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Exploring the link between Human Needs and Human Values using Synthetic Data

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Abstract

This research tests whether synthetic data can be used to explore the relationship between basic psychological needs and human values—two constructs rarely examined together empirically. We applied Exploratory Graph Analysis to LLM-generated responses assessing the 24-item Basic Psychological Needs scale and 10 Human Values dimensions. Results revealed substantive asymmetries: the LLM preserved the expected six-factor needs structure with complete stability, whereas values collapsed into three broader clusters. Joint hierarchical analysis revealed a higher-order dimension constituted by needs and values and cross-domain connections between needs and values dimensions, suggesting that the LLM encodes meaningful associations linking psychological needs to motivational value orientations.

Keywords: *LLM, Basic Psychological Needs, Human Values, Network Psychometrics.*

1. Introduction

The expansion of Generative AI and its capacity to produce large volumes of synthetic data is reshaping empirical inquiry across behavioral sciences (Bail, 2024; Arora et al., 2025). While much of this debate has focused on whether synthetic personas can reproduce human response patterns, a more specific question concerns whether such data can be used to explore relationships between psychological constructs rarely examined together in human samples.

This paper addresses that question by applying Exploratory Graph Analysis (EGA; Epskamp et al., 2018) to examine the joint dimensional structure of basic psychological needs (Deci & Ryan, 2000) and human values (Schwartz, 1992) and their connections in a combined matrix of 21,870 LLM-generated responses. Despite both frameworks ranking among the most widely cited in the social sciences — Google Scholar returns over 5,750,000 results for "Basic Needs

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Theory self-determination" and over 4,100,000 for "human values Schwartz" — their structural relationship has not been systematically explored empirically.

2. Material and Methods

2.1. Measuring needs and values

The Basic Psychological Needs scale (Deci & Ryan, 2000) operationalizes three fundamental needs — autonomy, competence, and relatedness — with four items per need and per valence, yielding six subscales that distinguish between need satisfaction and need frustration. This six-factor structure has been validated across more than 20 countries (Chen et al., 2015).

Human values were assessed through an adaptation of the Schwartz (1992) typology, which organizes ten motivationally distinct value types (see Table 1) along two higher-order dimensions: openness to change versus conservation, and self-enhancement versus self-transcendence.

Table 1: Full list of values and descriptions for the values task.

Code	Value	Description
V1	Power	Social status and prestige, control or dominance over people and resources
V2	Achievement	Personal success through demonstrating competence according to social standards
V3	Hedonism	Pleasure and sensuous gratification for oneself
V4	Stimulation	Excitement, novelty, and challenge in life
V5	Self-direction	Independent thought and action-choosing, creating, exploring
V6	Universalism	Understanding, appreciation, tolerance, and protection for the welfare of all people and for nature
V7	Benevolence	Preservation and enhancement of the welfare of people with whom one is in frequent personal contact
V8	Tradition	Respect, commitment, and acceptance of the customs and ideas that traditional culture or religion provide
V9	Conformity	Restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations or norms
V10	Security	Safety, harmony, and stability of society, of relationships, and of self

2.2. Creating synthetic personas and synthetic responses

A total of 21,870 responses were collected by administering both scales to 7,290 synthetic personas simulated using GPT-4o. In this study, a persona is defined as a combination of sociodemographic features and Big Five personality traits, designed to maximize diversity within the sample. The descriptions of the personality traits were taken from Jiang et al. (2023). In particular, each persona was defined by a unique combination of sociodemographic

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characteristics — gender, life stage, educational level, income level, and cultural background — and Big Five personality traits (see system prompt provided in Table 2).

Table 2: System prompt template to be instantiated for simulating a synthetic persona using GPT-4o

System Prompt
I want you to act as a person with specific characteristics. I describe these traits to help you better understand the perspective and position of this individual. You are a **{gender}**. This means that you **{gender-definition}**. Regarding your age, you are **{life-stage}**, and at this stage, people typically **{life-stage-definition}**. Your educational level can be defined as **{educational-level}**, which indicates that you have **{educational-level-definition}**. In terms of income, you qualify your income as **{income-level}**, meaning you **{income-level-definition}**. You were born in the USA, and your family cultural background is **{cultural-background}**, implying that you and your family value **{cultural-background-definition}**. Recently, in a personality test, you discovered that **{personality-trait-definition}**.

