The Common Integrative Framework (CIF)

by

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Abstract

While it is often assumed that the mind can only be understood in terms of the brain, this has been to the detriment of psychological science. The dearth of consensus on how to integrate diverse findings in psychological fields highlights this fact. This manuscript presents and explicates the Common Integrative Framework (CIF) as a viable dimensional model for the representation of all subjective, phenomenal states of consciousness, as well as the basis for a unified framework of general psychology. First we present the history of similar models before systematically laying out the relevant components and structural sections of the CIF: The four dimensions (executive-cognitive functioning [X], phenomenological intensity [Y], affective valence [Z], and sense of self [SoS]) as well as the quadrants and interquadrant regions of the vector space. The framework's presentation incorporates a transdiagnostic analysis of psychopathologies, as well as a phenomenological characterization of the major classes of psychoactive substances. A preliminary experience-sampling study yielded a dataset of experiences (n = 204), which were analyzed with a multitude of statistical and visualization methodologies including scatter and contour plots, heatmaps, and multiple OLS linear regression models. Results found that the configuration of experiences aligned with the predicted structures; demonstrated the utility of distinguishing groups, individuals, and concepts on the basis of characterizing subjective experience; and the predictive diagnostic capabilities of the applied framework when paired with demographic information. The preliminary findings of the study and literature review together support

the CIF as a valuable tool that provides context for both the design and interpretation of a wide range of psychological research, warranting future studies.

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Chapter 1: Introduction

Does Psychology need a unifying model like the standard model of particle physics, the periodic table of the elements for chemistry, or the theory of evolution by natural selection for biology? Certainly the value of the aforementioned frameworks cannot be overstated for the respective fields of science. Indeed, without these models as conceptual roadmaps the likelihood of these fields being where they are today, or at a comparable level in terms of sophistication in understanding, would be slim to none. Psychology and the various related fields of study which pertain to the human mind or subjective, phenomenal consciousness lack overarching unifying frameworks to contextualize new findings and to integrate them within established research (Zagaria et al., 2020; Osbeck, 2020). Thus, research is siloed and unable to be shared between the sub-disciplines without difficulty (Staats, 1999; Osbeck, 2020).

The lack of such a framework in psychology is a testament to the complexity of the human mind, and will not come without considerable challenges, as it must integrate understanding of the nature of the self, executive-cognitive systems, affective states, altered states of consciousness, stages of sleep and meditation, psychopathologies, flow states, mystical experiences, and must be capable of subsuming and mapping any new state or experience within the bounds of the framework. Lastly, it should be empirical in nature and design, and it should be representable using the language of mathematics (as with all other natural phenomena).

Pereira (2013) states:

> "A consensus seems to be emerging that there is little chance of a revolutionary empirical discovery in this field, and that scientific progress will derive mainly from an adequate theoretical framework to interpret the thousands of published results and to guide the planning of pertinent new experiments." (concluding remarks)

This is a vital point, as it implies that if a truly comprehensive theoretical framework is arrived at, then seemingly disparate and unrelated research from the range of consciousness-adjacent fields of study (cognitive science, psychiatry, neuropsychology, phenomenology, etc.) will be readily synthesizable. This provides a litmus test for any such integrative model.

This manuscript will present the Common Integrative Framework (CIF) and argue how it meets the aforementioned criteria for an integrative, interdisciplinary, translational, and empirical framework of subjective consciousness. This assumption will be assessed by testing a set of three hypotheses:

1. The range of experiences will approximate the CIF's theorized two (XY) and three dimensional (XYZ) structures.
2. The CIF can be used to distinguish between individuals, demographic groups, and individual types of experiences.
3. The dimensional variable data can be used to predict mental health diagnoses.

First, Chapter 2 addresses the relevant literature, beginning with some of the prior proposals for integrative dimensional models of consciousness. Next, this chapter will present and expound upon the CIF, covering the four spatial dimensions of the model, as well as a characterization of the regions of the XY plane (Figure 1) according to the egoic boundary, the quadrants and the interquadrant regions. Chapter 2 ends with an application of the CIF to the characterization of psychoactive substances according to their phenomenological effects.

Following this presentation of the framework and the literary basis for it, Chapter 3 lays out a preliminary experience-sampling study methodology conducted to quantitatively explore the validity and utility of applying the CIF to real-world phenomena (n = 204). Chapter 4 presents the results of the study, and Chapter 5 provides a discussion of the findings and their implications towards understanding the validity of the framework. Finally, Chapter 6 will conclude with final remarks on the CIF and directions for future research.

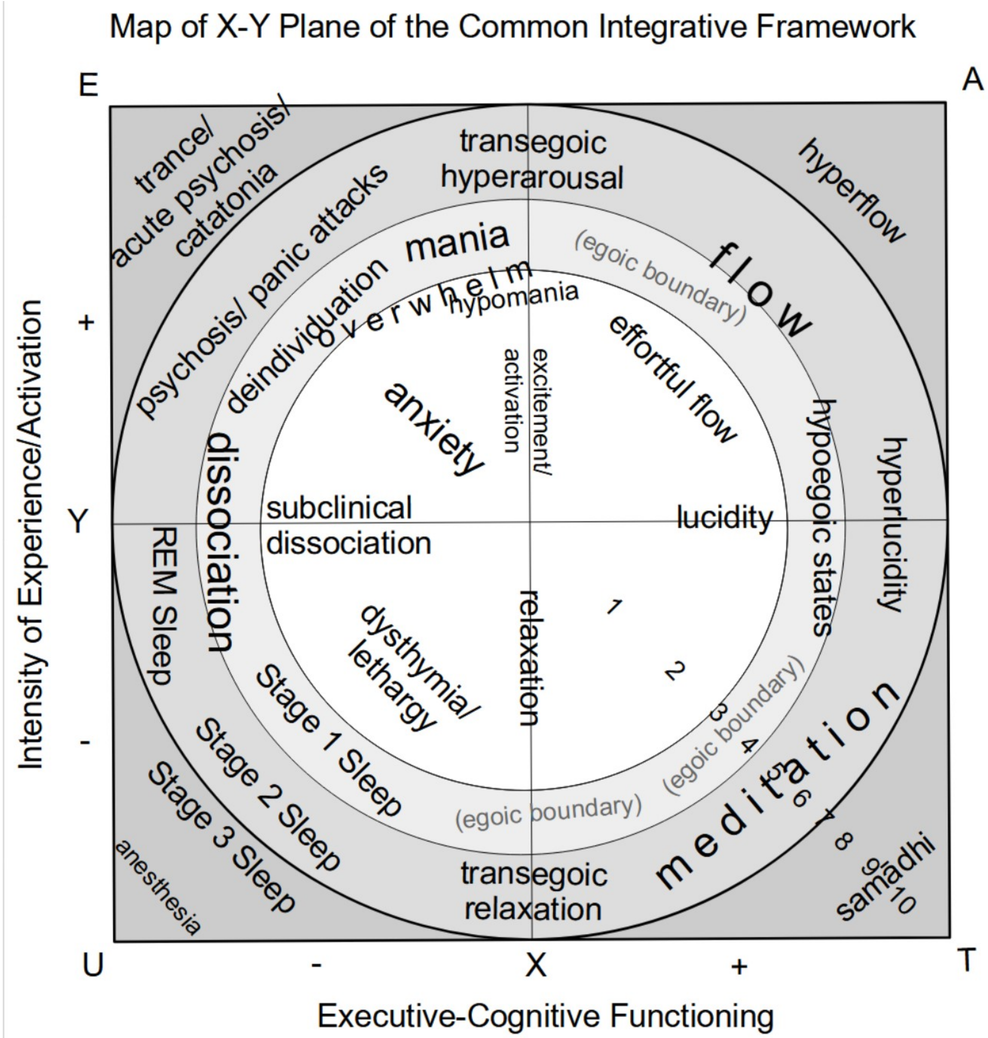


Figure 1: The XY Plane

This figure depicts the approximate structure and locations of major states of consciousness predicted by the CIF. The size of the terms denotes the approximate degree of spread, with the location representing the epicenter of that experiential category. The egoic boundary represents where sense of self tends to rapidly decrease, with the thick black circle filling the space representing the boundary of external awareness.

Chapter 2: Literature Review

Towards an Integrative Dimensional Model of the Mind

Of psychology's proposed dimensional models, the most consensual dimensions are the two dimensions of the circumplex model of affect: valence and a dimension that has been variously referred to as arousal (Mehrabian, 1980; Russell, 1980; Scherer, 2005; Posner et al., 2005; Trnka, 2011), intensity (Rubin & Talarico, 2009; Trnka et al., 2016), and activation (Posner, 2008; Scherer, 2005). Though these terms have been used interchangeably to refer to the second dimension of the circumplex, nuanced differences exist among them. Arousal (and activation) refers to a physiological response described as "a continuum of sensitivity of the organism to stimuli, both external and internal (Definitions of the RDoC Domains and Constructs)", while intensity refers to the subjective interpretation or phenomenology of the response (Rubin & Talarico, 2009). Nonetheless, the interchangeability of arousal and intensity has been demonstrated empirically (Rubin & Talarico, 2009), and for the purposes of this manuscript, the term 'intensity' is favored because the CIF is (chiefly) a model of conscious experience, as opposed to the more physiological implications of 'arousal' or 'activation'.

Models, frameworks, and general theories have attempted to use three or more dimensions going back to Wundt in the late 19th century (Trnka, 2011; Titchener, 1908). However, while none of these models have become as well-established as the two-dimensional circumplex model of affect/emotion, nonetheless, the higher dimensional models almost invariably build upon and include the two-dimensional models. Thus, it is clear that these two dimensions of the circumplex provide a viable foundation upon which a common, integrated framework of psychology can be devised.

This section will briefly review some dimensional, nosological, and integrative models of consciousness, emotional states, and psychopathology, namely: the updated circumplex models, PANA (Watson & Tellegen, 1985) and Vector model (Rubin & Talarico, 2009); as well as the models incorporating three or more dimensions such as Wundt's three dimensional theory (Titchener, 1908), the PAD model (Mehrabian, 1980), a 3-D hypercube projection model (Trnka et al., 2016), the Research Domain Criteria (RDoC) project proposed by the National Institute of Mental Health (Cuthbert, 2014a), and a review of seven dimensional models of emotion (Trnka, 2011).

Developments to the Circumplex Model

Two models that have built upon the circumplex model and have been experimentally supported (Rubin & Talarico, 2009) are the PANA and Vector models. The Positive Activation Negative Activation (PANA) model (Watson & Tellegen, 1985) uses the same dimensional structure of valence and intensity/arousal as the circumplex model, but takes into account that the positive valence and negative valence systems operate independently, and may co-occur. The Vector model (Rubin & Talarico, 2009) is another model which utilizes the same two dimensions as the circumplex model, but this theoretical model demonstrates that high-intensity, neutral valence and low-intensity, highly valenced affect may not actually have real phenomenological analogs. In other words, not all points within the dimensional space are weighted equally in terms of frequency of natural occurrence, and some may not even be possible to experience.

Dimensional Models Utilizing Three or More Dimensions

Nearly a century before introduction of the circumplex model, Wilhelm Wundt's three-dimensional theory of emotion (Titchener, 1908) consisted of the familiar dimensions of pleasantness-unpleasantntess, excitement-inhibition/tranquilization, and tension-relaxation, the latter two of which can easily be conceptualized as belonging to the same general phenomenological dimension of intensity/arousal.

The Pleasure-Arousal-Dominance (PAD) Model (Mehrabian, 1980) was proposed as a general psychological theory, and is the primary basis on which Russell (1980) developed and popularized the circumplex model of emotion. This PAD model posits that in addition to the two core dimensions of the circumplex, which the model terms “pleasure-displeasure” and “arousal-nonarousal”, a third dimension would be a continuum from dominance to submissiveness. This dominance-submissiveness dimension is described as the perceived sense of freedom or restriction to act in a variety of ways (Mehrabian, 1980)—essentially, “volitional freedom”.

A 3D hypercube-projection model of emotion was recently proposed (Trnka et al., 2016) which adds the dimensions of "controllability” and "utility" to the ubiquitous valence and intensity dimensions. “Controllability” refers to the extent to which an individual subjectively feels that their emotional state influences thinking and behavior. As a psychophenomenological dimension, “utility” requires personal assessment of the harm or benefit of each one of 16 listed emotions based off of the individual's subjective schemas, biases, and motivations; in other words, it is a value judgment. The wide variability of value judgments pertaining to states of mind—even of the same state of mind contemplated at a later time or experienced in a slightly different context—casts doubt on the universality of “utility” as a useful or powerful feature for characterizing subjective experiences. Trnka et al. (2016) acknowledge the reductionism of a two-dimensional paradigm (the circumplex model) in the characterization of emotion, however, a 3D hypercube-projection of four dimensions (including a value judgment) lacks the parsimony and practical elegance of great models like those of the physical sciences.

Trnka (2011) in an assessment of seven different dimensional models of emotional experience that utilize three or more dimensions found that all seven incorporate valence as a dimension, and five of the seven models include a dimension of intensity/activation. The review further found two of the models to include control as a third dimension in addition to valence and intensity. These commonalities across proposed models suggest that affective valence, intensity/activation, and control are fundamental features of human consciousness.

The Research Domain Criteria (RDoC) project, developed as a direct response to the shortcomings of the DSM-5, provides a promising direction for dimensional research in psychology. This framework stresses empiricism, the neuropsychological perspective, and is intentionally kept open to ongoing developments in psychometric research methodology and related fields (Cuthbert & Insel, 2013). Additionally, Cuthbert (2014b) describes the major postulates of RDoC as being dimensional, translational, agnostic to the currently established disorder categories, and making no assumptions of the linearity of the psychological phenomena studied, providing a helpful starting point in approaching an integrative framework. RDoC conceptualizes neuropsychological phenomena in terms of six dimensions: positive valence systems, negative valence systems, arousal, cognitive systems, social processes, and sensorimotor systems (Cuthbert, 2014a).

If taken together, these models suggest that a viable dimensional model of consciousness will include dimensions of valence and intensity. Moreover, co-occurrence of positive and negative valence (PANA model) should be incorporated and the problems of high-intensity neutral valence states and low-intensity heavily valenced states (Vector model) should be accounted for. In addition, the candidate dimensions beyond the two dimensions of the circumplex model mentioned above (control/controllability, dominance-submissiveness or “volitional freedom”, cognitive systems, social processes, and sensorimotor systems) should be incorporated/integrated.

Dimensions of the CIF

Y and Z: Dimensions of the Circumplex

The two fundamental dimensions of the circumplex model—namely, valence and intensity—are well-established as distinct psycho-phenomenological dimensions of the mind (Posner et al., 2005; Trnka, 2011). For the purposes of the CIF, the subjective experience of positive, negative, and neutral valence, as defined by Harmon-Jones (2017) as "a broad component referring to how positive or negative individuals, including non-human animals (we posit), evaluate their feeling state," is referred to as the Z dimension. The second dimension of the CIF (Y) refers to intensity of experience.

