Augmenting Photo Elicitation Methods: Using AI-Generated Images to Explore Personal Value Understandings

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Abstract

As values shape the design and governance of technology, it becomes critical to move beyond universal framings to explore the nuanced, subjective understandings individuals hold about values. Traditional value elicitation methods often identify values at play but overlook how they are interpreted through individuals' social identities and lived experiences. This paper introduces an AI-augmented value exploration method inspired by photo elicitation, which involves interviews supported by participant-taken photographs. Instead, we use AI-generated imagery to uncover hidden associations and insights around personal understandings of values. In an exploratory study with six participants, we focused on the value of well-being, examining how AI-generated visuals prompted diverse personal interpretations and facilitated deeper value reflections. Our findings show that this method uncovers implicit meanings and deepens discussions by translating abstract ideas into tangible interpretations to yield richer data on situated values.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

Situated Values, Generative AI (genAI), Photo Elicitation, Reflection

ACM Reference Format:
Fabio Antonio Figoli, Anne Arzberger, Catalina Lagos Rojas, and Sara Colombo. 2025. Augmenting Photo Elicitation Methods: Using AI-Generated Images to Explore Personal Value Understandings. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (CHI EA '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 14 pages. https://doi.org/10.1145/3706599.3719884

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ACM ISBN 979-8-4007-1395-8/25/04
https://doi.org/10.1145/3706599.3719884

1 Introduction

As technology becomes increasingly intertwined with daily life, ensuring those systems respect and reflect our human values has never been more crucial. The capacity of technology to align with these values hinges on the ways in which such values are captured, represented, and encoded during development. While approaches, such as Value-Sensitive Design, recognize the role of context in shaping values, many prevailing definitions and methods continue to treat values as universal and independent of social contexts and identities [26]. For instance, well-being in AI is commonly defined through quantifiable indicators –such as standardized happiness scores or quality-adjusted life years– that assume a single, uniform notion of human flourishing across different cultures and social groups. Such assumptions risk oversimplifying the inherent complexity, plurality, and situatedness of human values, potentially marginalizing or misrepresenting the lived experiences of particular communities [1, 30]. Coming from feminist epistemology, we advocate for a departure from such objective, universal framings of human values towards acknowledging their subjectivity and situated nature [13, 14]. Specifically, we draw from *photo-elicitation* to construct a method for unpacking one's personal understanding of values. Previously found effective in eliciting situated values [20], the traditional photo-elicitation utilizes photographs that the researcher or the participant took to initiate a discussion around hidden associations, feelings, meanings, and memories these images evoke. This method has been shown to highlight voices often minimized, devalued, or even silenced [3, 4], thus suggesting potential in uncovering personal value perceptions currently overlooked.

Following emerging research in HCI on personal informatics and reflection that begins to embrace the uncertainty and ambiguity introduced by AI (e.g. [2, 7, 29]), we turn to image generation to explore *"how can AI image generation support the unpacking of personal perceptions of human values?"*. Specifically, we see value in replacing the traditional self-taken photographs in photo-elicitation with AI image generation to:

(1) **Go Beyond the Literal:** While it is possible to capture abstract, emotional, or intangible aspects of values through photography, achieving this outcome heavily depends on the photographer's skill—a proficiency that is not commonly

found. In contrast, AI-generated images can more readily produce symbolic and imaginative visuals, consistently transcending the constraints of literal representation.

(2) **Overcome Environmental Constraints:** Photographs are constrained by the participant's or researcher's immediate surroundings. For instance, someone in an urban area may struggle to represent tranquillity if it is associated with natural landscapes. AI can generate visuals that match participants' mental images, bypassing these environmental constraints.
(3) **Outputs' Serendipity:** The serendipity of AI-generated visuals can lead to exploring new value facets and stimulating richer discussions about personal associations and priorities.
(4) **Time Efficiency:** Generating images reduces the time required for preparation compared to traditional photo elicitation. Furthermore, multiple images can be produced during the session, offering flexibility and minimizing the risk of relying on a limited set of photographs to achieve the desired outcomes.

In the following, we will report on a qualitative exploratory study with six participants to unpack the nuanced workings of our proposed *AI-augmented value exploration method.* The study's findings should be interpreted as exploratory rather than deterministic, as the investigation focused on testing the method's applicability without comparison to traditional photo elicitation approaches—a step planned for future research. Nevertheless, our results suggest that while engagement with AI image generation does not fundamentally reshape participants' perception of a value, it helps them refine and articulate their personal understanding of it with greater clarity.

2 Background and Related Works

2.1 Photo-Elicitation for Value Exploration

Photo-elicitation (or photovoice) is a qualitative research method that incorporates photographs or other visual media into interviews to elicit deeper and more nuanced responses from participants [9, 15, 21]. Variations of this method have expanded over time, including two primary variations: 1) researcher-generated visuals (such as archival photographs, context-dependent or independent photographs, and even videos), and 2) participant-generated visuals [23]. Both approaches draw from the power of visual stimuli to access deeper, often unobservable elements of human consciousness, resulting in richer data compared to traditional verbal interviews alone [16, 19]. Richard & Lahman [23] further unpack the uses and benefits of photo-elicitation from various researcher projects, highlighting its capacity to evoke suppressed feelings and memories, reveal cultural and social understandings, promote participant agency and collaboration, foster fluent thought and emotional responses, and bridge gaps across diverse backgrounds while enabling richer, more focused, and empowering interactions.

Photo-elicitation has proven effective in uncovering subjective interpretations of abstract, unobservable, and even subconscious perspectives. As such, it is a well-suited method for exploring understandings of values, which are often deeply personal, shaped by context, and challenging to articulate explicitly. Previous research [20] explored this relationship by deploying the photovoice method to elicit situated values through participant-taken photographs. When comparing photo-elicitation with other value elicitation methods, such as the portrait value questionnaire, researchers found that photo-elicitation was more effective in providing more descriptive and situated values. However, they also found that value tradeoffs and how those values influence behavior were challenging to obtain, requiring further guidance.

