining established theories of human values and applying them efficiently to qualitative data, such as interviews or chat logs, have not yet been published. However, such methods would be very tempting for practitioners, as they would limit the complexity of psychographic segmentation and keep costs low. Of course, AI tools will provide users with psychographic segmentation solutions, when told to do so. However, the results would largely be based on previous segmentations which the tool will adopt and apply the present task in a confirmatory way and strongly vary from tasks to task and tool to tool, making the validity and reliability questionable (Edris et al., 1990).

Against the backdrop of the developments outlined above, our article addresses the question of how AI can be used efficiently, effectively and reliably to segment customers in terms of their intrinsic values based on available qualitative data. We outline the development of an LLM-based tool to structure human values that we call *Value Map* and show possible applications for the Value Map in general and in the context of market and customer segmentation in particular.

## 2. Conceptual foundation

Applying the logic of human values in the business and marketing context has a long tradition in research, branding as well as organizational development (Torelli et al., 2012). Over the last decades, a number of models have tried to capture how values guide human perception and behavior, how target groups can be segmented based on values and, as a result, how brands and companies can successfully be positioned using human values (Kamakura and Novak, 1992). Value-based approaches can be divided into *traditional* and *AI-based* models.

*Traditional models* are mainly theory-driven and have long been used in psychology, branding and consumer research. Early approaches in psychology, such as Rokeach's Value Survey (Rokeach, 1973) established a systematic list of terminal and instrumental values. Maslow's (1943) hierarchy of needs, although not strictly a value model, has deeply influenced motivational theory by proposing a layered structure of human needs from physiological basics to self-actualization. One of the most prominent works is the Schwartz Theory of Basic Human Values (Schwartz, 2012). This framework proposes ten universal value sets, structured in a circular logic, representing motivational oppositions and compatibilities. These value sets include self-direction, security, benevolence, power, and others—grouped into higher-order dimensions such as openness to change vs. conservation and self-transcendence vs. self-enhancement. Initially, the model was designed primarily for psychological and sociological purposes. However, it has since often been applied in the fields of branding, organizational culture, or consumer segmentation even though a certain amount of adaptation is required. Mark and Pearson (2001) introduced archetypes into the field of branding, which were traditionally a widely used narrative-based model. Archetypes such as the Hero, the Caregiver, or the Explorer explain and position brand personalities in a mythological context, so that they differ from competition and fit best to consumer demands. There are further prominent models from organizational theory, cf. the Moral Foundations Theory (Graham et al., 2013), the Big Five Personality Traits (OCEAN-Model) or the Myers-Briggs Type Indicator, whereby their academic and empirical foundation for the latter is questionable.

More recently, *AI-based models* have become increasingly important. These LLMs are semantically and mathematically trained on values, as numerous AI models have been fed and trained with well-known value frameworks, enabling the AI to categorize human values. In addition, various models exist that represent values and words in semantic networks using mathematical structure: for example, word embedding models, such as Word2Vec; GloVe; BERT & Sentence-BERT; FastText or vector-based clustering and mapping models, such as Top2Vec, UMAP, t-SNE, or HDBSCAN. Recent studies and initiatives have increasingly started to look at AI based to support branding positioning and consumer segmentation approaches (cf. Sun et al., 2014; Wilson, 2019).

While traditional models are often highly theoretical in nature and often lack empirical and mathematical underpinning, AI-based logics are semantically and mathematically grounded, yet they lack the structure needed for practical application. The present Value Map aims to close precisely this gap by using the best of both worlds—the mathematically grounded semantic logic of AI models as a foundation, and organizing it into an understandable and usable structure inspired by established value models. At its core, the Value Map is a two-dimensional spatial representation of values, designed to support academic research, branding strategy, consumer segmentation, and cultural analysis. Unlike previous models, it is grounded in empirical language data and computational semantics aligned with the logic of proven, psychology value models, offering both theoretical coherence and practical applicability.

## 3. Creation of the Value Map

Our research follows the principles of design science research (Hevner et al., 2004), which aims to develop and evaluate artifacts that address practical problems (Österle et al., 2011). In this approach, the primary objective is not merely to describe phenomena but to create and test solutions that generate tangible benefits for practitioners (Halstrick, 2023; Stange et al., 2022).

Accordingly, we set out to design an artifact, evaluate its performance, and demonstrate its contribution in practice (Peffers et al., 2007).