Executive-Cognitive Functioning (X)

Given that willful self-control and awareness is fundamental to human consciousness, and given the role of the associated executive and cognitive systems and their dysfunction in both the etiology and symptomology of the majority of psychopathologies (Caspi et al., 2014; Eaton et al., 2015), an effective framework for the integration of psychological research must incorporate them. The CIF integrates these executive and cognitive functions into a meta-dimension "X". This executive-cognitive dimension encompasses conceptually overlapping systems including executive functioning (Snyder et al., 2015; Diamond, 2013), cognitive control (Mackie et al., 2013; Diamond, 2013), System 2 (Evans and Frankish, 2009; Gronchi and Giovannelli, 2018), metacognition (Borkowski et al., 2000), agency (Braun et al., 2018), volition (Frith, 2013), mindfulness (Groves, 2016), skill (Nakamura & Csikszentmihalyi, 2014; Csikszentmihalyi, 2009), and controllability (Coffee and Rees, 2008); and includes fluid intelligence and aspects of linguistic ability (Snyder et al., 2015)—possibly extending to all conscious cognitive processes. Integrating these subsystems into a unified dimensional construct of conscious experience is assumed on the basis of several shared features: Some neurological, namely, activation of the prefrontal and anterior cingulate cortices (Alvarez and Emory, 2006; Dajani and Uddin, 2015; Diamond, 2013; Mackie et al., 2013;

Snyder et al., 2015); some phenomenological (Horgan, 2015; Nahmias et al., 2004; Sheredos, 2016); and from a review of precedent research arguing for the integration of various executive and cognitive functions, to be discussed next.

Review of the Integrative Research of the Executive-Cognitive Subsystems. Several papers have been published integrating metacognition and executive function from the perspectives of both developmental and educational psychology (Marulis et al., 2019; Roebers, 2017). For instance, Marulis et al. (2019) in their presentation of an integrated model of the two systems cite similar development trajectories and overlap in terms of the subfunctions of self-regulation and cognitive flexibility, and the practical value in unifying both constructs for the purpose of improving learning outcomes and sense of agency. Similarly, Roebers (2017) proposes a unified framework of "cognitive self-regulation," which supports the value in integration of the two concepts from a developmental perspective.

One promising correlational study empirically demonstrated validity for the prior research, finding a statistically significant relationship between flow, mindfulness, postformal thought, as well as between mindfulness and the EF subsystem of cognitive flexibility (Sinnott et al., 2020). Similarly, another study empirically demonstrated that cognitive flexibility and mindfulness are good predictors of flow disposition (Moore, 2013).

Additional promising research shows the degree to which the X dimension is malleable and able to be strengthened—not only developmentally and in the treatment of psycholopathology, but also in developmentally normative, healthy adults. Such "Xboosters" include mindfulness practices (Van Dam et al., 2018; Gallant, 2018), physical exercise and biofeedback exercises (Bruin et al., 2016), bilingualism, play, and any cognitively demanding skills that are regularly practiced/developed (Diamond, 2013). Taken together with research suggesting that it is possible to increase fluid intelligence (Gard et al., 2014; Jaeggi et al., 2008; Sternberg, 2008), emotional intelligence (Malouff et al., 2013; Nelis et al., 2009) and executive functioning more generally (Bruin et al., 2016; Mitchell et al., 2013; Teper & Inzlicht, 2012; Zeidan et al., 2010), it is clear that executive-cognitive functioning can be cultivated and improved beyond baseline functional levels.

As a corollary to the post-conventional strengthening of executive-cognitive systems, their disintegration in the form of the general psychopathology factor termed the *p factor* has been shown to span all psychopathologies and distributes in a bell curve, similar to measures of general intelligence (Caspi et al., 2014). This p factor is reflected within the CIF as the states of reduced executive-cognitive functioning; "that is, high- p individuals experience difficulties in regulation/control when dealing with others, the environment, and the self" (Caspi et al., 2014, p. 13).

Finally, the Research Domain Criteria (RDoC) matrix includes a domain of Cognitive Systems (perhaps the broadest umbrella of executive-cognitive systems), which incorporates the constructs of attention, perception, declarative memory, language, cognitive control, and working memory (Morris and Cuthbert, 2012).

Taken together, these piecemeal studies and theoretical conceptualizations of the executive-cognitive systems and sub-systems appear to justify a unidimensional representation (X) of the general aspect of conscious experience that is agentive, volitional, flexible, and based in the present; associated with complex cognition and well-being in all areas of human life; and negatively associated with psychopathology. When combined with the insights of the circumplex models, the vector space depicted in Figure 2 results.

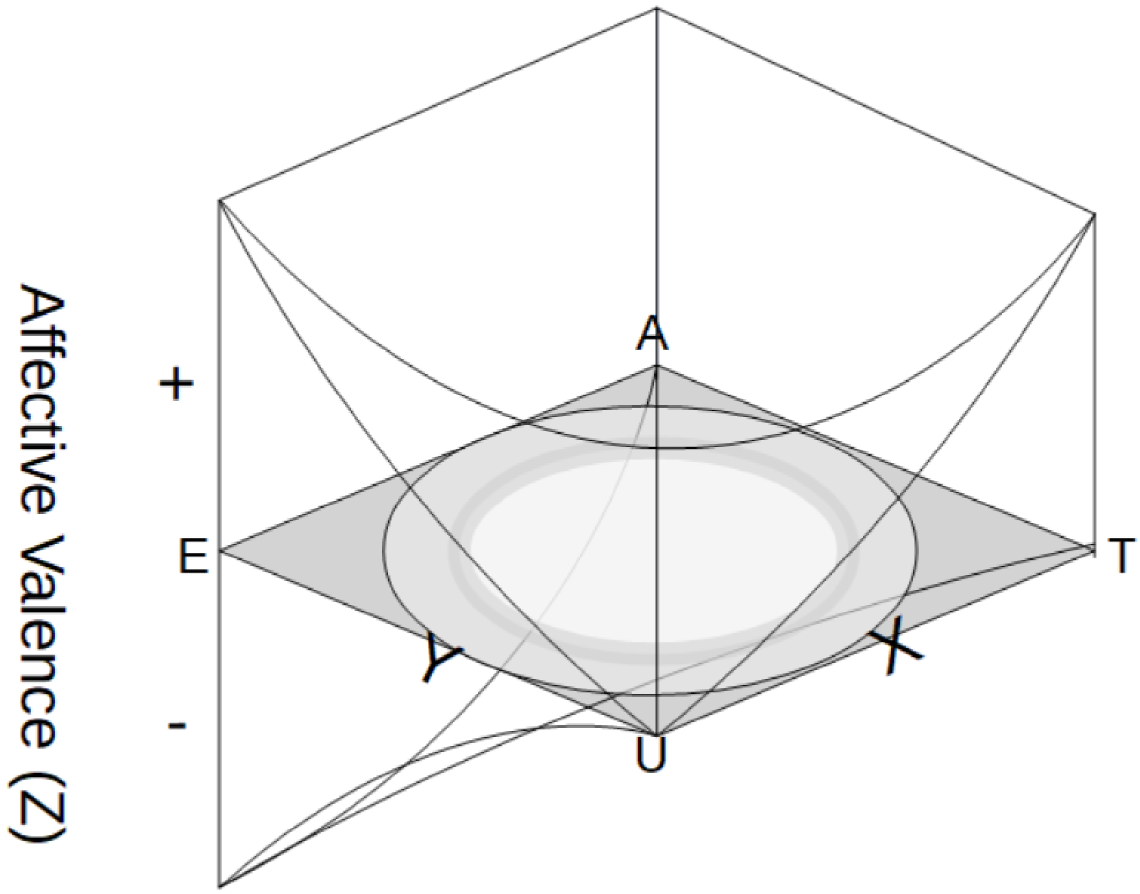


Figure 2: 3-dimensional representation of the CIF (XYZ space)

This figure represents the predicted 3-dimensional structure of experiences when plotted according to their X, Y, and Z values. In this structure the center is roughly spherical without extremes of Z. Deviation from center should see systematic changes to Z, with valence bifurcating to extremes in the E quadrant, negative Z dropping off in the T quadrant, positive Z increasing significantly in the A quadrant, and valence going to neutral in the unconsciousness quadrant.

Sense of Self (SoS): Egoic and Transegoic Consciousness

Not all experiences/conscious states (vectors) within the XYZ space are egoic, which is to say, involving an aspect of the experience of being or having a self. This sense of self termed the "'Me' self, self-as-object, self-as-known, the autobiographical self, and the narrative self," (Brown & Leary, 2017, p. 5) is a mental representation of the self in the third person. It is extended in time, leading to autobiographical narrative, rumination of the past, imagination of the future, and is judged and compared with perceived social expectations, filtered through implicit biases (Brown & Leary, 2017). The Sense of Self Scale (SoSS; Flury & Ickes, 2007), Embodied Sense of Self Scale (ESSS; Asai et al., 2016), and the Ego-Dissolution Inventory (Nour et al., 2016; Millière et al., 2018) show promise as psychometric tools for assessing this aspect of experience.

The delineation of egoic states against transegoic states (states without the experience of being/having a self) is represented in the XY plane by the inner circle (labeled "egoic boundary" in Figure 1), with egoic states in the center surrounded by transegoic states around the perimeter. Millière et al. (2018) describe how the phenomenology of self-consciousness is multifaceted and diverse, showing a range of phenomenological distinctions between states that can all be considered experiences of self-loss. Furthermore, Millière et al. (2018) also describe how states of self-loss, regardless of the cause or reason, have the common aspect of being altered states of consciousness, which is also reflected in the model by the central boundary. The CIF accounts for this range of phenomenological variation between states of loss of self with the central egoic boundary of normative states of consciousness. Beyond this central egoic boundary, where SoS is lost, it generally becomes impossible to accurately locate oneself within the framework. The boundary extends to a second circular boundary which represents the point at which an individual becomes disconnected with external reality, whether it be deep sleep, deep meditation, acute catatonia/ecstatic trance, or hyperflow. The precise locations of the egoic and external awareness boundaries likely depends on the individual, and may reveal information about their mental health, well-being, or personality characteristics (Culwell, 2008; Asai et al., 2016).

Review of the CIF's Structural Components

The following section will describe the overall structure of the CIF, focusing on the XY plane, which is symmetrically laid out in concentric circular boundaries (egoic and external awareness boundaries) from a normative central point. There are four quadrants which start in the egoic center as slight variations in experiences, and extend into the corners where experience is the most extreme. First, the high-X states and quadrants will be covered, before looking at the interquadrant region where these two quadrants meet. Finally, the low-X states/quadrants will be addressed.

The Characteristics Common to High-X States

The four common aspects of the high executive-cognitive functioning states of consciousness include hypoegoicism, improved affective valence, and equanimity. The first characteristic of high-X states is hypoegoicism, represented in the CIF as the +X side of the model and is most predominant outside of the central egoic boundary. Hypoegoic phenomena have been characterized as a reduction of identification with the self-as-object model, “and, thus, with lower self-preoccupation, ego-centrism, egoism, and heteronomy” (Brown & Leary, 2017, p. 9). These phenomena also possess the four interdependent characteristics of present focus, minimal introspection, concrete self-evaluation, and with less attention paid to the judgments/perceptions of others (Leary et al., 2017). Meditative and flow states are good examples of this (expounded below), as are some mystical experiences (Hood, 2017), as well as humility, altruism, allo-inclusive identity, and hypoegoic self-regulation (Leary et al., 2017).

The relationship between hypoegoic phenomena with more positive valence and less negative valence is well-established (Brown & Leary, 2017). A core component of a flow state is it being autotelic (Nakamura & Csikszentmihalyi, 2014). The positive effects of mindfulness/meditation on affective valence (Z) are also well established, reducing emotional reactivity in the amygdala (Desbordes et al., 2012) and promoting well-being even when not experiencing a meditative state (Keng et al., 2011; Gotink et al., 2016). The effects of mindfulness on reducing emotional reactivity likely play a large role in the promotion of equanimity as well. Leary, Brown, and Diebels (2017) found greater emotional equanimity to be a core quality of dispositionally hypoegoic individuals. It is possible that the equanimity and improved valence are both expressions of an underlying improvement in emotional regulation generally (Leary et al., 2017); however, the distinction is maintained here for thoroughness. Equanimity can be understood within the CIF as metacognitive control in the face of experientially intense or unpleasant stimulus where X is mediated to prevent an increase in Y and decrease in Z as response to the stimulus.

The High-X Quadrants of the XY Plane

Intro – explaining that if we look at the simple 2D structure of the XY plane, we can see two quadrants of high X, one with lower Y states, one with higher Y states. States of increased executive-cognitive functioning (+X) and increased intensity (+Y) match the characterization of flow states as high challenge (Y) meeting high skill (X) (Csikszentmihalyi, 2009; Nakamura & Csikszentmihalyi, 2014). Similarly, states of increased executive-cognitive functioning (+X) and greater subtley (i.e. decreased intensity; -Y) align with the characterization of meditative states (Wallace, 2006; Yates et al., 2017). Experimental evidence confirms the phenomenological distinction between flow and mindfulness as unique states (Sheldon et al., 2014), reflected in the model by the apotropic[1] and trophotropic[2] and quadrants (denoted in the corners of the XY plane as A and T, respectively).

The trophotropic quadrant refers generally to mindful or meditative states characterized by hypoarousal, hypoegoism, and greater executive-cognitive functioning. Meditation practice, called shamatha in Sanskrit (to use the Buddhist term), centers around concentration on an internal or external phenomenon, while protecting the mind's concentration against the two attentional imbalances of laxity/dullness and excitation/flightiness, through developing the corresponding antidote or opposing

1 Following the Greek naming convention used by Roland Fischer (1973).
2 Roland Fischer’s (1973) term for the meditative states.

capacities of clarity/vivdness, and stability/awareness respectively (Wallace, 2006; Yates et al., 2017). There are a series of nine (or ten) stages of shamatha, where each new stage sees an increase in the clarity and stability of the concentration on the object of fixation. The final goal or culmination of the practice is a pure, contentless, single-pointed awareness cut off from all external awareness (comparable to slow-wave sleep) called samādhi, which can be sustained for hours (Wallace, 2006; Yates et al., 2017; Forman, 1997).

Apotropic states refer to those conscious experiences that involve relatively equivalent, above-average measures of both executive-cognitive functioning and phenomenological intensity. Examples of apotropic states generally include flow states and *hyperflow*. Hyperflow is a newly proposed term, coined from flow, as it is characteristically similar in nature to flow, with difference primarily in the degree of both intensity and executive-cognitive functioning. Like flow it is transegoic (outside of the central circle delineating egoic states), but the heightened level of intensity and executive-cognitive functioning results in disconnection with awareness of the external world on par with acute catatonia, deep sleep, or samādhi, and often involving stable, self-generated vivid visualizations. The phenomenon is most commonly associated with tantric meditation within the Vajrayana Buddhist sects, but also exists in Hinduism and several other mystic practices. Preliminary research (Kozhevnikov, 2009) suggests the validity of hyperflow as a more intense/extreme experience of flow. Egoic flow states or effortful flow are slight, effortful deviations from central, normative states, but are easily disrupted by distraction, similar to the beginning stages of meditation where the mind easily loses concentration. Thus, the apotropic progression through the XY plane follows the continuum of: effortful flow → flow → hyperflow.