Other issues known concerning photo-elicitation mostly evolve around the photograph production, such as informed consent and who or what can and cannot be photographed (e.g.[9, 21, 22]), the skill of the photographer whether researcher or participant, inherent costs, and time issues (e.g.[8, 21]).

2.2 Image Generation and Reflection

While most photo-elicitation studies traditionally rely on photographs, it has been recognized that other visual media—such as paintings, cartoons, films, or graffiti—can serve similar purposes [16]. Building on this foundation, we propose a novel variation that introduces AI-generated visuals to complement existing paradigms that minimize researcher influence and provide participants greater creative freedom to explore values beyond physical or practical constraints. The element of surprise inherent in AI-generated imagery fosters reflective engagement, aligning well with established theories of reflection in HCI, particularly those advanced by Schön [5, 25, 27]. Schön's concept of reflection-in-action—where unexpected outcomes during task execution trigger reflection [18, 25]—is well-suited to AI-generated images' imaginative and sometimes surprising nature. Similarly, reflection-on-action, which involves retrospective analysis of past experiences [10], is enriched by the visual connections AI-generated images draw to participants' prompts. Moreover, building on Goldschmidt's concept of the "dialectics of sketching" [12], the iterative input-output exchange between the human user and genAI fosters a dynamic, co-constructive process of exploration [11, 31]. This interaction encourages participants to engage in a reflective dialogue with the emergent imagery, where AI-generated visuals act as the core catalyst.

In doing so, it resonates with reflective HCI research that highlights AI qualities such as surprise, ambiguity, and uncertainty as complementary to the conventional priorities of accuracy, productivity, and performance. Thus reframing the potential of AI as a creative collaborator rather than a tool for optimization. For instance, Caramiaux and Fdili Alaoui [7] show how artists embrace errors and surprises in AI interactions, valuing unpredictability as an expressive quality. Similarly, Arzberger et al. [2] and Van der Burg and colleagues [29] use "AI as a mirror" to learn something about themselves, levering human interpretation, AI bias, ambiguity, and surprise. These approaches align with our focus on leveraging AI-generated imagery to foster reflective, co-constructive dialogues, demonstrating how surprise can be an essential driver of exploration and value discovery.

3 Study Description

In this paper, we draw from the photo-elicitation method to construct an AI-augmented method for surfacing personal perceptions of values. In our study, we selected the value of *well-being* as the one to explore as it is a familiar concept that relates to concrete aspects of daily life (e.g., work-life), making it more accessible for participants to reflect on. By performing an exploratory qualitative study,

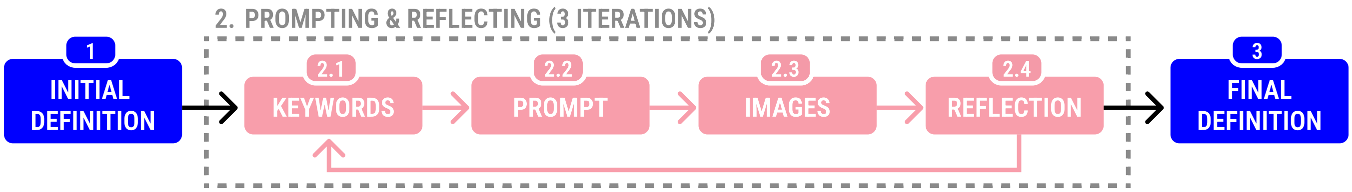

Figure 1: The AI-augmented value elicitation method protocol.

we investigated the feasibility and effectiveness of this method. We conducted three pilot studies to refine the method's design and implementation. We then evaluated the method through six user tests with PhD students from our professional network. Each evaluation session lasted approximately 20 minutes and followed a structured protocol, described in the next section. We obtained ethical approval from the Human Research Ethics Committee (HREC) of Delft University of Technology (application number: 4865) and informed consent from participants. Data collection included transcripts, notes and memos, keywords, and images generated during the sessions.

3.1 AI-Augmented Value Elicitation Method

As illustrated in Figure 1, our *AI-augmented value elicitation* method consists of three main phases: starting value definition, prompting and reflection, and final value definition. Each phase is interconnected, guiding participants through an iterative exploration of their understanding of the value. The method foresees a researcher facilitating a conversation with a participant, guiding the process, and handling the AI prompting. The protocol begins by asking the participant to define well-being (Figure 1–Step 1, Table 1).

Table 1: Participant 2 initial and final definition.

Initial Definition	Final Definition
Well-being for me constitutes a combination of me feeling physically well in my body, but also psychologically well. So, in my mind. I think I'm just at home in my body and mind and comfortable.	I think then maybe it's like a systemic thing. So, it is not about one person or about me at all. It is about this system of the natural environment and all living beings within it, but also the social environment. So me, but also all the people I relate to and who are within my community.

From this first definition, the participant is asked to extrapolate a set of three keywords (e.g., Participant 2: "mind," "body," and "connection") (Figure 1–Step 2.1). The researcher then incorporates these keywords into a predefined prompt for MidJourney[1] (Appendix A) through the Discord interface (Figure 1–Step 2.2), generating four images (Appendix B) (Figure 1–Step 2.3). The researcher encourages the participant to start with simple descriptions of what they see in the images and then invites the participant to connect the elements of the images to personal memories, feelings, and meanings that connect to their personal perception of well-being (Figure 1–Step 2.4). Based on these reflections, the participant is asked to select a new set of three keywords, which are used to initiate another round of image generation and reflection. These steps are repeated in a third and final iteration. Following this, the researcher presents the twelve generated images to the participant and asks again: "What is well-being for you?". This final step captures the participant's evolved definition, informed by the iterative exploration and reflection facilitated throughout the session (Figure 1–Step 3, Table 1).

In the next step, we organized the collected data from the six participants (e.g., notes and memos, transcripts, keywords, and images) on a Miro board, allowing us to view all the data side by side. This analysis not only forms the evaluation for our study but also forms an integral component of the method itself. The first step of the analysis involved coding the transcripts using In Vivo coding [24], which enabled us to capture the participants' exact language. This approach helped us to identify two key elements: what we refer to as the *value facets*, which represent components of the participants' perception of well-being, and the *visual catalysts*, which refer to the specific aspects within the generated images that prompted participants to describe those facets (Table 2).