For the Basic Psychological Needs scale, personas were asked to rate the degree in which each statement describe them on a scale from 1 (very inaccurate) to 5 (very accurate), using the following prompt: "*Considering all these features that shape your position in society and your personality, I would like you to complete a brief task. I will present you with a series of statements, and for each one, please select the option that most accurately describes you*." For the Human Values questionnaire personas rated the relevance of each value from 1 (very irrelevant) to 5 (very relevant), using an equivalent prompt asking them to select the option that most accurately described how relevant each value was to them. Each persona completed both scales three times on consecutive days, following a test-retest design intended to assess response reliability. Non-deterministic sampling was used throughout, with temperature and top-p set to 1 via the default decoding hyperparameters of the OpenAI chat completions endpoint. In total, 43,740 API calls were made, corresponding to 7,290 personas, 2 tasks, and 3 repetitions per persona.

2.3. Analyzing synthetic responses

We analyzed the item structure in the LLM-generated responses using EGA (Epskamp et al., 2018), which estimates latent dimensional organization by applying graphical LASSO to the polychoric correlation matrix to derive a regularized partial correlation network, then detecting communities with the Louvain algorithm. In the EGA framework, edges represent partial correlations between items (i.e., the association between two items conditional on all other items in the network), so the resulting communities reflect clusters of items linked by direct conditional dependence, rather than merely by zero-order correlations. EGA was preferred over classical exploratory factor analytic approaches because it does not require pre-specifying the number of dimensions and is well suited to large samples.

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To evaluate the robustness and scale-dependence of the recovered structure, analyses were conducted in three stages: (i) on the Basic Psychological Needs items alone, (ii) on the Human Values items alone, and (iii) on the combined item set. For each analysis, the stability of the community solution was assessed using parametric bootstrap EGA (500 iterations), with the association matrix re-estimated at each iteration to incorporate uncertainty in the correlation structure. Structural consistency and item stability were used as indicators of solution robustness. For the joint analysis, hierarchical EGA was additionally applied to assess whether the recovered communities were further organized into broader dimensions. In the joint analysis, partial correlations (*pcor*) used for substantive interpretation were derived from the lower-order community network estimated as part of the hierarchical EGA procedure (i.e., the network among lower-order communities that is subsequently organized into higher-order dimensions), rather than from the original item-level network. Finally, for the joint item analysis, the community structures identified by standard EGA and by the lower-order hierarchical EGA solution were translated into confirmatory measurement models and compared using confirmatory factor analysis with the weighted least squares mean and variance adjusted (WLSMV) estimator, which is appropriate for ordinal indicators. Model fit was assessed using CFI, TLI, RMSEA, and SRMR. All analyses were conducted in R using the EGAnet package (Golino & Epskamp, 2017).

3. Results

3.1. Network structure of Basic Needs and Human Values

The analyses revealed substantive differences in how well the LLM-generated responses preserved the theoretical structure of the two psychometric constructs.

Basic Needs. For the 24-item Basic Needs scale, EGA recovered the expected six-community structure (see Figure 1, left panel), with communities corresponding to autonomy satisfaction (*AS*: N1–N4), autonomy frustration (*AF*: N5–N8), relatedness satisfaction (*RS*: N9–N12), relatedness frustration (*RF*: N13–N16), competence satisfaction (*CS*: N17–N20), and competence frustration (*CF*: N21–N24). This replicates the factor structure validated by Chen et al. (2015) across countries. Bootstrap analyses confirmed complete stability (median = 6, 95% CI [6, 6]).

Human Values. For the 10 Human Values items (Figure 1, right panel), EGA identified three communities rather than the full ten-value structure: (i) Power–Achievement (*PA*: V1–V2), (ii) Hedonism–Stimulation–Tradition–Conformity–Security (*HStTCSe*: V3–V4, V8–V10), and (iii) Self-Direction–Universalism–Benevolence (*SdUB*: V5–V7). Bootstrap analyses confirmed this as the modal solution (72.6% of replications), though a four-community solution also appeared (27.4%), indicating lower structural precision than observed for Basic Needs.