Hyperlucidity: The High-X Inter-quadrant Region

The range of states of heightened executive-cognitive functioning with neutral intensity are not as well understood as either flow or meditation, and certainly not when compared to the research of the states involving decreased X (including stress, psychopathologies, sleep, and the majority of inebriated states). While formal research is limited, anecdotal evidence and folk wisdom about such states have used labels such as enlightened, masterful, sagely, self-realized and the like, with some considerable degree of overlap in terms of the qualities reflected in the individuals who experience these states (Stein, 2019; Johnson & Friedman, 2008; Costeines, 2009; Kilrea, 2013). Today, psychological research (especially within positive psychology, humanisitic psychology, and transpersonal psychology) points to such a range of mental phenomena as well—here termed “hyperlucidity”. Hyperlucidity represents the polar opposite of the pathologically disordered mind, and a clear North Star for clinical psychology and psychiatry. Three characteristics define hyperlucid states: ease of entering both flow and meditative states, marked improvement in metacognition, and high experiential complexity.

The spatial mapping of hyperlucidity reflects the ease of entering flow and meditative states for such an individual. Sheldon, Prentice, and Halusic (2014) found, via a series of three concurrent studies that mindfulness and flow are negatively correlated at the momentary level of experience in terms of absorption, but with possible positive association with mindfulness via sense of control (X). Two correlational studies corroborate this association (Sinnott et al, 2018). Additionally, Leary, Brown, and Diebels (2017) found that one aspect of individuals exhibiting dispositional hypoegoicism is a propensity to experience hypoegoic phenomena, giving the specific examples of awe, flow, and mystical states—highlighting the shared "requisite cognitive states that underlie these experiences" (p.306). Paralleling the tripartite apotropic continuum described above, the progression is therefore: lucidity → hypoegoic lucidity → hyperlucidity.

Though no research has directly examined the general metacognitive control of dispositionally hyperlucid individuals, scattered findings support the existence of this latent potential. For instance, metacognitive control has been found to depend on underlying executive and cognitive functions (Souchay & Isingrini, 2004), which, as has been explained above, can be cultivated and improved beyond baseline functional levels. Additionally, educational psychology research has demonstrated the capacity for developing metacognition specifically (control and awareness/monitoring) (Callender et al., 2015; Kazemi et al., 2012; Finley et al., 2010), and has suggested it may extend generally, rather than being domain-specific to structured learning environments (Schraw, 1998). Furthermore, metacognitive awareness has been shown to be negatively correlated with depression (Teasdale et al., 2002) and anxiety (Normann et al., 2014)**.**

Imagine the simultaneous experiencing of multiple, contradictory experiences (i.e. cognitive dissonance). Such states are termed *complex experiences* and are represented by the multivectored state: placing one's conscious experience in more than one location of the CIF at the same time. One aspect of complex experience is that it can provide a more expansive view or awareness of alternative viewpoints, but it can also be arousing (+Y), unpleasant (-Z), or lead to an overall reduction of executive-cognitive functioning (-X) as in cognitive dissonance, where the positive and negative valence systems are activated simultaneously (Watson & Tellegen, 1985). Leary, Brown, and Diebels (2017) point out that in the dispositionally hypoegoic person, the increase in attunement to alternative viewpoints from one's own promotes prosociality and empathy, but also that "the habit of trying to set aside one's own perspective to consider multiple viewpoints is characteristic of people whom others view as wise" (p. 302). This supports the common perception of sage-like or "enlightened" individuals as being both wise and highly compassionate[3].

Just as how in nature there are no physical examples of truly perfect spheres, it is nonetheless clear that there is a common abstracted representation of the form of a sphere to which many natural bodies conform. Similarly, the greatest examples of enlightened or realized individuals conform to this range of experiences deemed hyperlucid. This is why the most developed individuals are exalted as sages, prophets, or even gods, and why both the character and the moral teachings of figures like Jesus of Nazareth and Siddhartha Gautama (the Buddha) were so similar: As an Olympic athlete trains their body to realize its pinnacle performance and control, the same can be done with the mind. It is not terribly hard to access or experience enlightened states of consciousness through

3 Application of the concepts of the CIF so far presented allows for the disambiguation of sympathy, empathy, and compassion. Sympathy represents a courteous response to another's suffering but no significant change to the sympathetic individual's experience. In empathy, the empathic individual experiences a shift in their experience to match or approximate the experience of the suffering person. Compassion, representing a complex experience, allows for the holding of both one's own experience as well as that of the suffering person.

meditation, spiritual/mystical experiences, psychoactive chemicals and in some cases, maybe even by accident, as in experiences of awe (Hood, 2017). What appears to be difficult is sustaining and mastering such states to the point of effortlessness where the average of one's waking mental states is positive (+X) beyond the boundary of the ego. It is evident that there is value in the continued characterization and scientific study of these profoundly positive psychological states.

Transdiagnostic Psychopathology: Common Factors of Low-X States

The most common transdiagnostic characteristic of psychopathology is reduction of executive-cognitive functioning (X), as expressed by the p factor. Research (Caspi et al., 2014; Gluschkoff et al., 2019; Lahey et al., 2012) has pointed to three component factors (of p): internalizing, externalizing, and thought-disorder, which is far more severe than either internalizing or externalizing (two pathways of expression of similar levels of p-factor). Another proposed transdiagnostic factor of psychopathologies is hyperegoicism (Moore et al., 2017), bolstered by rumination research (Nolen-Hoeksema & Watkins, 2011). Lastly, transdiagnostic research has considered the role of affective valence (Z), both in terms of increased negative valence and reduced positive valence. All of these transdiagnostic factors—p factor, hyperegoicism; and the simple difference in valence—can be accounted for and represented together within the CIF, holding promise for future reconceptualizations of the nosology of psychopathologies.

Component factors of the p factor were first found with the bifactor internalizing-externalizing model of psychopathologies, and have been well established (Krueger &

Eaton, 2015; Gluschkoff et al., 2019; Eaton et al., 2015; Lahey et al., 2012). The primary expansion of the internalizing-externalizing model is the addition of a third, advanced version of the p factor that extends beyond the severity of the internalizing-externalizing distinction, namely: thought disorder or psychosis-related factor (Caspi et al., 2014; Eaton, Rodriguez-Seijas et al., 2015). This dimensionalized approach is supported by research finding that about 30% of individuals with non-psychotic common mental disorders and 7% of the general population report psychotic symptoms/experiences (Van Os, 2015), which suggests that clear delineations between psychopathologies do not exist. This dimensionalization of the p factor is reflected in the CIF, which maps psychotic/thought-disordered states as fully transegoic vectors of significantly reduced executive-cognitive functioning, and with neutral to advanced phenomenological intensity (see Figure 1). A similar pattern appears with non-psychotic psychopathologies, but with fewer and less severe transegoic states. Thus, whether conceptualized as the single p factor or the dimensionalized component factors (internalizing-externalizing and thought disorder), the CIF model can serve as a viable transdiagnostic dimensional model for mapping psychopathologies.

Moore et al. (2017), in light of hypoegoicism research, analyzed the diagnostic criteria of a range of disorders in the DSM, including: generalized anxiety disorder, social anxiety disorder, major depressive disorder, anorexia nervosa, and body dysmorphic disorder, narcissistic personality disorder, bipolar disorder (specifically mania), borderline personality disorder, schizophrenia, and delusional disorder; and proposed hyperegoicism as a viable transdiagnostic factor. Four interrelated features of hyperegoicism were identified: (1) rumination about the past or future; (2) evaluative introspection of thoughts, feelings, and motives; (3) abstract self-conceptualizations in an ISG (internal, stable, global) attributional style; and (4) concern about the evaluations from others about oneself. Additional research by Nolen-Hoeksema and Watkins (2011) reviewing the literature on rumination as a possible transdiagnostic factor of psychopathologies supports the hyperegoicism theory, as the first (literally rumination), second, and fourth of the interrelated features are examples of rumination.

Valence or emotional affect, specifically negative valence/affect, is a common, nearly universal aspect of psychopathologies. Negative valence not only increases, but the range or capacity of positive valence also decreases with psychopathology (Böhnke et al., 2014; Barlow et al., 2017; Paulus et al., 2015), with autonomic arousal (+Y) being an additional shared feature of the anxiety disorders (Brown & Barlow, 2009). Largely, research highlighting this transdiagnostic factor has done so only as applied to mood and anxiety disorders (Böhnke et al., 2014; Brown & Barlow, 2009; Fusar-Poli et al., 2019), but nonetheless, within this limitation the work is quite robust and suggests that one treatment protocol may be used if targeting the underlying transdiagnostic factors, rather than multiple diagnosis-specific protocols (Brown & Barlow, 2009; Barlow et al., 2017).

The common dimensional features of reductions along the X (p factor and hyperegoicism) and Z (valence) dimensions within the model represent the experiential overlap between psychopathologies and points to shared etiological factors, as well as transdiagnositc treatment protocols. Moreover, these factors can be shown mapped onto the CIF, suggesting that psychopathologies can generally be reflected in individual vector maps. To be sure, more research is needed to go beyond the limited range of disorders that have been studied transdiagnostically (predominantly anxiety, mood, and substance use disorders), as well as to shore up problems with heterogeneity and incoherency in this nascent area.

The Low-X Quadrants of the XY Plane

Ergotropic experiences are characterized by increased intensity (+Y), but decreased executive-cognitive functioning (-X), and are System 1 dominant, such as states of anxiety (Fischer, 1973). More extreme ergotropic experiences include hallucinations and negatively impacted executive-cognitive functioning as in an ecstatic trance (Flor-Henry et al., 2017), hallucinogen-induced trips (Garcia-Romeu et al., 2016), psychosis (Van Os, 2015; Fluyau et al., 2019), or traumatic experiences (Gusich, 2012). The aforementioned psychotomimetic or thought-disordered states are good examples of highly ergotropic experiences (Caspi et al., 2014; Eaton et al., 2015).

Lastly, unconsciousness is the lack of significant degrees of executive-cognitive functioning, intensity, or valence, and includes the four NREM sleep stages, REM sleep, as well as depressive, dissociative, lethargic, and hypnotic states, which have been correlated with sleepiness (Móró et al., 2011; Fava, 2004). Stage 1 sleep is the threshold of sleep, experienced while crossing the egoic boundary into transegoic sleep, and the NREM stages “roughly parallel a depth-of-sleep continuum, with arousal thresholds generally lowest in stage 1 and highest in stage 4 sleep” (Carskadon & Dement, 2011, p.

17). The sleep cycle tells us that REM sleep is arrived at from stage 2 sleep, and is the most phenomenologically active period of sleep (Carskadon & Dement, 2011).

Applying the CIF: Mapping the Subjective Effects of Psychoactive Substances

Psychiatric medications exhibit psychoactive effects, just as recreational substances, but conventionally these effects are considered mere incidental "side-effects", with the mechanism of action targeting presumed underlying disease-specific processes (Moncrieff et al., 2013). The conventional understanding, however, has failed to be supported over more than half a century of rigorous neuropsychological research, which instead suggests that any disease-specific neuropharmacological actions are not independent of the psychoactive effects (Moncrieff et al., 2013). This raises concerns over both the validity and relevance of modern diagnostic systems such as the DSM-5 and ICD-10/11; regarding which, Moncrieff et al. (2013) explain:

> "Using psychiatric drugs explicitly for their psychoactive effects implies the need for a different understanding of the nature of psychiatric problems, one that focuses not on diagnoses or syndromes that are presumed to represent the manifestations of a discrete underlying pathology, but to an individualized appreciation of the nature, context, and origins of each person's particular behavioral and emotional difficulties." (pp. 413-414)

The CIF approaches psychiatric problems in such a manner, because in its application a unique vector map is recorded for every individual, which can reflect even subtle, unique aspects of an individual's mind that can be compared against population averages, past recorded vectors of the individual, and other objective measures of patterns of vector maps correlated to other established, reliable psychometric tools. Such psychometric tools for measuring and explicating psychological effects of psychoactives abound, but a single tool which provides conceptual context in relation to all potential states of consciousness does not otherwise currently exist.

The following section will demonstrate the applicability of the CIF to the task of describing, understanding, and characterizing the subjective effects of psychoactive substances, covering some of the major classes of psychoactives and endeavoring to place each class within the CIF.

Phenomenological Characterization of the Psychoactive Classes

A review of papers addressing the effects of different psychoactive substances in conjunction with the CIF and the factors described in the preceding section yielded Table 1 and Figure 3, respectively. Figure 3 suggests that two overarching tendencies of excessively large doses of most substances results in either psychotomimetic states or unconsciousness before the lethal dose (Gable, 2006; Preston et al., 2021). These two common vector trajectories, along with the two attentional imbalances of excitation/flightiness and laxity/dullness, respectively (Wallace, 2006; Yates et al., 2017), suggest two gravitational centers for experiences in the CIF vector space.

Table 1: Phenomenological Characterization of the Classes of Psychoactive Substances

Psychoactive Classes	Vector Shift	Suppleness/Pliancy	Scaling Effect	Complexity
Classical Psychedelics	++Y	+	++	++
Entactogens	-X, ++Z	-	-	++
Cannabinoids	-X, ++Z	mixed	+	mixed
Stimulants	+X, +Y, +Z	-	-	-
Depressants	-X, -Y, +Z	-	-	-
Antipsychotics/Tranquilizers	--Y	--	--	--
Dissociatives (Ketamine)	-X, --Y, +Z	-	-	mixed
Opiates	-X, ++Z	--	-	--

Notes. (++) indicates a significant increase of the factor; (+) some increase in the factor; (-) some decrease in the factor; (–) significant decrease in the factor; (mixed) indicates a combination of increase and decrease in the factor, either across the substances of that class, or individual experiences with the same substance.

Vector shifts are the spatial coordinates changing, which is experienced as a change in conscious state. Conscious states are always changing subtly, in accordance with internal and external stimuli. Impactful events or stimuli, such as psychoactive substances, cause more grossly apparent vector shifts.

Suppleness/pliancy: When metacognitive control is unobstructed in consciously directing vector shifts it is an example of *suppleness* or *pliancy* of mind. Different psychoactive substances can make the mind more or less supple/pliant in some or all directions.

Vector scaling, the third factor, acts like a multiplier applied to vector shifts, whether conscious or unconscious. Scaling can be increased or decreased in any or all directions, depending on the psychoactive ingested and other relevant conditions affecting the mind, like underlying psychiatric illness and genetic/psychological diatheses. One example would be how cannabis tends to have a positive scaling effect on vector shifts in any direction, facilitating easier changes to consciousness (Russo, 2011). A contrasting example would be how tranquilizers/antipsychotics have a negative scaling effect in all directions except for the direction of unconsciousness (Moncrieff et al., 2013; Gevins et al., 2002).

Complexity refers to the multi-vectored states, covered in the above section on hyperlucidity.