Table 2: An example of a transcript passage coding.

Transcript	Value Facet	Visual Catalyst
"...And on the other one, it looks like a boy with all these people out of his reach. Right. So maybe that means that he cannot; how do you say? He is not very supported or seeking support, but he cannot reach it."	supported by others (connection)	People out of reach

After coding the six transcripts, we built a table (as observed in Figure 2) for each participant. In these tables, we organized the keywords (KW) and coded elements of each emerged facet into five rows, corresponding to the sequential stages of the process: initial definition (ID), first iteration (1), second iteration (2), third iteration (3), and final definition (FD). This structure helped us organize how the facets evolved during the interview, clarifying their chronological development and the interconnections between them. Most importantly, two key dimensions emerged: the horizontal dimension, referred to as the facets' *breadth* (e.g., the range of facets explored), and the vertical dimension, referred to as facets' *depth*

[1] *Prompt: "/imagine a poetic scene of well-being as [keyword 1], [keyword 2], [keyword 3] in expressionist style –c 100 –weird 50 –s 250 –style raw –v 6.1 –no close-up"*. We developed it through an iterative trial-and-error process, focusing on three main aspects: Connection to well-being dimensions, the balance between abstract and accurate, and variety and unpredictability.

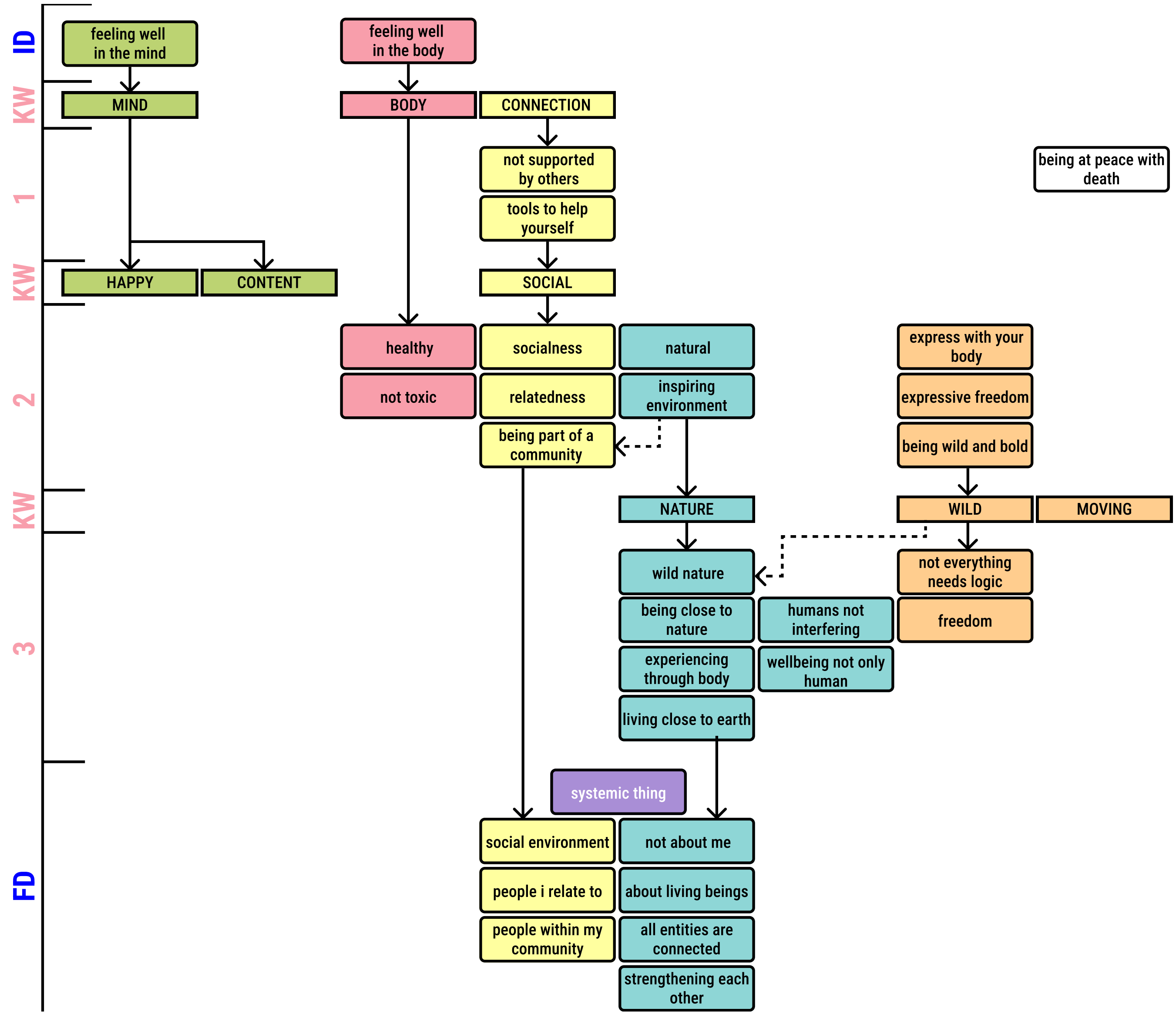

Figure 2: The breadth and depth diagram of participant 2, illustrating the evolution of well-being facets (colored columns) throughout the interview stages (from top to bottom: ID (Initial Definition), KW (First Keywords), 1 (First Iteration), KW (Second Keywords), 2 (Second Iteration), KW (Third Keywords), 3 (Third Iteration), and FD (Final Definition).

(e.g., the level of detail and nuance with which each facet was unpacked). We refer to these tables as *breadth & depth* (B&D) *diagrams* (Appendix C). We first analyzed the six B&D diagrams individually to understand each participant's unique evolution of facets and then conducted a comparative analysis to identify patterns, similarities, and differences across participants.