### 3.1 Compilation of Value-Related Terms

The compilation for the foundation of the Value Map started with an extensive collection of general words, terms and values. We began by aggregating values from a wide range of value models, personality taxonomies, emotional lexicons, and branding frameworks. Sources included the Schwartz value inventory, Rokeach's terminal and instrumental values, character strength models such as Peterson and Seligman's (2004) VIA framework, the LOV (list of values; Kahle and Kennedy, 1988), Values and Lifestyle Survey (cf. Mitchell and McNulty, 1981), characteristics related to the Moral Foundations Theory (Graham et al., 2013), as well as marketing-oriented frameworks describing brand values and corporate purpose. To ensure a broad variety and comprehensiveness, we included emotion descriptors (e.g., '*joyful'*, '*ashamed'*), character attributes (e.g., '*curious*', '*humble*'), and motivational constructs (e.g., '*ambition*', '*belonging'*). This list was further enriched with question batteries from qualitative research instruments and brand positioning toolkits. In addition, we compiled scale batteries (Bearden and Netemeyer, 1999) and scanned existing brand value surveys. Finally, we added AI-generated lists for human values, emotions, and characteristics to further broaden the list. The final raw set consisted of 2,517 terms reflecting a broad spectrum of values, emotions, and characteristics.

### 3.2 Semantic Condensation via Large Language Models

With considerable semantic redundancy and overlap in the list (e.g., synonymic or morphologically related terms such as '*friendly'*, '*friendliness'*, '*kind'*, and '*kindness'*), a reduction step was necessary. We applied GPT-4o OpenAI to reduce the list, by merging highly similar terms into unified representations, ensuring that each retained concept was semantically distinct yet representative. Special attention was given to edge cases where semantic similarity was high but contextually divergent. The condensation process reduced the list to 494 consolidated value terms, each sufficiently distinct in meaning. This refined list formed the basis of the Value Map set.

### 3.3 Mapping Values in a Two-Dimensional Space

The next step involved determining the relative spatial positioning of the 494 values in a semantically meaningful two-dimensional space. We employed Word2Vec, a widely used neural embedding model that represents words based on their co-occurrence patterns in large text corpora. Word2Vec creates dense vector representations—typically of 100 to 300 dimensions—where semantically similar words occupy nearby positions in the high-dimensional space (Mikolov et al., 2013). To generate the embeddings, all value terms from our list were given into the Word2Vec model. The resulting vectors encoded the contextual meaning of each word based on surrounding terms in natural language usage. For example, values such as *autonomy*, *freedom*, and *independence* yielded closely clustered vectors, whereas terms such as *tradition*, *discipline*, and *responsibility* were situated in different regions of the vector space, reflecting their distinct semantic profiles. After the 494 values were represented as a high-dimensional vector, we computed a pairwise distance matrix based on cosine similarity, which quantifies the angular difference between two vectors. This matrix served as the fundament for calculating the semantic proximity between every pair of values.

To render the structure interpretable and visually accessible, we applied dimensionality reduction techniques to project the high-dimensional vectors onto a two-dimensional map. We primarily used t-distributed Stochastic Neighbor Embedding (t-SNE) and Uniform Manifold Approximation and Projection (UMAP), nonlinear techniques designed to preserve local and global structures, respectively (Van der Maaten and Hinton, 2008; McInnes et al., 2018). These methods retained the relative distances and groupings from the original embedding space, resulting in a layout where semantically related values clustered together and conceptually dissimilar values appeared further apart. For example, values such as '*stability'*, '*security'*, and '*tradition'* clustered tightly, while being distant from terms like '*adventure'*, '*innovation'*, and '*risk-taking'*. The spatial proximity between any two values thus reflects their semantic closeness. This process produced a mathematically derived map of the 494 values as a 'value cloud.' Unlike pre-structured theoretical models, this mapping emerged purely from linguistic data, offering a bottom-up representation of value space.