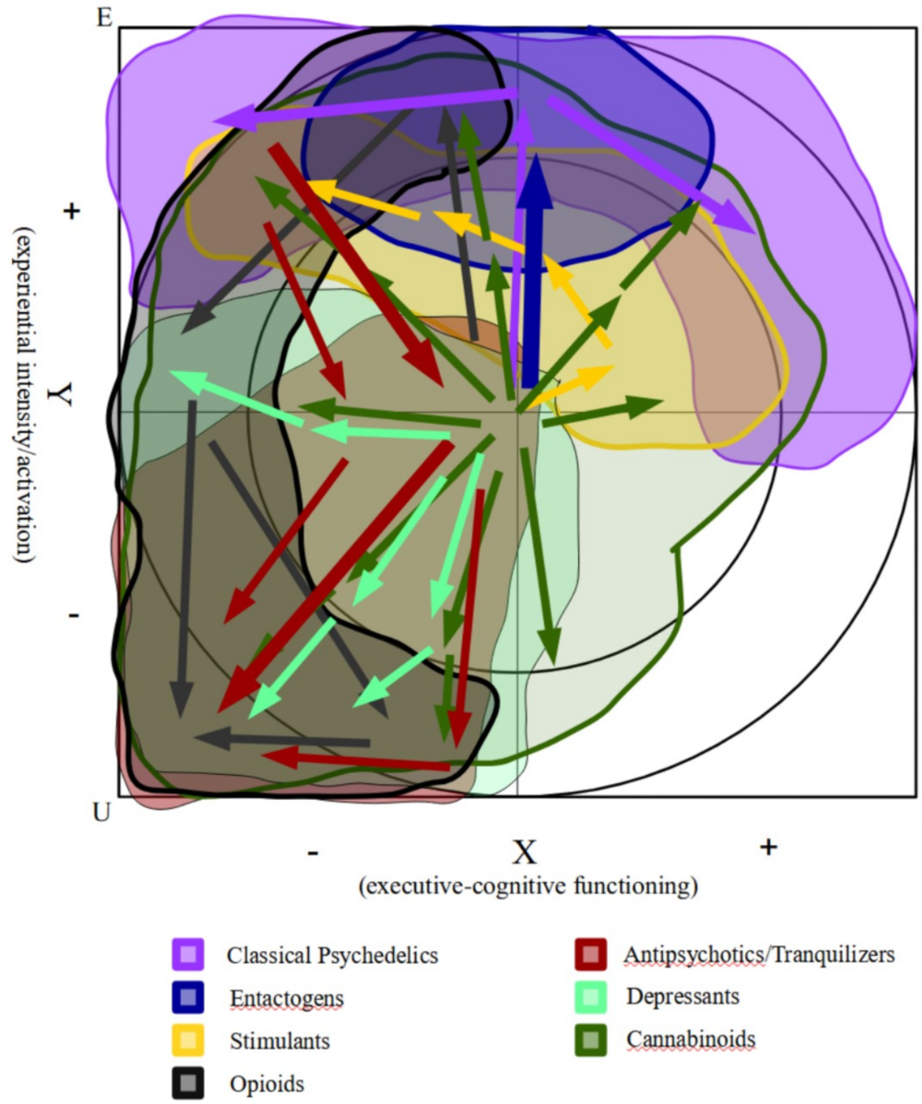


Figure 3: CIF mapping of psychoactive substance classes

The arrows indicate the path of progressively increased dosing, along with the general vector shifts that tend to occur, but it is limited to the XY plane, rather than the full XYZ space. Perhaps the most notable feature of this graphic is how psychoactive substances do not seem to be capable of inducing advanced meditative states. Future studies testing this assumption are warranted.

One notable aspect of some psychoactives is the dissolution of the egoic or minimal embodied self (represented in the CIF by the center-most circle), and psychedelic hallucinogens are widely established to have such an effect in a profound manner along with a significant increase in phenomenological intensity (Y) (Bayne & Carter, 2018; Millière, 2017; Garcia-Romeu et al., 1999; Hood, 2017; Farb et al., 2017).

Regarding stimulants, Mattay et al. (2003) suggests the validity of the inverted-U structure of amphetamines (and other stimulants), with gains in executive-cognitive functioning (X) at low-to-moderate doses, and in cases where deficits are present, but deterioration at high doses and where no deficits in X are present (see also Lakhan & Kirchgessner, 2012). The low dose cognitive gains have been further demonstrated through literature review (Favrod-Coune, & Broers, 2010), survey (Morgan et al., 2013) and experimental studies (Gevins et al., 2002). High doses (Berman et al., 2009) and combinations of different stimulants (Vanattou-Saifoudine et al., 2012) tend to provoke adverse reactions and have been implicated in stimulant-induced psychosis. This can all be summarily represented within the framework by the stimulant trajectory (the yellow arrows in Figure 3), beginning with general gains in wakefulness, then as the psychostimulant levels increase the arrows lead into the ergotropic quadrant, representing the move to stimulant-induced psychosis.

Opiates, Depressants, and Antipsychotics/Tranquilizers had similar rankings of scores in various beneficial and harm categories in a major international survey of active drug users (Morgan et al., 2013). The most common side effect of medications is sedation, and the effect is dose-dependent (Gevins et al., 2002; Moncrieff et al., 2013).

These are represented in Figure 3 by the red, mint green, and black arrows leading to the lower right quadrant—the direction of unconsciousness.

Additional psychoactive substances include entactogens, cannabinoids, and ketamine. Entactogens have many of the qualities of both psychedelics and psychostimulants (Garcia-Romeu et al., 2016; Hermle et al., 1993). Cannabinoids have the most remarkable range of psychoactive effects, depending on the exact cannabinoid and terpenoid profile (Russo, 2011; Piomelli, & Russo, 2016). Some general notable effects include an omnidirectional vector scaling effect, increase in low-X suppleness, and significant boost in valence (Morgan et al., 2013). Systematic research of ketamine confirms it has some psychotomimetic effects, but also sedative effects (Garcia-Romeu et al., 2016), and that it does not reproduce full psychosis or schizophrenic symptomology (Pomarol-Clotet et al., 2006).

It is notable that following this literature review of the effects of psychoactives, meditative (trophotropic or high-X/low-Y) states are the only kinds of states that appear not to be inducible by psychoactive substances alone (Millière et al., 2018).

Chapter 3: Method

Procedure

The data collection for this experience-sampling (Shiffman et al., 2008; Moskowitz, & Young, 2006; Balaskas et al., 2021) study began February 22, 2022, and continued until July 14th, 2022. Participants were unpaid and recruited through social media including Reddit, Facebook, and LinkedIn, as well as the Hood College study participation system. Following recruitment they signed up for an account with a login on the study website cifdb.org, and answered a demographic questionnaire. Additionally, they were instructed to download and set up the Samply Research App for the random daily prompts, and the EncephalApp Stroop Test for the objective measure of functioning (Belghali et al., 2020; Faria et al., 2015; Scarpina & Tagini, 2017). After creating a login and filling the demographic questionnaire, along with setting up the two mobile apps, participants were instructed to click a reminder prompt randomly sent to the user's mobile phone twice each day at their convenience, availability, and discretion. Clicking the prompt sent the users to the experience-sampling website in their phone's browser to input their present experience using the measures listed in the below section.

Users were also instructed:

> "If you are unable to respond to all prompts, there is no need to submit the incomplete current experience—either respond in full when you have a moment to safely do so or skip that entry (please do not answer questions when in a situation where doing so is unsafe, i.e. while driving). Skipping entries is not a

problem for the study (as the study's focus is on aggregating this data over an extended period of time), so do not hesitate to ignore the prompt if completing it feels at all stressful/unsafe given your present situation."

Additionally, users were encouraged to do the EncephalApp Stroop Test immediately afterwards and follow the instructions for submitting the completed tests as often as possible to have an objective measure of cognition/processing speed, but this was expressly not required to submit experiences.

Anonymization was assured by the lack of recording any names for individuals, as well as the encryption of sensitive data such as the email, password, and birth-date using the MD5 hash function, with the database and website stored on the Hood College university server.

All Python scripts used for analysis were run through Jupyter Notebook and are included as Appendix B for reference.

Participants

Volunteer participants (aged 18 and up) numbered 26 after filtering the 44 initial volunteer participants by those who contributed experiences (rather than merely initially signing up). Seven of the 26 participants also contributed Stroop Test results. 12 participants provided only a single experience. Participants averaged 7.846 each, with three individuals alone accounting for 70.1%, and one individual with 69 experiences recorded accounted for 33.8% of all the experiences. Average length of participation was

16.808 days per participant, with the longest period between first and last experience entries at 101 days.

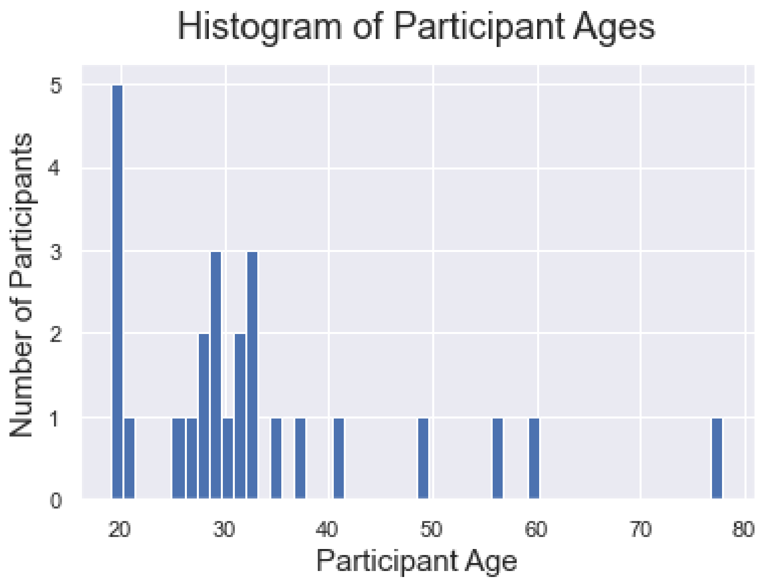


Figure 4: Histogram of participant ages (n = 26)

Participant ages (Figure 4) ranged from 19 years to 78 years, with a mean of 33.1 years. The racial breakdown in order of size was Caucasian (n = 24, 92%), Asian (n = 1, 4%) , and Two or More Races (n = 1, 4%). Participant gender was 23% male (n = 6), 58% female (n = 15), and 19% nonbinary/genderqueer, however, only two participants (8%) chose to code as an explicitly transgender identity. For the sake of demographic analysis, the nonbinary/genderqueer participants were recoded as transgender, as the term applies to individuals outside of the traditional gender binary.

Participant ideologies were assessed with listing religious affiliation, cultural stance, and economic stance. Religions listed by frequency included: Atheists (6), agnostics (5), Christians (5), Buddhists (3), Spiritual, but not religious (3), undisclosed (3), and other religion (1). Economic and cultural stances were given on a 5-point Likert scale. Economic stances (from left/progressive to right/conservative) were as follows: left (7), center-left (12), center (7), and center-right (4). Cultural stances (from left/progressive to right/conservative) were as follows: left (9), center-left (9), center (7), and center-right (1).

All participants had at least one year of college-level education, and all but 3 were located in the United States (92%). No participants identified as veterans. Two participants (8%) identified as having a disability of some kind, while three participants (12%) chose not to disclose their disability status. Self-perceived socioeconomic class was chosen along a five-point scale with scores following a normal distribution: Poor/Poverty (n = 3, 12%), Working Class/Lower-Middle Class (n = 6, 23%), Middle Class (n = 11, 42%), Upper-Middle Class (n = 4, 15%), Wealthy/Upper-Class (n = 1, 4%).

Prior-known psychiatric diagnoses are listed in Table 2 below. 8 participants (31%) listed no confirmed or suspected mental health diagnoses of any kind, 3 participants (12%) listed only suspected diagnoses, and 15 (58%) had at least one confirmed diagnosis.

Table 2: Counts of participant diagnoses (n = 26)

Diagnosis	Number of Confirmed	Number of Suspected
Major depressive disorder	9	1
GAD	8	3

PTSD	6	2
Eating disorder/s	4	4
Social Anxiety	4	2
Sleep disorder/s	3	2
OCD	2	1
Bipolar disorder	0	2
Dissociative disorder/s	0	2
Psychotic disorder/s	1	0
Dysthymia	0	1
Personality disorder/s	0	0
DID	0	0
dementia	0	0

Measures

Below are listed the measures recorded at each of the randomized daily experience-sampling prompts.

Description/Keywords. The description was typed into a text box with the following prompt: “These should be kept simple: Focus on the few most prominent/salient aspects of the experience, as you would define or think about it. Please use relationships instead of the actual names of people so your experience can be searchable by researchers.”

Executive Functioning. This measure used a range slider between -5.0 and 5.0 at 0.1 increments following the prompt: “This aspect of subjective experience is measuring your felt sense of effectiveness, executive-cognitive function, or self-efficacy. Some alternative framings include: in-control of yourself and your faculties vs. out of control.”

On this scale -5.0 indicates Completely Ineffective/Non-Functional and 5.0 indicates Extremely Effective/Super-Functional.

Intensity of Experience/Activation/Arousal. This measure used a range slider between 0.0 and 10.0 at 0.1 increments following the prompt: “This parameter refers to the experience of physiological arousal, also referred to as "activation" or "intensity of experience". Intensity of experience ranges from extreme subtlety (deep meditation, sleep, etc.) to extreme intensity (panic attack, intense flow state, use of high-dose stimulants). Also referred to as affect intensity.” On this scale 0 indicates Undetectable Intensity/Activation and 10 indicates Extremely Intensity/Activation.

Affective Valence. This measure used a range slider between -5.0 and 5.0 at 0.1 increments following the prompt: “Affective valence refers to how good/positive you feel versus bad/negative. Bad/negative is not necessarily the same thing as pain, as it is possible to have a good experience even while experiencing pain (and vice versa). The middle of the slider represents neutral valence—neither distinctly positive nor negative.” On this scale -5 indicates Extremely Unpleasant/Negative/Suffering while 5 indicates Extremely Positive/Pleasurable.

Sense of Self. This measure used a range slider between 1 and 5 at increments of 1 following the prompt: “Sense of Self (SoS) is defined by the American Psychological Association as ‘an individual’s feeling of identity, uniqueness, and self-direction.’ SoS is weakened in certain situations/contexts including mental illness, trauma, the effects of psychoactive drugs, tiredness, and more.” On this scale 1 indicates minimal or no selfhood or stability/certainty of self present in the experience, 5 indicates feeling "like yourself"/who you are feels very stable and clearly defined, and 3 indicates that your sense of who you are feels fuzzy or less stable/well-defined/clear/absolute.

Stroop Test (Optional). This measure was kept optional for participants so as not to discourage regular responses, and was completed in a mobile app called EncephalApp Stroop Test (Bajaj et al., 2015). The results of this objective measure of functioning can be used alongside the subjective measure of functioning to determine the approximate level of accuracy of the self-measures. Measures from the results of these tests of interest included overall accuracy and overall response time (Allampati et al., 2019).

Chapter 4: Results

Summary Statistics and Distributions of Participant Experiences

Participant experiences in aggregate showed an approximately bimodal distribution for the X and Y dimensions (Table 3 and Figure 8), while the centroids showed normal distributions, (Table 4, Figure 7), with SoS being negatively skewed by approximately one SD (Figures 5 and 6). Aggregate participant experiences covered the full range of possible scores on all four dimensions.