4 Results and Discussion

4.1 From Fragmented to Holistic Understanding of Well-Being

First, we compared the facets present in each participant's first and final definitions (Table 3). The comparison revealed that the facets consistently evolved, indicating that each participant actively engaged with and responded to the visual prompts. Notably, the initial definitions showed significant overlap among the participants, with five out of six focusing on well-being as a physical and mental matter. However, by the end of the process, each participant arrived at a distinct and personalized definition, diverging from the others. We identified two main ways these changes occurred: *Exploration of Initial Facets* and *Replacement of Initial Facets*. In the first case, some initial facets are further developed, with sub-facets emerging to elaborate on the original facets. In the second case, some initial facets are entirely dropped in favor of new facets that better reflect the participant's evolving understanding.

To better understand the transition between the initial and final definitions, we refer to each participant's B&D diagrams (Figure 2 and appendix). They reveal a key difference between the initial and

Table 3: main facets within initial and final definitions for each participant.

P	ID	FD
1	Personal, Physical, Emotional, Promoting, Spiritual	Connecting, Journey, Self
2	Feeling Well in the Mind and in the Body	Connection (Nature, Community, Freedom)
3	Happiness, Stress-Free, Time	Openness, Freedom, Tranquillity
4	Physical, Mental, Energy, Doing	Being Capable, Social Connection, Environment
5	Mental, Physical, Health	Mind, State, Reflection, Position
6	Agency, Time, Physical	Agency, Freedom, Beauty, Isolation

Table 4: Participant's 2 facets ranking based on the number of the three sub-properties of iteration, articulation, and relation.

Properties N.	0/3	1/3	2/3	3/3
Relevance	**low**	**moderate**	**high**	**core**
P2	peace with death	mind, body	community, freedom	connection, nature

final definitions: the initial definitions often present facets as standalone entities, whereas the final definitions adopt a more holistic vision, where the facets are no longer isolated components of well-being but are interconnected. This shift illustrates how participants moved from fragmented perceptions to a more integrated understanding of well-being. A recurring pattern observed during the interviews reveals that participants gradually moved from abstract facets to more concrete and nuanced ones (e.g., Participant 2: from "connection" to "people within my community") or vice-versa (e.g., Participant 2: from "express with your body" to "freedom"). This progression allowed them to articulate each facet with greater clarity, ultimately fostering the emergence of meaningful connections between them.

In this scenario, the two dimensions of breadth and depth are essential to understanding the participants' reflective processes. Breadth is represented horizontally in the diagram and reflects the number of different facets (i.e., colored columns) explored by the participant. It enables the participant to break down well-being into new components and sub-components. Depth, represented vertically, captures the level of facet articulation. It allows the participant to move between abstract and concrete understandings, enriching their reflection.

The diagrams reveal variations in breadth and depth among participants, with some exhibiting greater breadth and others greater depth. Importantly, we observed that breadth and depth enhance each other, working together to foster more profound and comprehensive reflections. However, imbalances between the two can result in less complete reflections: a lack of breadth leads to missing values' components and relational links, while a lack of depth results in limited concreteness and shallow understanding changes.

4.2 Ranking Facet Relevance

When analyzing the B&D diagrams, a key challenge lies in identifying the most relevant facets among those mentioned by the participants. We propose that the most relevant facets are typically those retained throughout the interview and included in the final definition, a property we refer to as *facet retention*. To better understand this, we compared the dropped facets with those appearing in the final definition. This analysis led to the identification of three key sub-properties that influence facet retention: *iteration* –i.e.frequency of a facet's appearance along the interview–, *articulation* –i.e., depth and richness of the facet's nuances–, and *relation* –i.e., connection to other facets. By analyzing the facets through these properties, we were able to classify them into four different levels of relevance: *low*, *moderate*, *high*, and *core* (Table 4). This ranking should be understood as an orienting framework that provides researchers with a preliminary guide for interpreting the data during an initial analysis. It is particularly valuable as it describes a simple structure for analyzing the data and exploring the intermediate stages between the initial and final definitions of the value. Indeed, facets that were dropped may hold a certain degree of relevance, and understanding their significance enables the researcher to delve deeper into them, both during and after the interview.

4.3 AI Images as Facilitators of Reflection and Communication

We observed the AI images to serve two pivotal roles in the process: *reflection facilitator* and *boundary object for communication*.

As reflection facilitators, the images support participants in exploring their perception of the value [31]. The AI image's balance of serendipity and fidelity to participants' input is particularly effective in triggering reflection. This aligns with the *random stimulus* principle of lateral thinking [6], which recognizes the importance of introducing foreign conceptual elements to disrupt preconceived notions and habitual thought patterns. The AI-generated images stimulate deeper engagement with the explored value by encouraging participants to integrate unexpected visual elements into their interpretation process.

The generated images often include incomplete scenes, prompting participants to "fill in the gaps" by adding sense-making, context, or meaning (see example Figure 3). Participants seem to naturally engage more deeply with the images by imagining themselves within the scenario. This reflective triggering occurs in three ways:

- *Recalling*: Images evoke personal connections, such as memories, emotions, or experiences, prompting participants to reflect on their own lives.
- *Envisioning*: Images allow participants to project aspirational or utopian visions of the value, imagining idealized scenarios that they associate with well-being.

Figure 3: Example from the third iteration image set of participant 2, demonstrating serendipity and fidelity to participants' prompt. Prompt: *a poetic scene of well-being as wild, nature, moving in expressionist style –no close-up –chaos 100 –style raw –stylize 250 –weird 50 –v 6.1*

Figure 4: AI-generated image for participant 5. The image evoked the concept of "slowly disintegrating," aiding the participant in better articulating the well-being facet of "transitioning between states." Prompt:*a poetic scene of well-being as change, reflection, recovery in expressionist style –no close-up –chaos 100 –style raw –stylize 250 –weird 50 –v 6.1*

- *Contrasting*: Images may not always align with the participants' visualization of well-being. In such cases, participants use the images as a point of comparison or contrast, enabling them to identify facets that, in their opinion, are misrepresented or missing in the visualization.