### 3.4 Identification of Conceptual Axes

Next, we conducted the conceptual interpretation of the two-dimensional layout. Axis identification was crucial to make the map both interpretable and usable in applied settings. In an interactive triangulation process, we identified three overarching conceptual axes that structure the value space (see Figure 1):

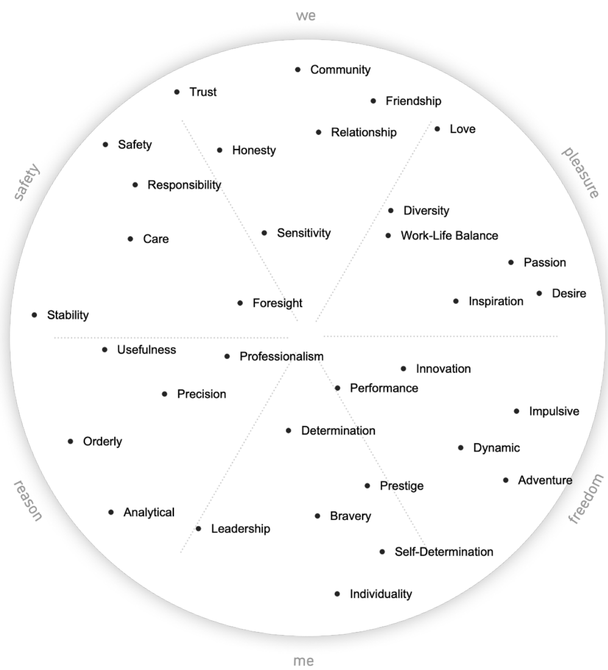
**Axis 1: "We" ↔ "Me":** This axis contrasts *communal, altruistic, and relational values* (e.g., empathy, community, belonging) with *individualistic, self-oriented, and achievement-driven values* (e.g., ambition, status, independence). It reflects the extent to which a value is centered around collective good versus personal gain.

**Axis 2: "Safety" ↔ "Freedom":** Here, *security-oriented and control-focused values* (e.g., responsibility, safety, protection) are contrasted with values emphasizing *openness, change, spontaneity, and autonomy* (e.g., analytical, adventure, rebellion). This axis reflects the tension between structure and exploration.

**Axis 3: "Reason" ↔ "Pleasure":** The third axis distinguishes *rational, goal-oriented, and efficiency-related values* (e.g., logic, orderly, discipline) from *experiential, emotional, and hedonistic values* (e.g., joy, passion, creativity).

We compared the results to existing psychology value models and found strong similarities in the structure, as a number of established frameworks (cf. Schwartz Theory of Basic Human Values, Archetypes) describe relatable, conceptual axes. The Schwartz Theory of Basic Human Value (Schwartz, 2012) follows a similar semantic structure, although axis names vary. In a next step, the value cloud was slightly rotated to align these axes with horizontal, vertical, and diagonal orientations to aid readability and use. Their intersection creates a navigable map that allows precise placement of abstract concepts and empirical inputs. Figure 1 shows the final Value Map with the three axes and six areas. For illustrative purposes, the figure thereby shows 33 of the 494 values positioned in the Value Map as examples.