Table 3: Summary statistics of aggregated experiences (n = 204)

	X	Y	Z	SoS
mean	0.710	5.337	0.875	3.613
SD	2.505	2.583	2.797	1.137
min	-5.000	0.000	-5.000	1.000
25%	-1.525	3.000	-1.425	3.000
50%	0.950	5.000	1.250	4.000
75%	2.600	7.325	3.200	5.000
max	5.000	9.900	5.000	5.000

Table 4: Summary statistics of experience centroids for each participant (n = 26)

	X	Y	Z	SoS
mean	0.843	5.724	0.613	3.712
SD	1.728	1.772	1.650	0.803
min	-2.600	2.300	-3.200	2.000
25%	0.000	4.813	0.013	3.271
50%	0.583	5.480	0.780	3.775

75%	1.825	6.375	1.675	4.000
max	4.200	9.500	3.200	5.000

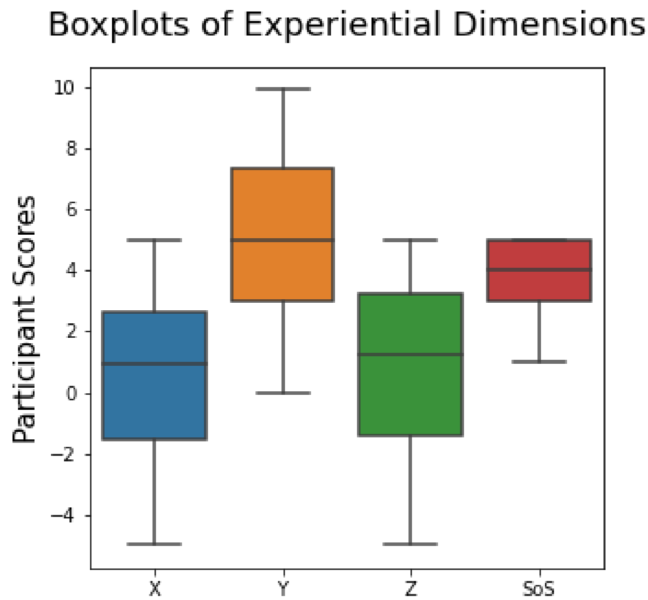


Figure 5: Boxplots of dimensions (n = 204)

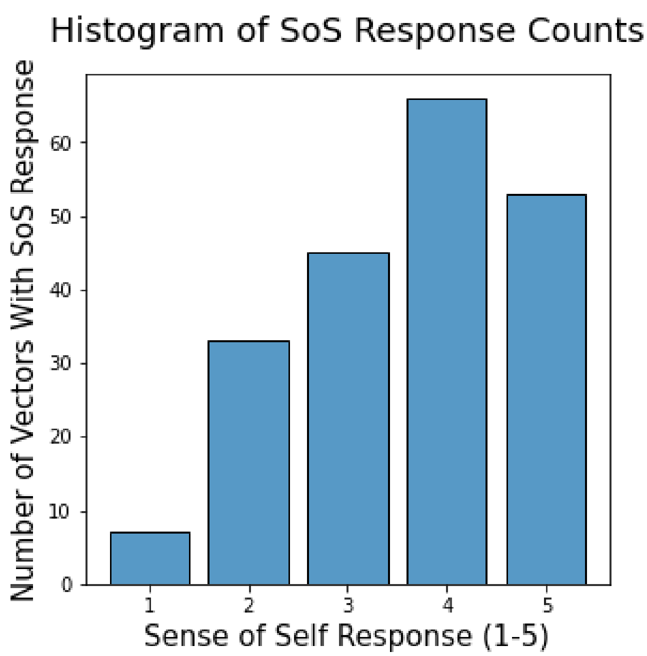


Figure 6: Histogram of SoS responses (n = 204)

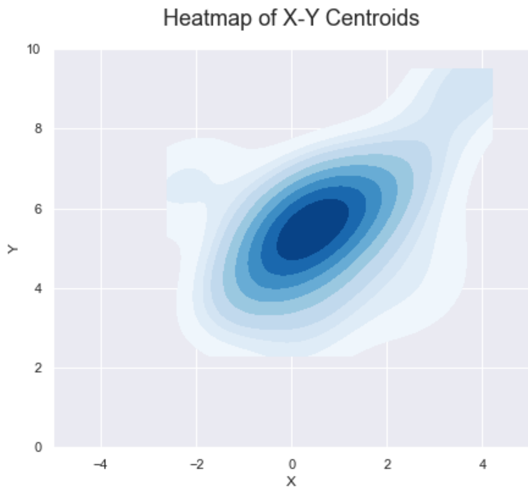


Figure 7: Heatmap of XY centroids (n = 26)

This graphic shows the clustering of experience centroids close to the center of the XY plane.

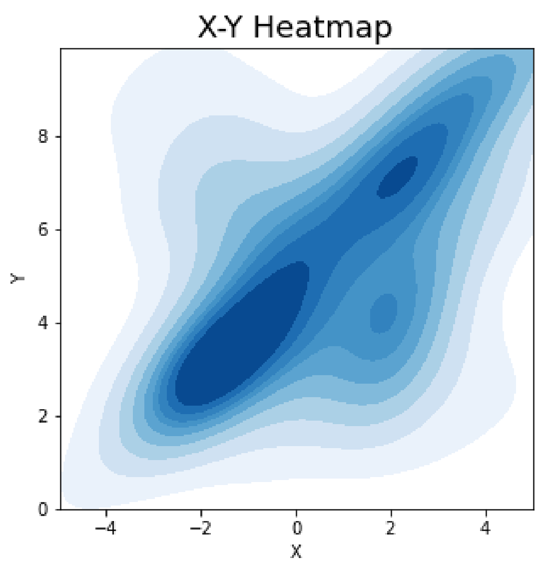


Figure 8: XY heatmap all experiences (n = 204)

A heatmap of all experiences, while possibly skewed by the over-weighting of some participants shows bimodal clustering along the XY diagonal.

Relationships Between the Dimensions

The dimensions of experience showed similar patterns of correlation both in aggregate and when averaged to a centroid for each participant. For both the aggregated experiences and centroids the Y dimension showed the most independence from the other dimensions, while the strongest correlation[4] was between X and Z (Figures 9 and 10). SoS and Z were also highly correlated in the centroid group, and moderately correlated in the aggregate group. X was moderately correlated with SoS and Y in both the aggregate and centroid groups.

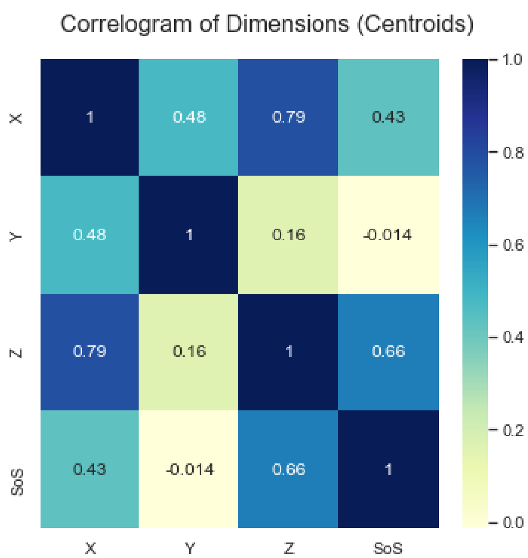
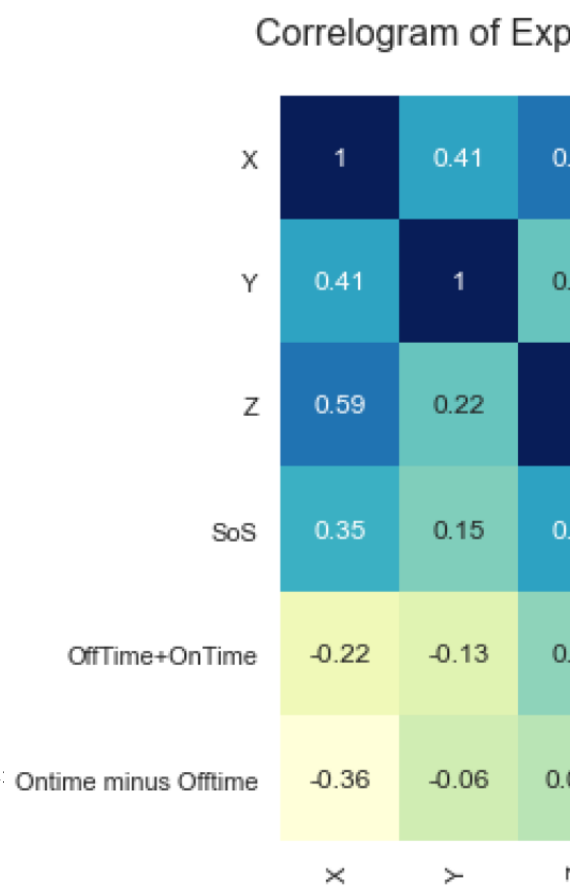


Figure 9: Correlogram of centroid dimensions (n = 26)



4 Terms for assessing the strength of correlations are coded as follows:
< 0.5; and Strong ≥ 0.5.

Stroop Test data measured both the total length of time to complete the Stroop tasks (OffTime+OnTime in Figure 9), as well as the difference between OnTime (when Stroop effect was turned on) and OffTime (Stroop effect turned off). These variables, although from limited data, did show weak and moderate negative correlations with X, suggesting that a higher degree of X correlated with a reduction in time to complete the Stroop test, as well as less of a difference between when the Stroop effect was on or not.

Multiple (OLS) linear regression models assessing relationships between the dimensions yielded the results of Table 5. The Multiple R-squared value (coefficient of determination) was quite high, explaining over 90% of variation for each dimension when the other participant dimension centroids were paired with demographic variables. No dimensions can be approximated by the other three dimensions alone, but this becomes possible when demographics are included in the model. Demographics alone were also insufficient to predict dimensional means with any strength. The Adjusted R-squared values were lower due to the high number of independent variables.

Table 5: Results of Multiple OLS regression models on dimensional variables (n = 14)

Dependent/Independent Variables	R-squared	Adjusted R-squared
X / dimension means (SoS, Y, Z) and demographics	0.926	0.521
X / dimension means (SoS, Y, Z)	0.387	0.203
X / demographics	0.767	0.395
Y / dimension means (X, SoS, Z) and demographics	0.958	0.726
Y / dimension means (X, SoS, Z)	0.046	-0.240
Y / demographics	0.795	0.466
Z / dimension means (X, Y, SoS) and demographics	0.967	0.789
Z / dimension means (X, Y, SoS)	0.412	0.236
Z / demographics	0.689	0.190
SoS / dimension means (X, Y, Z) and demographics	0.914	0.442

SoS / dimension means (X, Y, Z)	0.036	-0.254
SoS / demographics	0.607	-0.021

Demographic Analysis

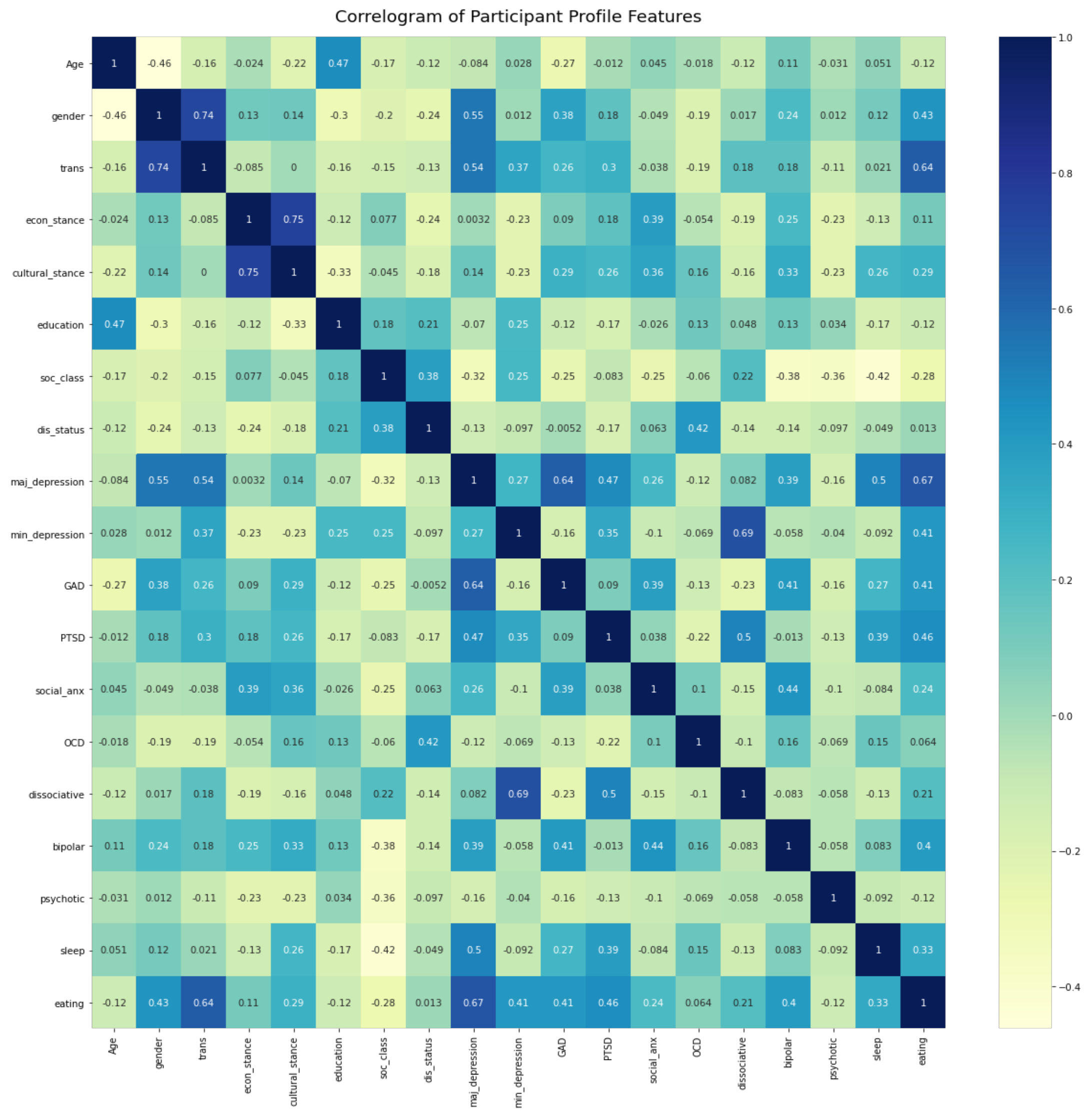


Figure 11: Correlogram of participant profile features (n = 26)

The only high correlation between demographics and mental health diagnoses was between gender (including the transgender/cisgender variable) and major depressive disorder. No male participants listed major depressive disorder as a confirmed or suspected diagnosis, compared with 40% of female participants and 80% of nonbinary/genderqueer participants who did.

Moderate correlation was found between gender and a confirmed or suspected diagnosis of generalized anxiety disorder (GAD). Identifying as gender-nonconforming was moderately correlated with dysthymia and PTSD. Economic and cultural stances were moderately correlated with social anxiety diagnosis. Cultural stance was also moderately (positively) associated with bipolar disorder diagnosis. Social class was moderately negatively correlated with major depression, bipolar disorder, psychotic disorder, and sleep disorder diagnoses. Disability status was moderately correlated with an OCD diagnosis (suspected or confirmed).

The mental health diagnoses themselves were more highly positively correlated with each other overall than they were with demographic features. High correlations between diagnoses included: Major depression and GAD, sleep, and eating disorders; dysthymia and a dissociative disorder; and PTSD and a dissociative disorder. Moderate correlations between diagnoses included: Major depression and PTSD; major depression and bipolar disorder; dysthymia and PTSD; dysthymia and eating disorder; GAD and social anxiety, bipolar, and eating disorders; PTSD and sleep and eating disorders; social anxiety and bipolar disorder; and eating disorder and bipolar and sleep disorders.

When participants were filtered by those who contributed more than one experience (to reduce skew when assessing relationships between dimensions and profile features), the only strong positive correlation was between Z and age, and a strong negative correlation existed between X and disability status (Figure 11). Moderate positive correlations were found between X and both age and economic stance. Moderate negative correlation was between Y and economic and cultural stances, eating disorder, and additional suspected diagnoses. Z was moderately positively correlated with education level, major depression, OCD, bipolar, and other known diagnoses. Z and SoS were moderately negatively correlated with social class and disability status.