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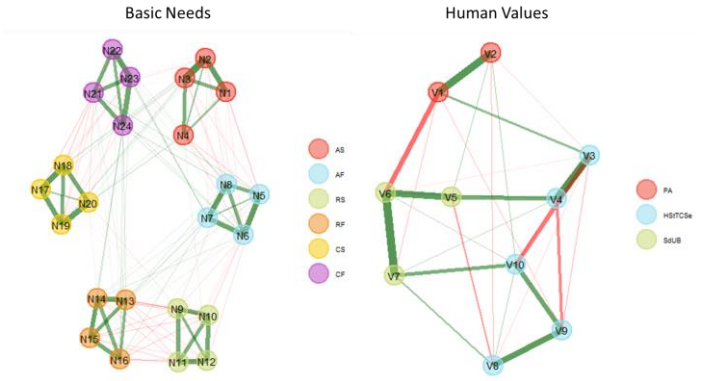


Figure 1. EGA community structure for Basic Needs and Human Values (analyzed separately). Green edges indicate positive partial correlation and red edges indicate negative partial correlation

3.2. Interconnections between Basic Needs and Human Values

To analyze links between Needs and Values, we applied EGA and hierarchical EGA to the full 34-item set. When Basic Needs and Values items were analyzed jointly, standard EGA yielded a six-community solution (Figure 2, left panel) in which the Basic Needs structure was largely preserved, but relatedness satisfaction and frustration merged into a single community (N9–N16), and all ten values items collapsed into a single undifferentiated community (V1–V10). This compression indicates that, within a regularized partial-correlation framework, the conditional dependencies among Basic Needs items are stronger than those among Values items; when both scales are modeled jointly, the values domain loses finer differentiation.

To recover differentiation within the values domain and examine cross-domain organization, we applied hierarchical EGA, which yielded an 11-community lower-order solution. Confirmatory factor analysis comparing the standard EGA partition and the lower-order hierEGA partition strongly favored the hierarchical solution: the 11-factor model showed substantially better fit (CFI = 0.996, TLI = 0.995, RMSEA = 0.117, SRMR = 0.090) than the six-factor EGA solution (CFI = 0.860, TLI = 0.847, RMSEA = 0.626, SRMR = 0.433. Bootstrap analyses supported the stability of the hierarchical dimensionality (lower order: median = 11, 95% CI [11, 11]; higher order: median = 3, 95% CI [2.8, 3.2]). We therefore interpret the joint structure primarily on the basis of the hierarchical EGA results (Figure 2, right panel).

At the lower order, the Basic Needs structure was largely reconstituted: relatedness satisfaction and frustration separated again, while the autonomy frustration block (N5–N8) split into two micro-communities (N5–N6 and N7–N8). The Values block differentiated into four subclusters: Power–Achievement (*PA*: V1–V2), Hedonism–Stimulation (*HS*: V3–V4), Self-Direction–Universalism–Benevolence (*SdUB*: V5–V7), and Tradition–Conformity–Security (*TCSe*: V8–V10). At the higher order, the 11 lower-order communities organized into three broad

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dimensions (Figure 2, right panel). To characterize this structure, we examined the partial correlations among the lower-order communities, considering links within and across higher-order dimensions.

Dimension 1: Autonomy–Competence. This dimension grouped autonomy satisfaction, the two autonomy frustration subclusters, competence satisfaction, and competence frustration—all Basic Needs communities, with no values subclusters. Within this dimension, the two autonomy frustration subclusters showed a strong positive partial correlation (*pcor*= .59), indicating a shared frustration-related conditional dependence despite their separation at the lower order. Autonomy satisfaction was negatively connected to both autonomy frustration subclusters (*pcor*= −.23; *pcor*= −.11) and positively connected to competence satisfaction (*pcor*= .34). Competence satisfaction and competence frustration showed the expected negative partial correlation (*pcor*= −.39). Both autonomy frustration subclusters were positively connected to competence frustration (*pcor*= .14; *pcor*= .19), suggesting that thwarted autonomy and ineffectiveness cohere within the conditional dependence structure.

Dimension 2: Relational–Agentic Values. This dimension grouped relatedness satisfaction, relatedness frustration, Power–Achievement, and Self-Direction–Universalism–Benevolence, thereby bridging Basic Needs and Human Values. Relatedness satisfaction and relatedness frustration showed a strong negative partial correlation (*pcor*= −.54). Key cross-domain links emerged within this dimension: relatedness satisfaction was positively connected to Self-Direction–Universalism–Benevolence (*pcor*= .28) and negatively connected to Power–Achievement (*pcor*= −.11), while Power–Achievement and Self-Direction–Universalism–Benevolence were negatively connected (*pcor*= −.29), a pattern consistent with the self-enhancement versus self-transcendence contrast in Schwartz's framework.