However, given the exploratory nature of our study, we also acknowledge the possibility that the process could steer the participant's associations and reflections in directions that do not reflect the person's true perceptions of the value. Comparing the process to photo elicitation, where pictures are deliberately taken and chosen, the researcher or the participant could lack intentionality during the image generation process. The act of prompting—or potentially developing and training a model specifically for this purpose—could play a crucial role in mitigating this risk by enabling more deliberate choices in image generation. However, further research is needed to explore this aspect in greater depth. The second role of the images, as boundary objects, focuses on facilitating communication between the interviewer and the participant [28]. When discussing abstract values, words can be challenging to articulate [17], and even when articulated well, they may be interpreted differently by those who listen, leading to potential misunderstandings that can hinder the overall conclusions of the process. This risk can be mitigated by sharing a tangible artifact, such as images. Compared to traditional photographs, AI-generated images appear more effective in conveying abstract concepts due to their imaginative qualities, which often go beyond literal representation and incorporate symbolic elements. For example, one of participant 5's core well-being facets was "transitioning from one state to another," a recurring theme throughout the interview. When they observed Figure 4, they identified "slowly disintegrating" as a specific moment within this transition, further deepening their understanding of the facet. While articulating this idea, they pointed out specific symbolic elements within the generated image (e.g., fading and fragmented colors), visually illustrating their conceptual reasoning to the interviewer. Seeing the same visual elements, the interviewer gained a clearer understanding of the participant's thoughts, even when expressed in a metaphorical way, fostering alignment and reducing ambiguity in the discussion.

Nonetheless, from our study, it remains challenging to distinguish definitively the contributions of AI-generated images from those of traditional photography in the photo-elicitation process. Future research should employ a contrastive study design to systematically compare photo elicitation outcomes using AI-generated images versus traditional photographs, thereby clarifying each approach's distinct benefits and limitations.

5 Conclusions and Future Works

In this exploratory study, we propose an AI-augmented value elicitation method to uncover subjective understandings of values. In line with emerging research on reflective HCI, we integrate AI-generated images instead of traditional photographs, overcoming constraints such as reliance on tangible realities, physical environments, and time-intensive preparation. The results indicate that the method facilitated participants' articulation of the value of well-being by breaking it down into distinct facets. This process facilitated shifts between abstract and concrete dimensions, ultimately enabling the construction of a holistic understanding in their final definitions. We emphasize that the richness of the data lies primarily in the intermediate stages between the initial and final definitions. To unpack this complexity, we propose to analyze data with the breadth and depth diagrams and the facet relevance ranking. The images played a pivotal role in this process, striking a balance between serendipity and user input, effectively triggering participants' reflections and enhancing communication between participants and the interviewer.

We acknowledge several limitations in this study that should be addressed in future, more deterministic investigations. Regarding the study structure, the absence of a control group prevents a direct comparison between our proposed method and traditional approaches, positioning the findings as exploratory rather than conclusive. Additional structural limitations include the relatively small and homogenous participant pool and the multiple layers of interpretation embedded in the process (e.g., MidJourney outputs, prompt formulation, and data analysis). These factors highlight the need to test the method in diverse contexts, particularly with different values; while we focused on well-being, alternative values might yield different results. Concerning the limitations of AI-generated visuals as support for value exploration, we recognize potential issues such as the steering of participant reflections, inherent bias in the model, visual homogeneity, and lack of ownership of genAI images. Despite these constraints, we view this study as a valuable initial step in an emerging field of inquiry, laying the groundwork for future research to further evaluate the potential and applicability of this method across varied settings.

Looking ahead, we envision two key directions for further development. On the one hand, efforts could focus on substituting the human interviewer with an AI agent, automating the process to make it scalable, and enabling participants (or users) to engage with it autonomously. This could be particularly valuable for applications such as self-reflection practices, workshop ice-breaking, or stakeholder communication. On the other hand, the data collected through this method holds promise for addressing the issue of AI value alignment. By leveraging large amounts of high-quality, situated, and contextualized data, this approach could enhance the capacity of AI systems to generate better representations and outputs that more accurately reflect the diversity and richness of human values.

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A Appendix: Prompting

Table A. The prompt elements and their achieved effects on the generated images.

Prompt Element	Effect
Poetic Scene	Creates evocative and symbolic imagery.
well-being	Focuses the theme on well-being concepts.
expressionist style	Adds chromatic intensity and bold visuals.
–c 100	Introduces high variability and unpredictability.
–weird 50	Adds unique and unconventional elements.
–s 250	Balances realism and abstraction.
–style raw	Reduces the "Midjourney stylization".
–v 6.1	Produces images quickly.
–no close-up	Encourages expansive, contextual compositions.

B Appendix: Images

Figure A. Participant 2 first iteration image set. Prompt: ***a poetic scene of well-being as mind, body, connection in expressionist style –no close-up –chaos 100 –style raw –stylize 250 –weird 50 –v 6.1***

Figure B. Participant 2 second iteration image set. Prompt: ***a poetic scene of well-being as social, happy, content in expressionist style –no close-up –chaos 100 –style raw –stylize 250 –weird 50 –v 6.1***