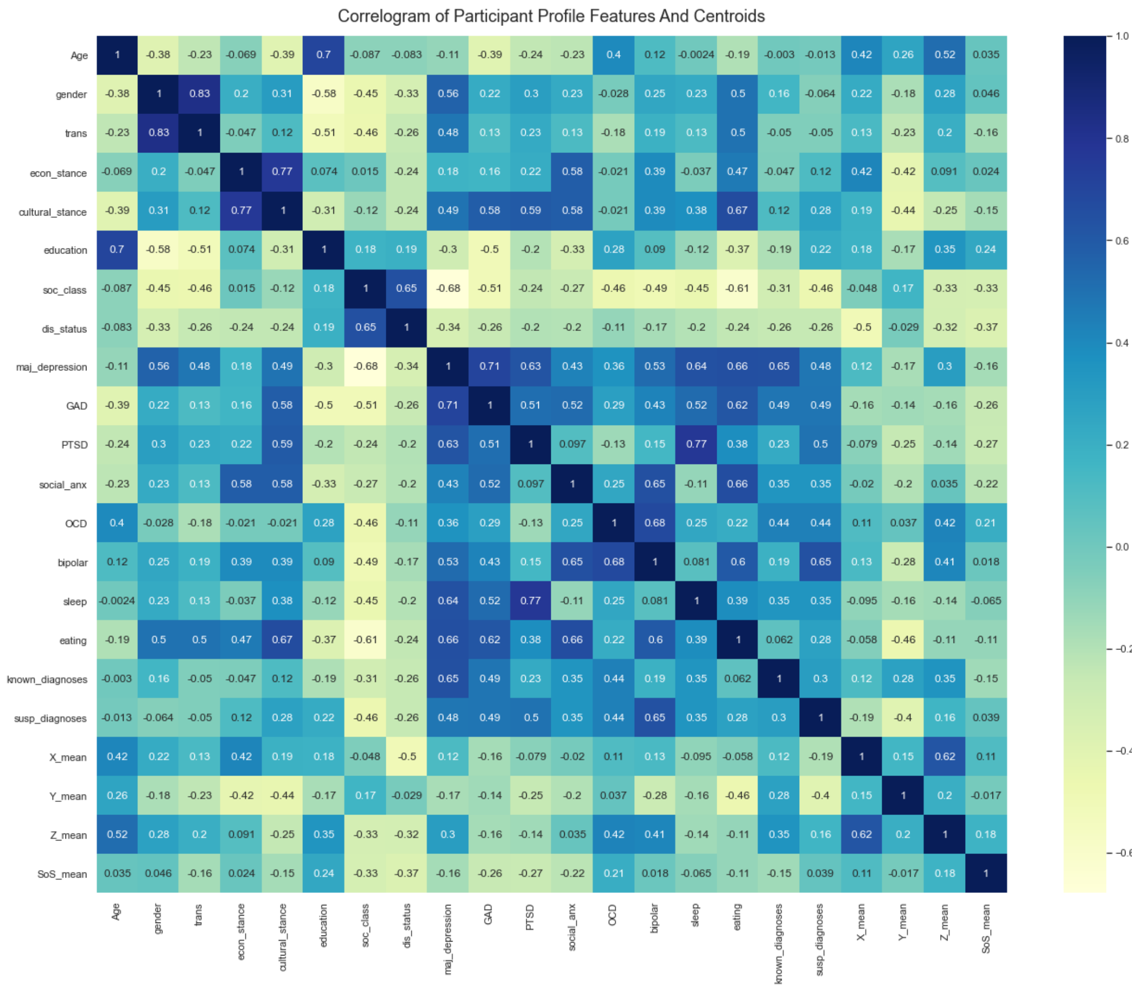


Figure 12: Correlogram of participant profile features and centroids (n = 14)

This correlogram only represents the 14 participants who contributed more than one experience, to reduce the amount of skew when assessing relationships between dimensions and profile features.

The binary demographic groups to compare were chosen according to the variables with strong correlations and size of the representative samples for each potential group. The groups were also assessed for potential skewing caused by single-entry outliers. A comparison of older and younger cohorts was removed from the analysis because the older group was significantly skewed by one such single-entry outlier.

Table 6: Mean and SD for major demographic groups (n = 26)

	X	Y	Z	SoS	Count
Mental health diagnosis (mean) (std)	0.742 1.758	5.787 1.827	0.420 1.879	3.615 0.831	18
No mental health diagnosis (mean) (std)	 1.070 1.753	 5.581 1.755	 1.049 0.916	 3.931 0.739	8
Depression (mean) (std)	1.532 1.447	5.819 2.347	1.412 1.013	3.832 0.525	10
No depression (mean) (std)	0.413 1.791	5.665 1.386	0.115 1.798	3.637 0.945	16
GAD (mean) (std)	0.760 1.104	5.152 1.843	0.896 0.897	3.733 0.602	11
No GAD (mean) (std)	0.904 2.110	6.143 1.655	0.406 2.045	3.697 0.944	15
Transgender (mean) (std)	1.103 1.033	4.745 1.782	1.184 0.765	3.867 0.602	6
Cisgender (mean) (std)	0.765 1.903	6.017 1.704	0.442 1.816	3.666 0.862	20

Two-sample T-tests of each of the binary groups represented in Table 6 above only allow for rejection of the null hypothesis in the case of the X and Z values of the cohorts with and without major depressive disorder ($p < 0.05$).

Lexical Analysis

The total word count from all vectors was 750. The number of unique words used was 372. The top ten most used terms (grouped where conceptually appropriate; i.e.: coffee and espresso) are listed below in Table 7. The word "with" is used 19 times (third most of individual words and fourth most of conceptually grouped terms in Table 7) and in all but three instances of its use, it's referring to interacting with other people or pets. The relationship terms used—both with “with” and in other contexts—total 35 (see Table 8 for the counts of these terms).

Table 7: Top ten most frequently used terms

Word	Count
work/working/worked/ homework/housework	40
tired/sleepy	21
relax/relaxing/relaxed	20
with	19
coffee/espresso	12
bed	12
play/playing	12
watching/watched	12
tv/television	11
kids	11

Table 8: Count of each specific relationship term

Word	Count
kids	11
friend/friends	8
husband	5
grandson	3
family	2
child/children	2
sister	1
brother	1
dog	1
[personal name]	1

Five of the most used terms, broken into related conceptual groupings, provide a point of comparison between types of experiences. The conceptual groupings match those of Table 4 (above), with the exception of the “relationships” group, which includes the relationship terms used in Table 5 (above), as well as the word “party” which appeared only once. The differences of mean and variance between experiential categories are illustrated by Table 9 and Figure 13, below.

Table 9: Mean and SD for five most common conceptual terms

Conceptual Group	X	Y	Z	SoS	Count
work-related (mean) (std)	0.595 2.528	5.700 2.466	0.078 2.830	3.625 1.148	40
(social) relationship-related (mean) (std)	 1.335 2.348	 5.665 2.393	 2.500 1.941	 3.824 0.999	36
tired-related (mean) (std)	-0.348 1.720	4.819 2.446	0.333 2.436	3.524 1.030	21
relax-related (mean) (std)	1.465 1.638	5.410 2.091	1.935 1.652	4.100 0.718	20
coffee-related (mean) (std)	1.750 2.965	5.658 3.280	2.142 2.783	4.417 1.084	12

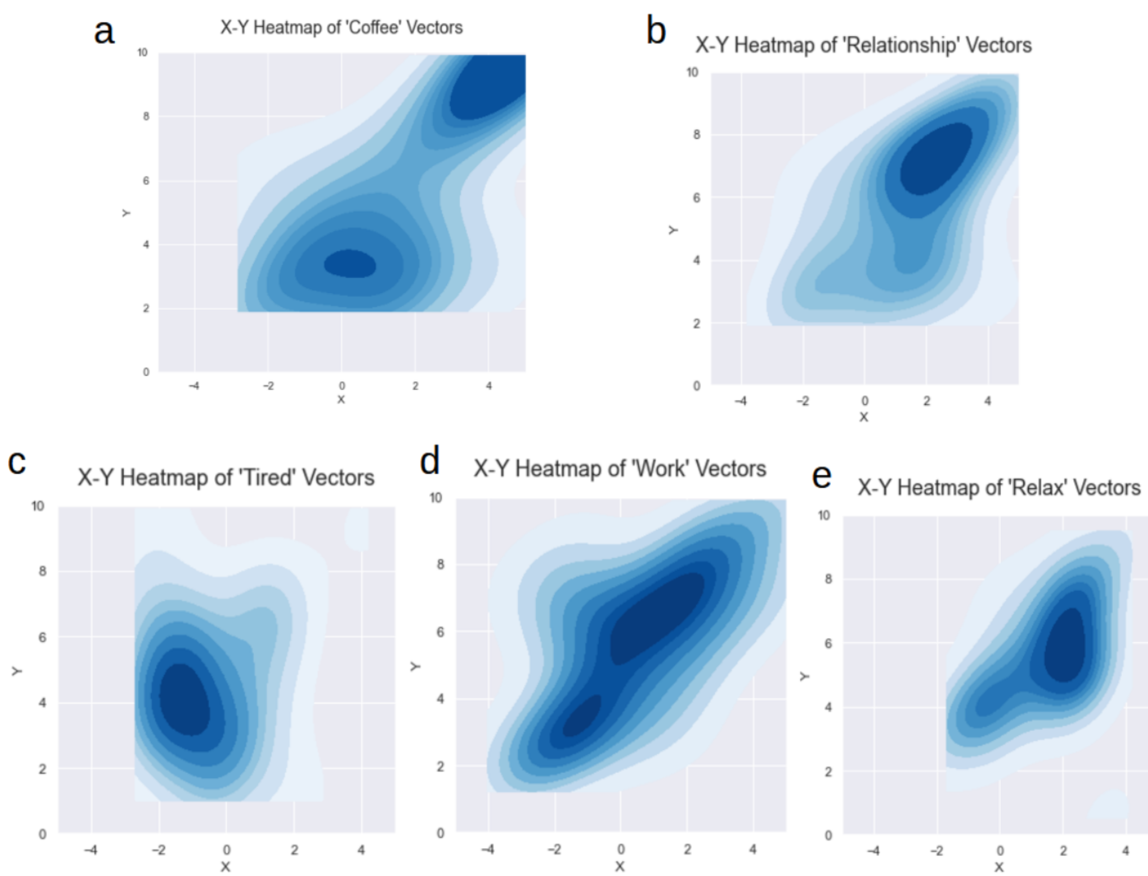


Figure 13: Heatmaps of lexical groups

a. "Coffee" appears to be bimodal, in both flow and neutral areas. b. Social experiences in relation to loved ones is associated with flow states. c. Experiences with the inclusion of the term "tired" show a cluster within the region with slightly lower-than-average intensity and functioning. d. Experiences with the inclusion of the term "work" (and related terms) show the most variation of the lexical groups , covering flow, disengagement, and some anxiety. e. "relax" was associated with mild flow.

Case Studies

Three participants (P16, 20, and 25) provided disproportionate numbers of experiences, when compared with the rest of the participants (69 [34%], 33 [16%], and 41 [20%], respectively). In fact, P16 alone recorded more experiences than the bottom 88% of participants combined. Summary statistics for each individual are presented in Table 10, with the control group representing the combination of the 23 other participants.

Table 10: Summary statistics for P16, P20, P25, and control group (n = 26)

	X	Y	Z	SoS	Count
P16 (mean) (SD)	0.644928 3.193907	5.384058 3.122387	0.776812 3.513468	3.449275 1.450520	69
P20 (mean) (SD)	0.521212 2.405431	5.381818 2.458589	0.615152 2.818036	3.242424 0.902438	33
P25 (mean) (SD)	1.121951 1.863265	5.241463 1.953711	1.726829 2.116604	4.073171 0.905269	41
Control Group (mean) (SD)	0.609836 2.029097	5.324590 2.396919	0.555738 2.146977	3.688525 0.866814	61

Two sample T-tests between the pairs of participants and control group yielded significant results ($p < 0.05$) on the SoS dimension between P25 and P16, P20 ($p < 0.001$), and control group, as well as between P20 and the control group. The Z dimension was also significantly different ($p < 0.01$) between P25 and the control group.

Comparisons between dimension correlograms (Figure 14) and heatmaps of the experience entries (Figure 15) recorded by P16, P20, P25, and the control group also show a wide range of variation in terms of the characterization of experience from individual to individual. Correlation between X and Y ranged from a weak negative correlation for P20 to a strong positive correlation for P16 and P25. Correlation between X and SoS was moderately positive for all four groups of experiences. Z and Y showed a range of correlation between weak negative correlation for P20, to weak positive correlation for the control, to moderate positive correlation for P16 and P25. Comparisons of the correlations between dimensions for these four groups showed consensus of the weak to non-existent relationship between Y and SoS, and moderate to strong positive correlation between X and Z, as well as between Z and SoS.