Dimension 3: Hedonic–Conservation. This dimension grouped only values subclusters—Hedonism–Stimulation and Tradition–Conformity–Security—which were linked by a strong negative partial correlation (*pcor*= −.57). This suggests a bipolar values configuration broadly consistent with the opposition between openness-to-change and conservation.

Cross-dimensional bridges. Beyond within-dimension connections, several partial correlations linked lower-order communities across higher-order dimensions. The strongest cross-dimensional bridge connected competence satisfaction (Dimension 1) to Power–Achievement (Dimension 2) (*pcor*= .33), indicating direct conditional dependence between experienced mastery and achievement-oriented values despite their placement in different higher-order dimensions. One autonomy frustration subcluster (Dimension 1) showed a negative connection to Self-Direction–Universalism–Benevolence (Dimension 2) (*pcor*= −.12). Relatedness satisfaction (Dimension 2) showed a modest positive connection to Tradition–Conformity–Security (Dimension 3) (*pcor*= .11), while relatedness frustration showed weaker negative links to the values-only dimension.

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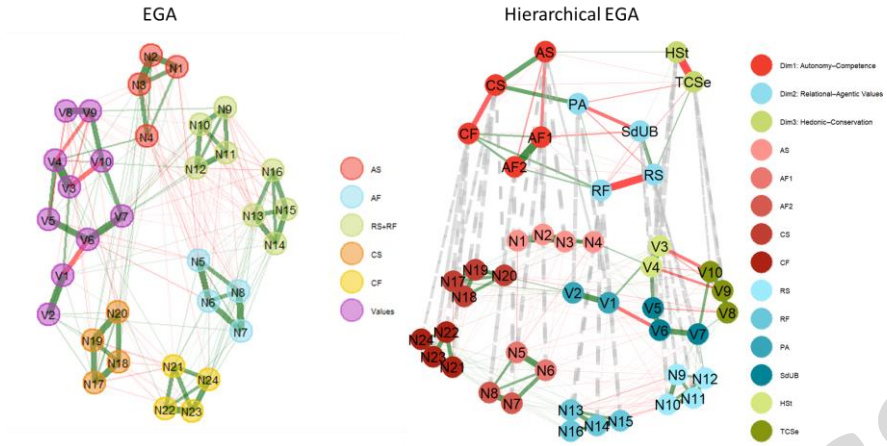


Figure 2. EGA and hierarchical EGA solutions for the combined Basic Psychological Needs and Human Values item set. Gray dashed edges indicate hierarchical links connecting lower-order communities to the higher-order structure, green edges indicate positive associations and red edges indicate negative associations

4. Discussion

LLM-generated responses encode the structure of Basic Psychological Needs more faithfully than Human Values. For Basic Needs, EGA recovered the expected six-community structure with complete stability. For Human Values, only three communities emerged—yet this solution remains psychologically coherent, separating self-enhancement from self-transcendence values while grouping remaining values along the openness-to-change vs. conservation axis. The LLM captures the higher-order motivational structure but lacks granularity for adjacent values within Schwartz's circumplex.

This asymmetry suggests that LLMs better reproduce well-established psychological structures with strong internal coherence, while compressing constructs with more diffuse conditional dependencies (Rossi et al., 2024). LLMs' difficulty in capturing human-level value complexity underscores the challenge of alignment between AI and human values (Russell, 2019). Future research should examine whether LLMs' limited performance on Schwartz's (1992) adapted values scale is due to (i) an inherent difficulty with abstract constructs, (ii) the choice of decoding hyperparameters, or (iii) the prompt's profiles.

Despite this difficulty, the hierarchical EGA revealed meaningful cross-domain bridges—competence satisfaction connected to Power–Achievement, relatedness satisfaction to Self-Direction–Universalism–Benevolence—indicating the LLM encodes coherent implicit theories linking needs to values.

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Several limitations apply. We used a single LLM and analyses collapsed across all synthetic personas rather than examining structural variation by persona characteristics. Future work should test whether network structure varies by sociodemographic or personality profile. Such analyses would illuminate the implicit assumptions LLMs encode about how psychological constructs covary across social positions.

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