C Appendix: Participants' B&D Diagrams

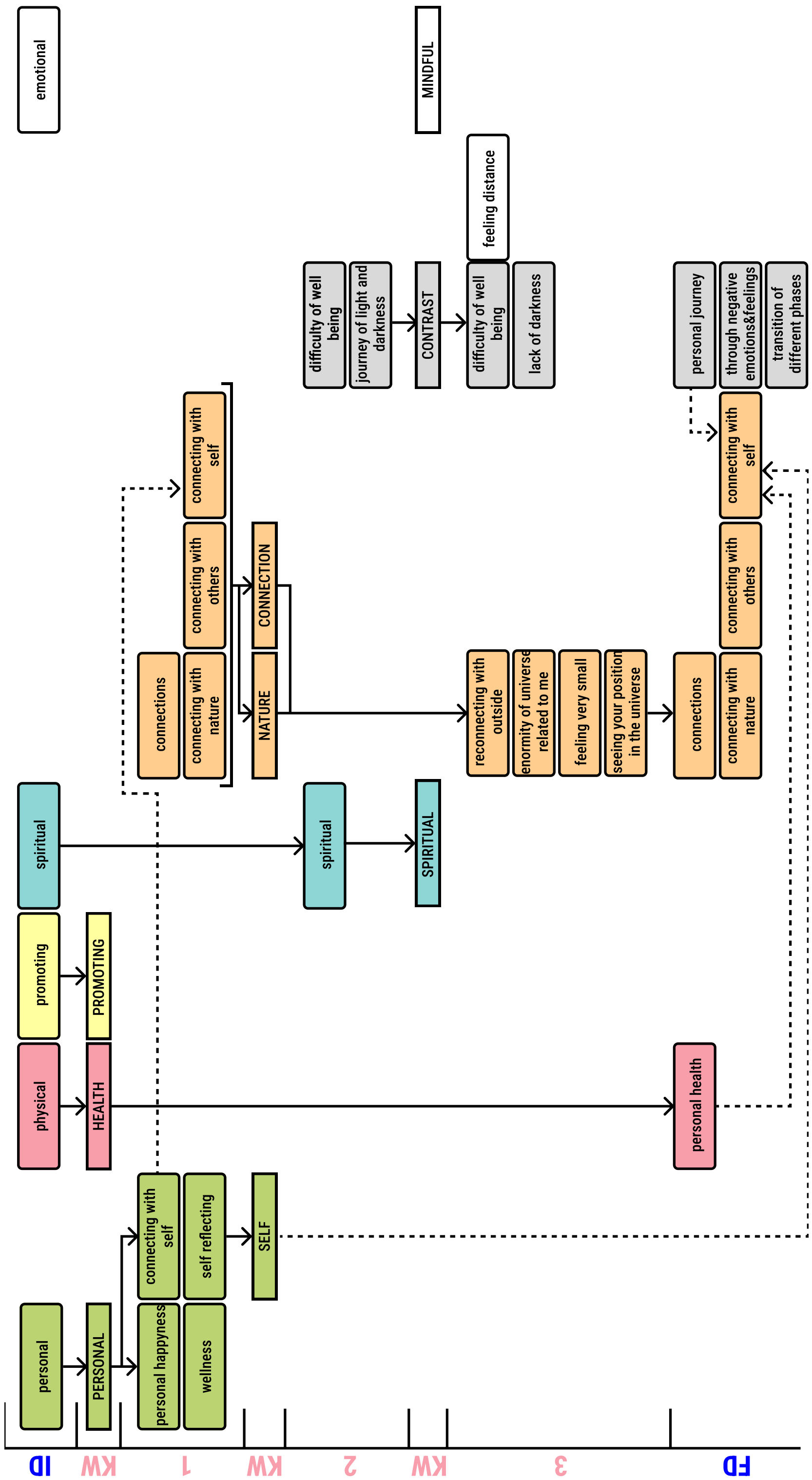

Figure C. Participant 1 B&D diagram.

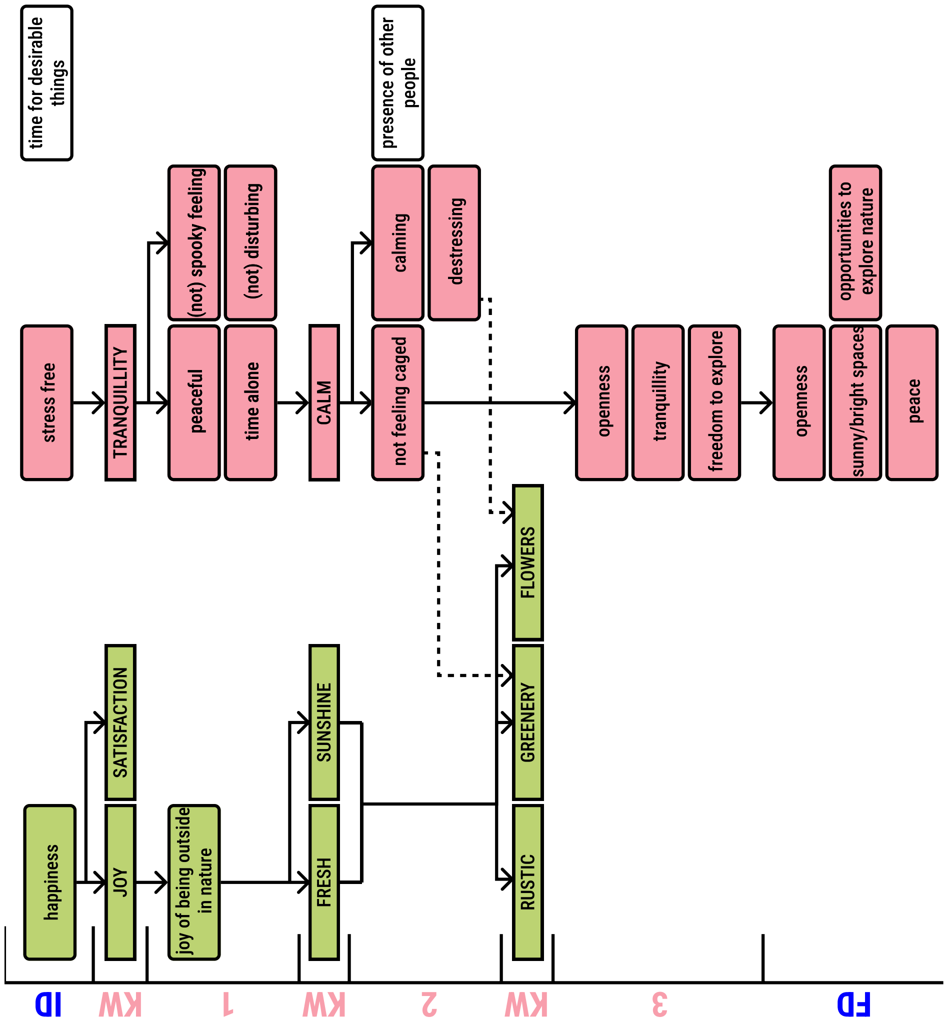

Figure D. Participant 3 B&D diagram.