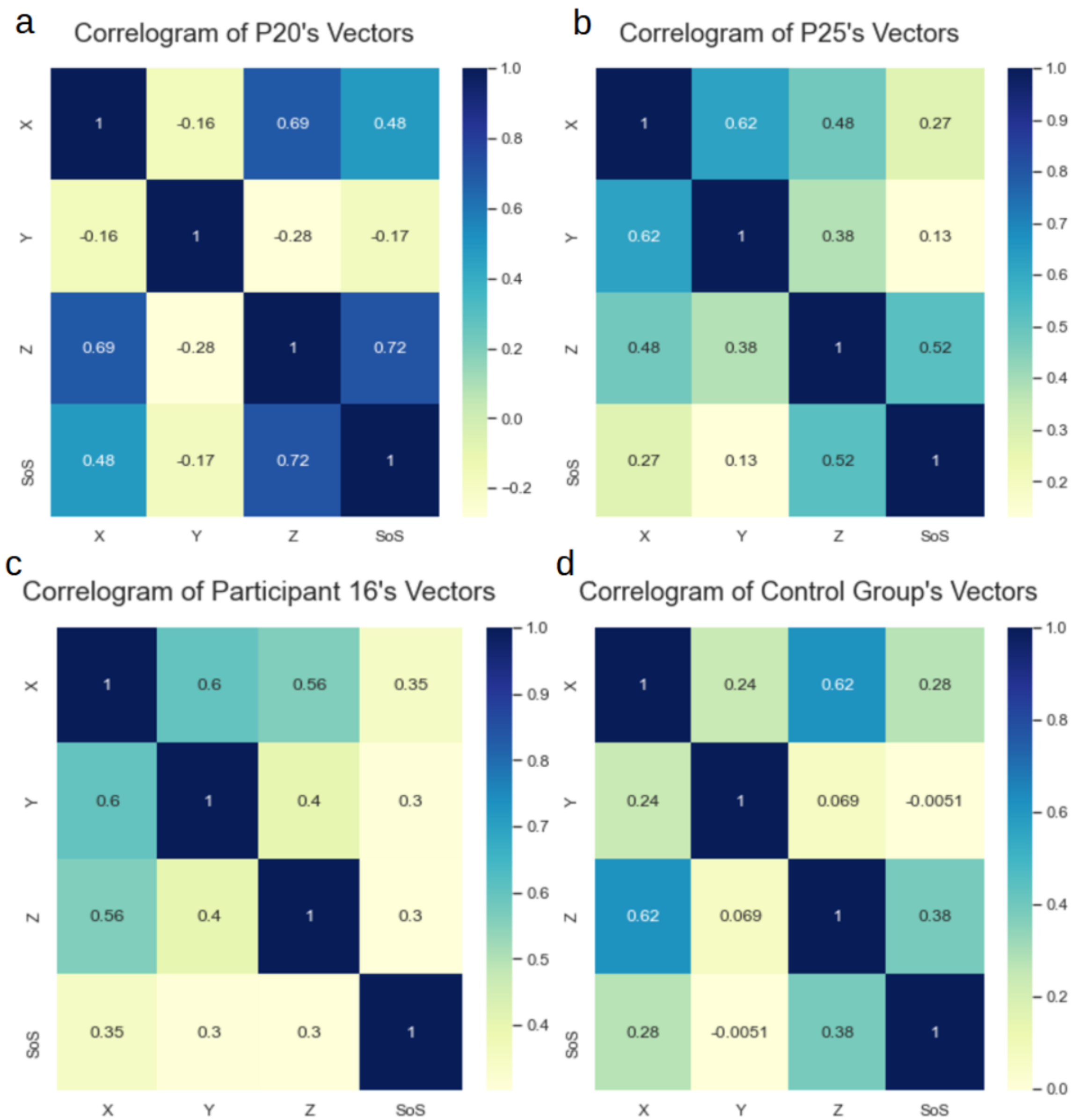


Figure 14: Correlograms of P16, P20, P25, and control group (n = 23) dimensions

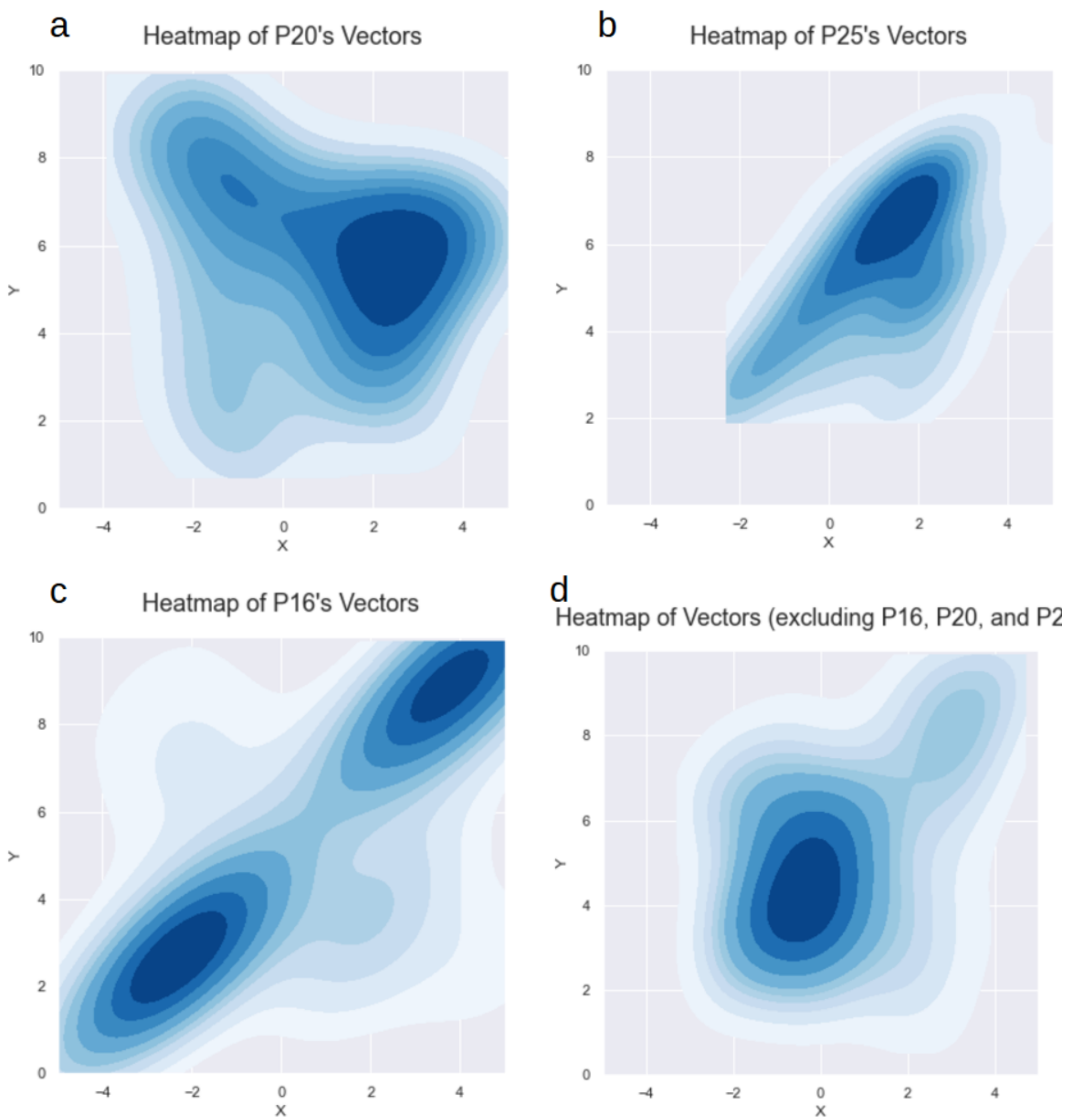


Figure 15: XY heatmaps of P16, P20, P25, and control group (n = 23) experiences

Predicting Mental Health Diagnoses

Multiple (OLS) linear regression models assessing relationships between the dimensions and profile features to predict mental health diagnoses yielded the results of

Table 11. The Multiple R-squared value (coefficient of determination) was quite high, explaining over 93% of variance for 8 mental health diagnoses indicated by the cohort non-single-entry participants. Excluded diagnosis variables were due to low sample size (0 participants) and included the variables representing dysthymia, dissociative disorder, psychotic disorder, DID, and dementia.

Table 11: Multiple OLS regression mental health diagnosis predictions (n = 14)

Dependent / Independent Variables	R-squared	Adjusted R-squared	Count
Clinical depression / dimension means and demographics Clinical depression / dimension means Clinical depression / demographics	0.951 0.207 0.795	0.363 -0.145 0.466	6
GAD / dimension means and demographics GAD / dimension means GAD / demographics	0.987 0.101 0.821	0.837 -0.298 0.535	9
PTSD / dimension means and demographics PTSD / dimension means PTSD / demographics	0.995 0.141 0.617	0.936 -0.241 0.003	3
Social anxiety / dimension means and demographics Social anxiety / dimension means Social anxiety / demographics	0.970 0.105 0.689	0.616 -0.293 0.193	3
OCD / dimension means and demographics OCD / dimension means OCD / demographics	0.989 0.236 0.660	0.862 -0.103 0.116	1
Bipolar disorder / dimension means and demographics Bipolar disorder / dimension means Bipolar disorder / demographics	0.934 0.339 0.548	0.141 0.046 -0.176	2
Sleep disorder / dimension means and demographics Sleep disorder / dimension means Sleep disorder / demographics	1.000 0.040 0.786	0.999 -0.387 0.443	3
Eating disorder / dimension means and demographics Eating disorder / dimension means Eating disorder / demographics	1.000 0.226 0.976	0.999 -0.118 0.937	4

Chapter 5: Discussion

Summary Statistics and Distributions of Participant Experiences

Aggregated experiences and experiential centroids have similar means for each dimension well within one SD of all four dimensions. Additionally, all four dimensions are well within one SD of the hypothesized means of the center-points of each scale. The slight difference measured for each dimension likely reflects the reality that these correlated dimensions are also positively associated with the capacity and willingness to answer the experience prompts. Nowhere is this more clear than the almost one SD negative skew of SoS's distribution of responses—highlighted by the fact that there were only 7 experiences recorded with a SoS value of 1, and all by the same individual. The relative lack of such entries may also simply reflect the biases that individuals can have to exaggerate certain positively perceived traits. Future research should utilize the 12 item Sense of Self Scale to understand the causal basis for this result.

When SoS is projected onto the XY plane with a contour plot (Figure 16), the result shows a greater overall degree of egoicism closer to the center, and pockets in the corners, especially those with high X.

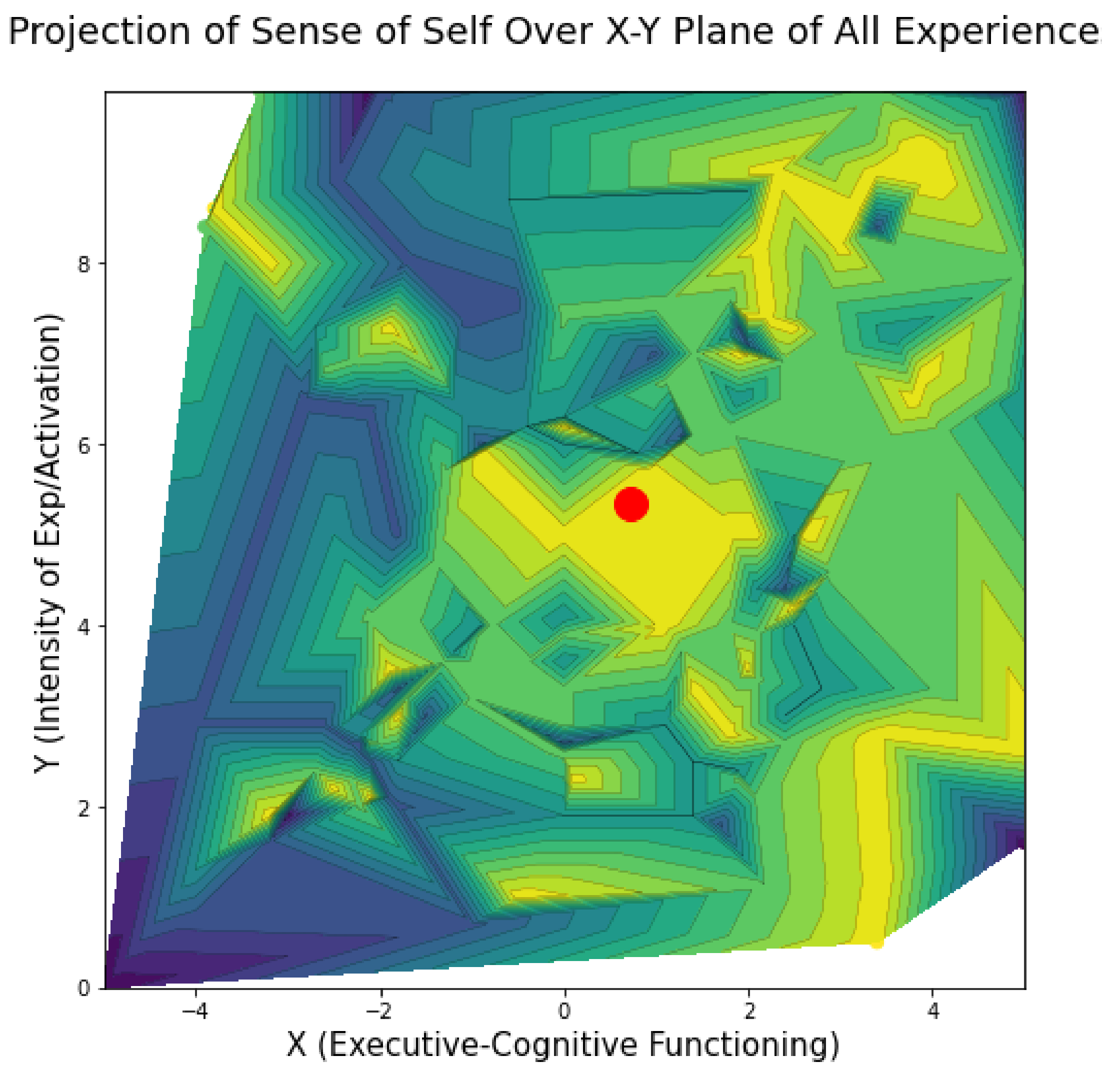


Figure 16: SoS contour plot over XY plane (n = 204)

Key: Yellow indicates SoS score of 5; dark blue indicates a SoS score of 1. The red circle points to the centroid of all experiences recorded.

Both the 2D and 3D experience plots have gap areas where there are no examples of particular experiences. In the XY plane (Figure 17) there are no entries in the area posited to be lucid and hypoegoic (very high X, average Y, low SoS), no examples of hyperarousal (high Y) without falling into either a flow state (high X, high Y) or ergotropic state (low X, high Y), as well as no examples of hypothesized clinical dissociation (low X, average Y), and only two examples of deep relaxation (neutral X, very low Y). These gaps are caused in part by the correlation between experiences making such differences between dimensions (i.e. one neutral, one at an extreme) less likely, and in part by the nature of these experiences: either quite uncommon (i.e. hypoegoicism), or make answering the experience prompts extremely difficult (i.e. dissociative states).

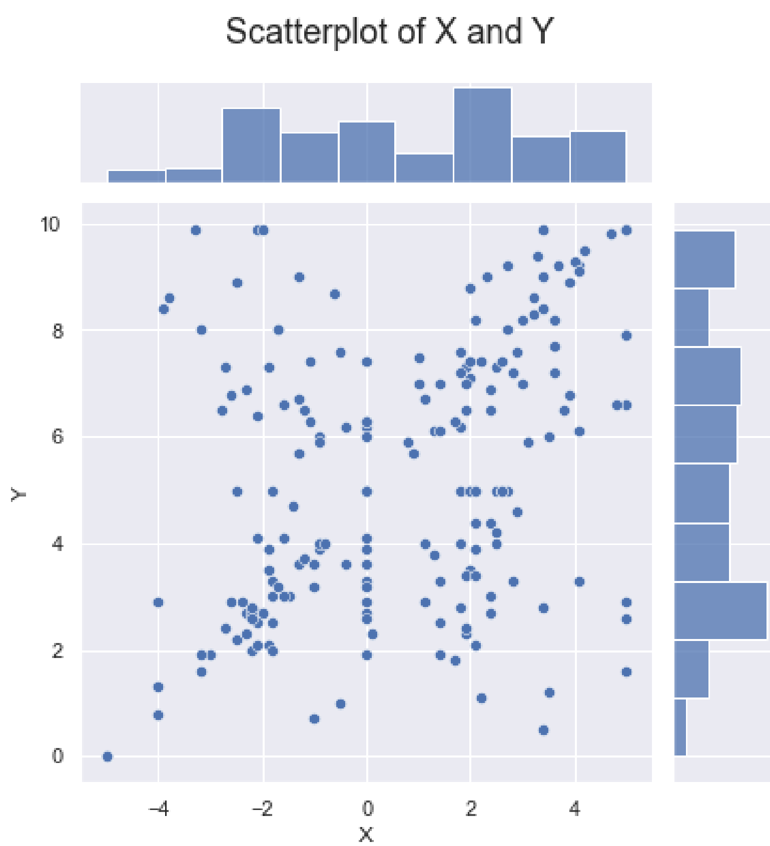


Figure 17: XY scatterplot with histograms (n = 204)

Additionally, there were not many entries in the meditation region, but the few that were present included entries such as: “washing dishes”, “at home eating lunch relaxed”, “putting kids to bed”, “roasting coffee”, and “exercising with tv hungry”. These experiences, while not formal meditation, can at least have meditative qualities to them.