**Figure 1: Value Map with exemplary values**

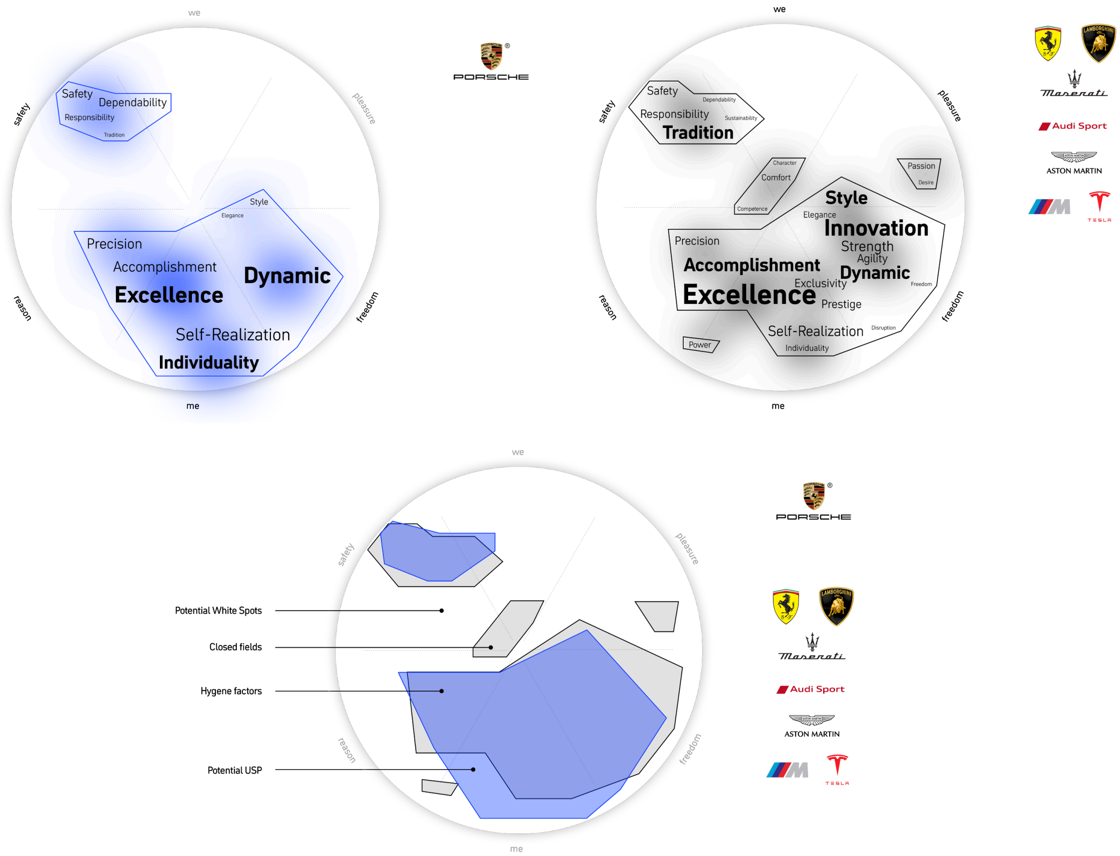



### 3.5 Validation Through Use-Case Testing and Expert Validation

To assess the usability and face validity of the Value Map, we tested the Value Map by checking various brand positionings. After assessing different AI platforms (*OpenAi GPT-4; Claude Sonnet 4; Mistral Medium 3; Llama 3.3 8B Instruct and Gemini 2.5 Flash Preview 05-20*), we first extracted the communicated values of over 220 brands using a trained GPT-4 AI model. We then assessed, quantified and mapped the associated values of each tested brand. The results showed considerably robust, repeatable outcomes, highlighted distinct brand value clusters, competitive overlaps or hygiene factors, and closed fields for strategic repositioning. Figure 2 provides an example of the results achieved. The results shown here relate to the brand Porsche and illustrate how the brand is positioned in the overall relevant competitive environment (Ferrari, Lamborghini, etc.). The relevant results for all brands analyzed were reviewed and evaluated in terms of their apparent consistency. None of the cases analyzed showed any significant deviations from the researchers' impressions, confirming the face validity and practicality of the Value Map as a cognitive, analytical, and visual tool.

The contribution of the Value Map was also confirmed by an expert focus group study involving both academic researchers and practitioners. The panel’s evaluations confirmed that segmentation results generated with the Value Map were perceived as more usable, actionable, and credible than those produced without it. Experts highlighted that the model’s structured approach to capturing values added clarity and interpretive depth, making the results not only easier to understand but more directly applicable to real-world marketing strategies and organizational decisions.

**Figure 2: Brand Positioning Analysis (Example: Porsche vs. Competitors)**



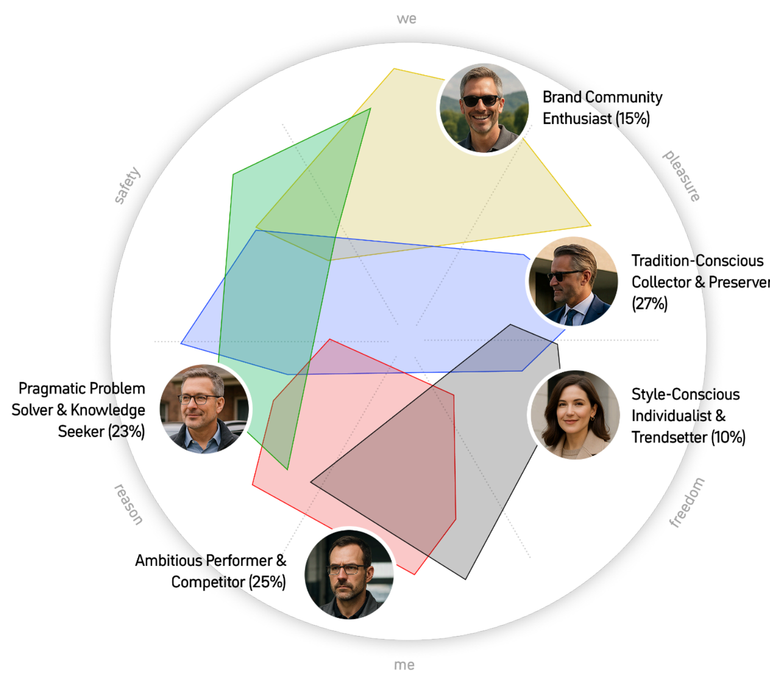

### 3.6 Use Cases and Strategic Applications

The Value Map offers a flexible, scalable framework that supports a wide range of academic and professional applications. Below are four key use cases in a business, consulting and research context.