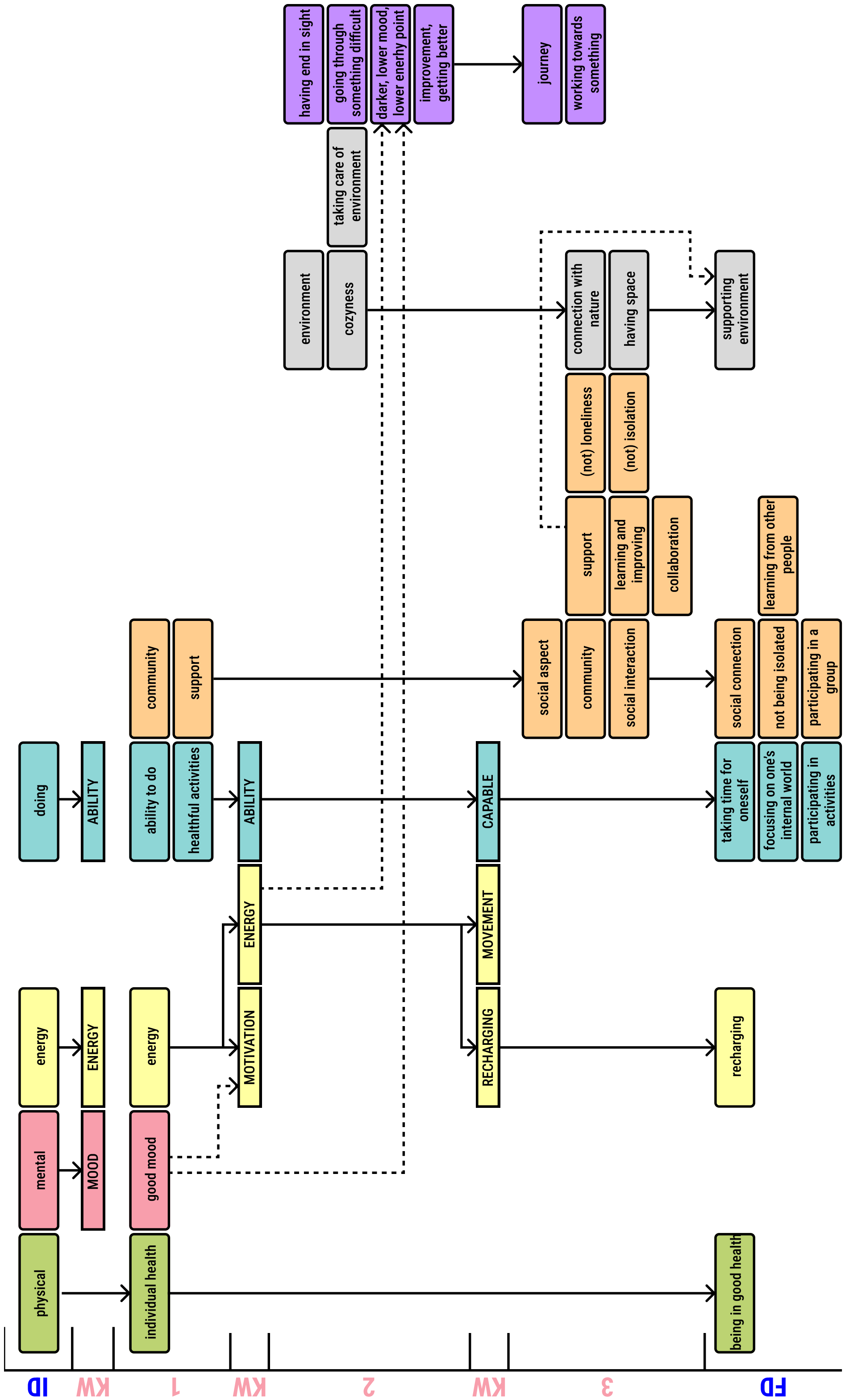

Figure E. Participant 4 B&D diagram.

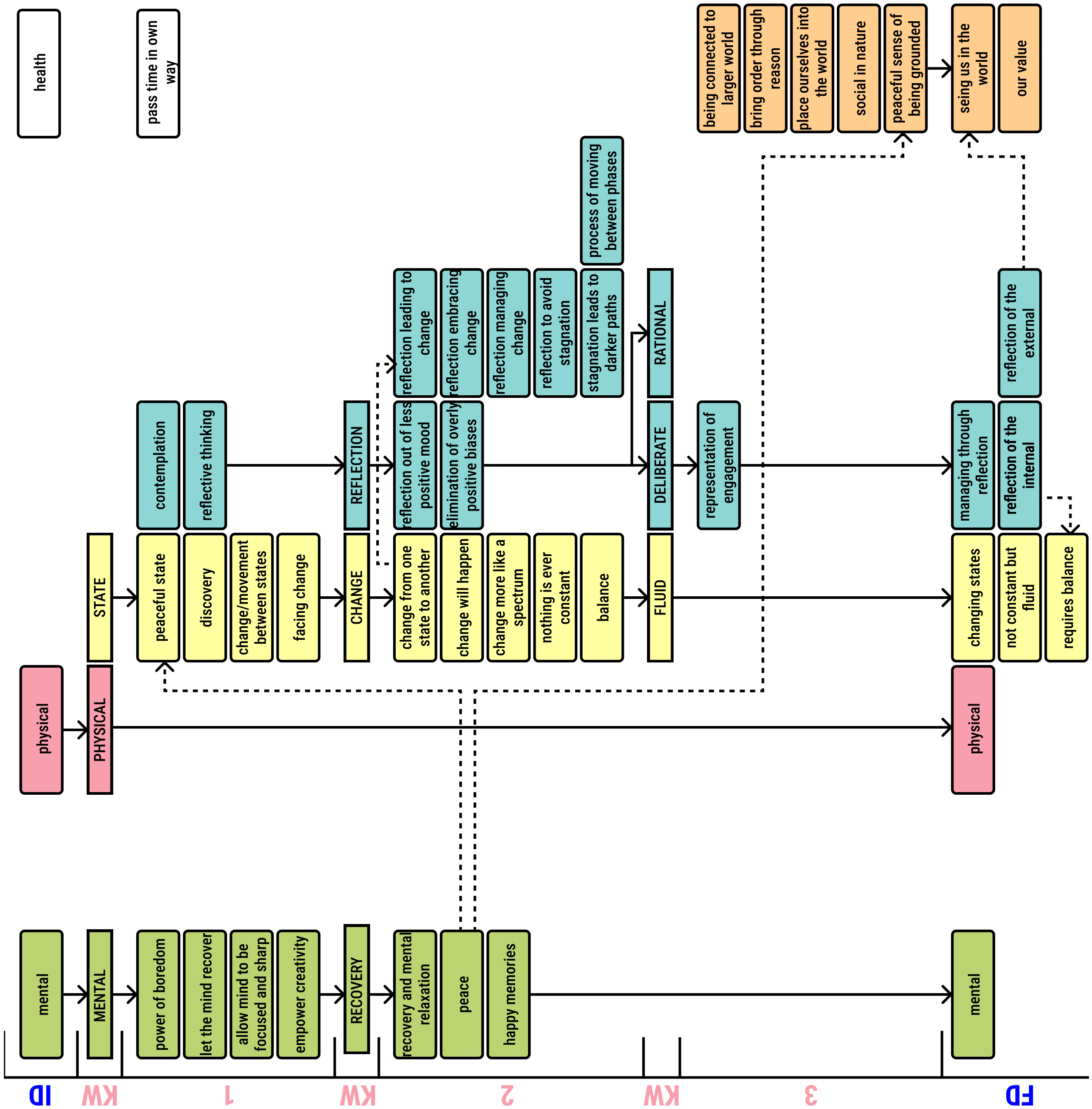

Figure F. Participant 5 B&D diagram.

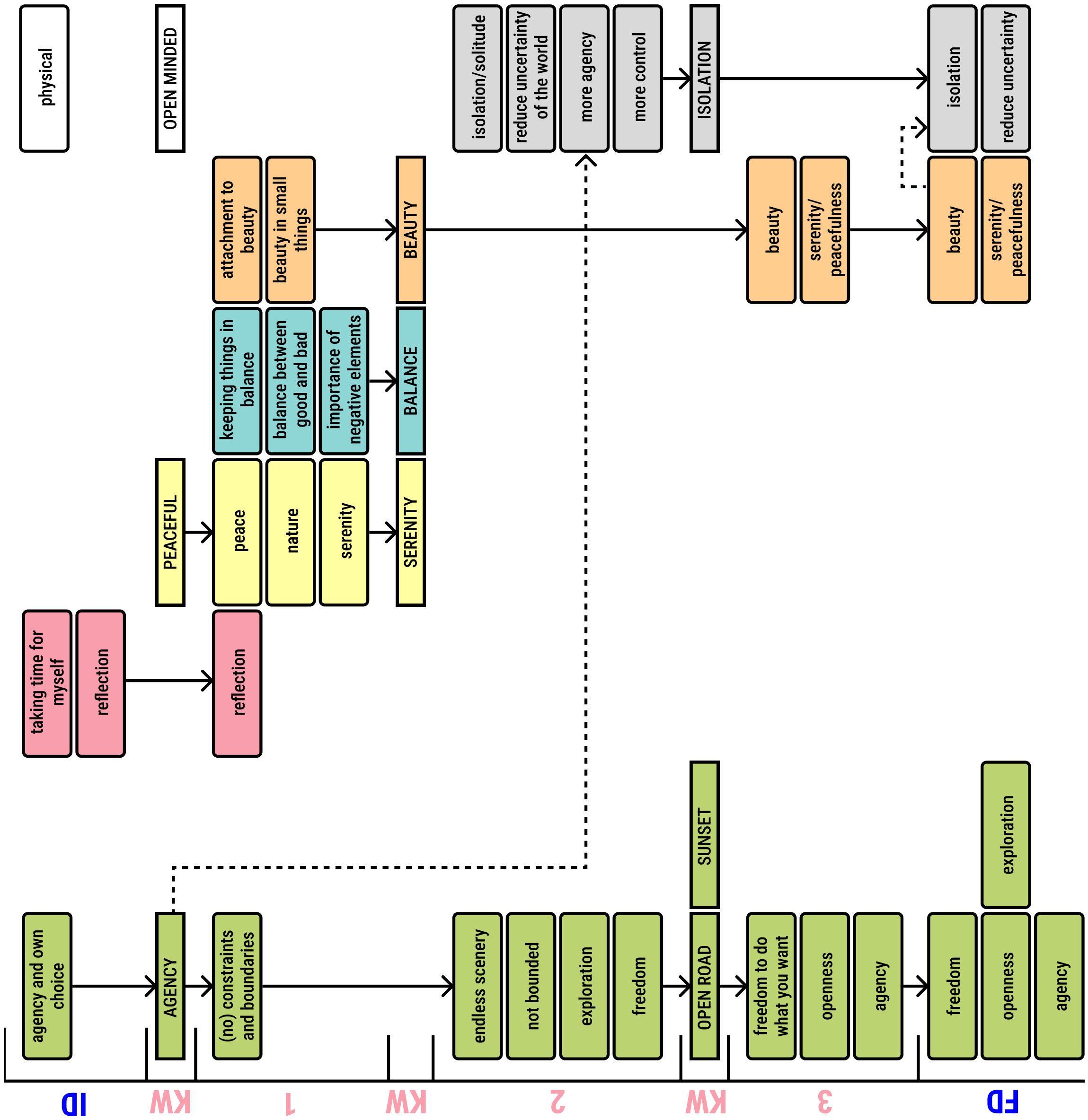

Figure G. Participant 6 B&D diagram.