#### *Use Case 1: Target group Segmentation and Value Mapping*

Consumer surveys, ethnographic insights, social listening data or online discussions, can be translated into value expressions and positioned on the Value Map. This allows for a comprehensive visualization of target group values and it facilitates segmentation based not on socio-demographics but on deep motivational logic. Consumers can be segmented on a psychographic level according to their values. As a consequence, marketing and communication strategies can then be tailored to match the dominant values of different personas. Figure 3 provides an example of customer segments that have been created with the Value Map using active users of a brand community (the Porsche Rennlist) and, based on their comments in the forum, divided them into 5 segments.

**Figure 3: Segmenting Brand Community Members (Example: Porsche Rennlist; results using Claude Sonnet 4 with support of Value Map)**




### *Use Case 2: Brand and Competitive Analysis*

Brand managers can apply the Value Map to analyze their own positioning or compare themselves with competitors. By classifying the core values, a brand communicates—whether via advertising, website content, or product messaging, supported by AI or scraping tools—it becomes possible to identify and visualize the brand's, as well as the competitors' positioning. Companies can thereby assess a brand's unique selling proposition, strategic competitive overlaps or white-space opportunities. Similarly, brands may compare their 'intended' brand image with their 'actual' brand image (e.g. by using survey data) and evaluate the respective (mis-)fit. This enables data-informed brand differentiation and strategic positioning.

### *Use Case 3: Internal Culture and Alignment Assessment*

Organizations, people managers or human resources can also use the Value Map to surface cultural perceptions and internal company discussions. During workshops, brainstorming sessions, or interviews, employee input such as '*what do we stand for*' or '*what are we good/bad at*' can be mapped to reveal perceptions and ideas. This structured discussion format accelerates alignment processes and supports cultural transformation initiatives; it can be the baseline for employer branding strategies or human resources initiatives.

### *Use Case 4: Campaign, Content, and Communication Evaluation*

The Value Map can further be applied to analyze past or planned campaigns. Textual analysis of slogans, headlines, and storytelling can help identify the core values being communicated—and whether they align with brand identity and audience needs. The Value Map can thereby visualize and evaluate how well a campaign or activity represents the intended brand values. This supports more coherent and value-consistent communication strategies.

**5. Discussion & Conclusion**

Overall, the Value Map offers a novel, empirically validated, and theoretically coherent solution for integrating AI into psychographic analysis. In contrast to purely theoretical taxonomies or unstructured AI approaches, the Value Map combines the strengths of both: the usability and interpretability of psychological value models and the scalability and mathematical accuracy of state-of-the-art language embeddings and clustering techniques. This hybrid foundation enables a more precise and consistent mapping of motivational constructs and creates an empirical basis for the application of artificial intelligence in analyzing, comparing, and visualizing human values. In a nutshell, the Value Map bridges the gap between abstract motivational theories and operational AI tools, setting the stage for more rigorous and impactful segmentation practices in both research and management.

Nevertheless, several limitations should be noted, offering clear opportunities for future research. First, although the model is grounded in large-scale language data and draws on established theories, it inevitably reflects biases in its training corpora. Semantic embeddings are shaped by the linguistic and cultural contexts in which they are created, potentially over- or underrepresenting specific groups or cultural nuances. An application in a multilingual context may ensure broader applicability.  Second, the model's real-world impact on consumer behavior has not yet been tested. Future studies may assess whether segmentations based on the Value Map lead to measurably better outcomes, such as higher engagement or sales performance compared to traditional segmentation methods. Third, although the Value Map improved the consistency and interpretability of AI-driven segmentation, the process remains dependent on prompt design and the specific language model employed. As LLMs evolve rapidly, ongoing research will be needed to evaluate how different AI architectures interact with the Value Map and to refine prompt engineering strategies for optimal results. By addressing these limitations, future work can continue to enhance the model's robustness, extend its applicability, and maximize its impact on both theory and practice.

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