In the circumplex (YZ) scatterplot, a similar X shape appeared (Figure 18). The absence of experiences in the top section of this plot (high Y, average Z) is in accordance with research around the Vector model variation of the circumplex model, which suggests that such states are impossible; when activation is increased to a high level valence also moves to an extreme, whether positive or negative (Remington, Fabrigar, & Visser, 2000). The vector model also suggests that low arousal (Y) states tend towards neutral valence, like the CIF, which was not reflected by the data in this study. Instead, extremes of the unconsciousness quadrant ($X \leq -2$ and $Y \leq 2$) appear to be as valenced (biased against neutral valence) as the extremes of the apotropic and ergotropic quadrants.

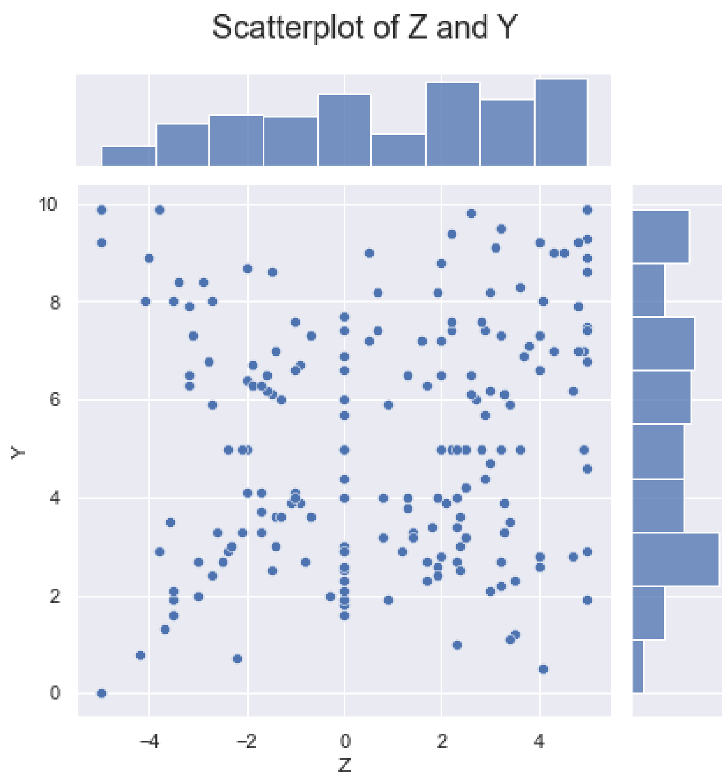


Figure 18: YZ scatterplot with histograms (n = 204)
Vector model prediction visible in top part of graphic, with bifurcation of valence as Y increases, but only to a point: Z appears to bifurcate above a Y value of 8. The Vector model's positing that low-Y, highly valenced states do not exist was not supported, however.

When all recorded vectors are plotted in this XYZ space, some of the most noticeable empty regions include what would be highly valenced states ($Z > 8$ or < 2) near the center of the XY plane, along with the complete lack of negatively valenced states in the meditative (trophotropic) quadrant (Figure 19). The resulting 3D structure is a roughly spherical cluster in the center, with bifurcations biased against neutral valence (Z) states as an experience moves to the extremes of the corners – with the notable exception of negatively valenced meditative states. This closely matches the expected 3D structure (Figure 2), with the differences likely due to the fact that the space mapped by this study does not constitute the entirety of the CIF's posited experiential space. This is because of the inherent limitation that the experiences recorded in this study only represent the conscious states that allow an individual to answer the prompt. By definition, a person who is asleep, deeply meditating, clinically dissociating, or having a psychotic break will be completely unable to comply with any experience sampling methodology of this nature.

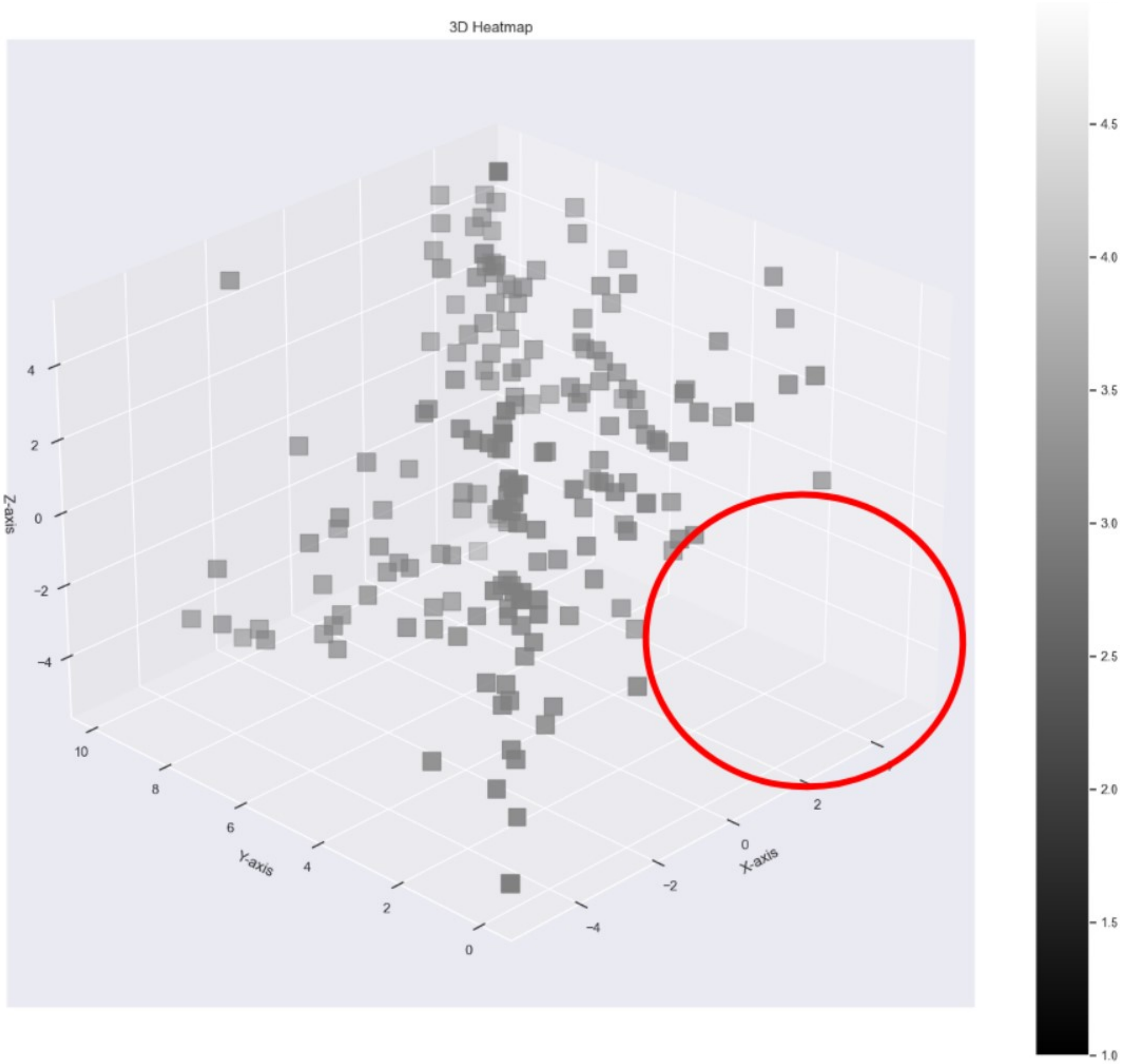


Figure 19: XYZ scatterplot of recorded experiences (n = 204)

This 3D scatterplot shows how experiences are spatially distributed, and notably, what areas remain empty. Circled in red is the empty area which would otherwise represent negatively valenced meditative (trophotropic) states.

One unexpected result was the lone entry for a positively valenced ergotropic or ecstatic experience, however, such experiences are not extremely common, compared with the states represented, and the dataset is limited by the small sample size.

Relationships Between the Dimensions

In every analysis of correlation between the dimensions—at the level of the individual participant, raw aggregated vectors, aggregated centroids, and the centroids of the 14 participants who provided more than 1 experience, X and Z remain moderately to highly correlated, as suggested by the literature on high-X states covered in Chapter 2. This relationship is reflected by Figure 20 below, where the majority of high valence states are in high X states.

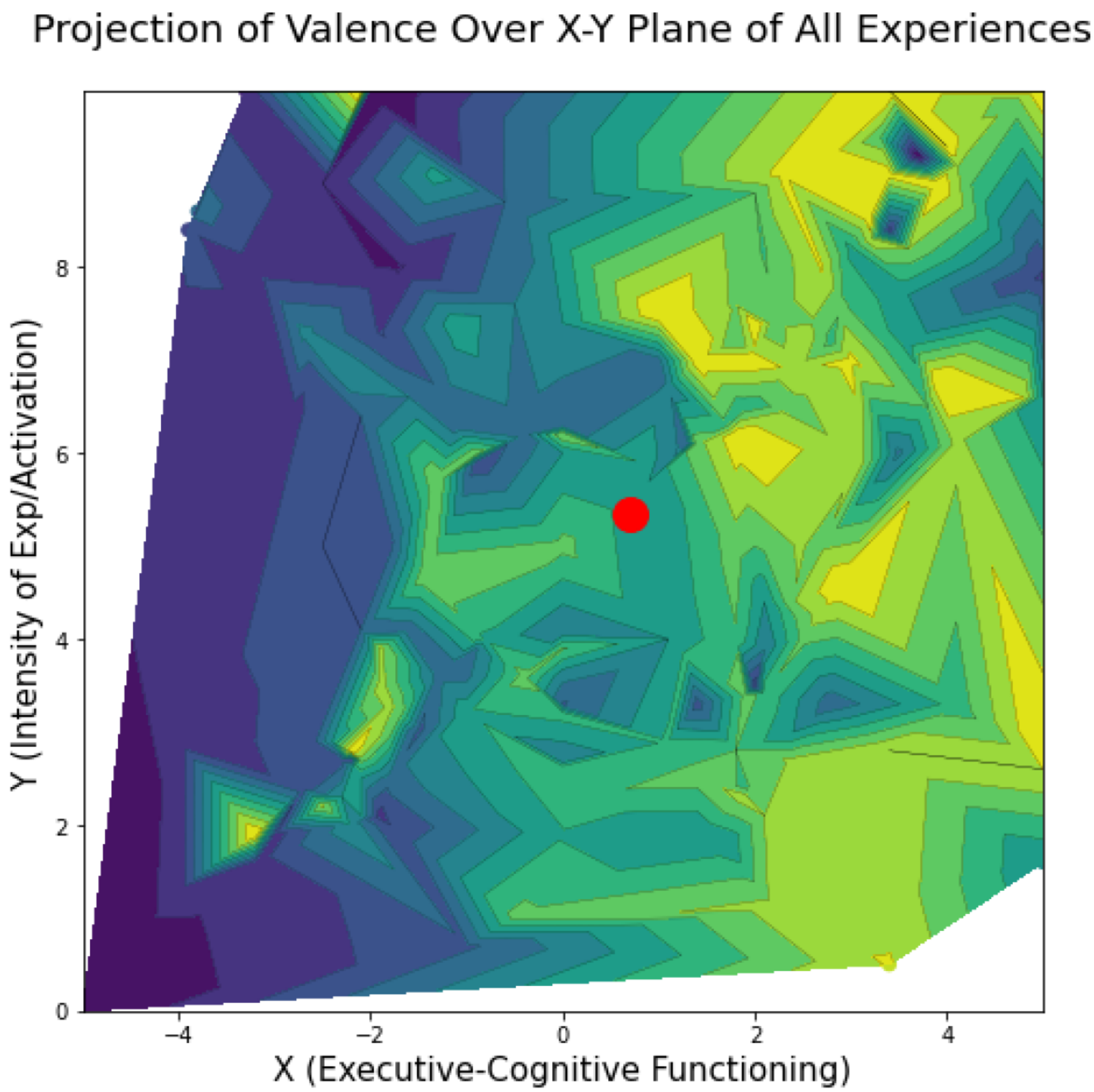


Figure 20: Contour plot of Z over XY plane (n = 204)

Positively valenced states (yellow/yellow-green) are very heavily weighted to the right (+X) half of the XY plane, while negatively valenced states are highly weighted to the states with the lowest executive-cognitive functioning (X).

The correlation between SoS and Z is weak to moderate, as are the relationships between X and SoS, and X and Y. Y and Z are weakly correlated, and Y and SoS appear to be fully uncorrelated.

Correlations between demographics and the mental health diagnoses were overall more pronounced than the correlations between the dimensions and the profile features as a whole. The strong positive correlation between age and valence reflects extant research on the matter, which found a decrease in negative affect with age (Charles et al., 2001), possibly mediated by socioemotional selectivity theory (Charles et al., 2003). The strong negative correlation between X and disability status is unsurprising, as disability is a significant reduction of functioning in all or specific contexts.

Without further research it is unclear whether the moderate correlations between the dimensions and profile features are reflective of either how certain experiential states are merely biased against responding to a voluntary sampling prompt, or a generalizable reality for individuals with similar demographics/diagnoses.

The results of the multivariate regression models allude to the strength of combining dimensional and demographic information, which may be further validated with larger, more representative datasets. When limiting the independent variables to the other dimensions the R-squared value was much lower, suggesting that the dimensions are confirmed to be independent variables, in spite of their high degree of correlation with one another. However, demographic variables were also insufficient alone as the independent variables to reach above 0.9 R-squared for predicting dimensional means.

The highest R-squared was 0.967 for Z, suggesting that 96.7% percent of variation in Z can be accounted for with demographics and X, Y, and SoS values, and that future studies may be able to exclude it as a sampling variable without compromising the strength and utility of the data.

Demographic Analysis

The depression/no-depression group differences in means were counter-intuitive: X was higher for the group with depression than the no-depression group, and Z was more than a SD higher in the group diagnosed with or suspecting major depressive disorder. In spite of the inability to reject the null hypothesis, the scores for the GAD/no-GAD pair was also counter-intuitive: Individuals with GAD scored over one half-SD lower intensity of experience, and one half-SD more positive overall valence. Beyond the lack of sufficient sample size, what could be the cause of such unexpected differences between groups? What I believe may be happening here, is that for individuals with any kind of mental health condition, they are more likely to respond to a questionnaire prompt, as required for this voluntary study. Individuals without mental illness would be operating at a higher baseline, and therefore may be more likely to respond even when experiencing difficult states of mind.

The comparison of centroids in Table 6 of participants who self-identified as at least suspecting a diagnosis of some kind, versus those who did not, agrees with common sense: Reduced sense of functioning, increased intensity of experience, reduced valence, and slightly reduced SoS. The comparison of transgender and cisgender group means showed higher X, lower Y, and a Z score more than a SD higher for the transgender group, in accordance with extant research assessing the psychological benefits of gender affirmation for transgender individuals (Glynn et al., 2016).

Lexical Analysis

The majority of terms used by participants to describe their experience centered around several major areas: working, socializing, recreation such as games and television, feelings (tired/sleepy/anxious), and caffeinated drinks. Comparisons of the summary statistics and XY heatmaps of the five exemplary terms revealed clear differences between the experiential categories. With sufficient data this lexical approach, and in particular the utilization of heatmaps for each word or group of conceptually equivalent terms, could be used to create searchable phenomenological maps for many terms, both supporting and drawing from semantic mapping research.

Case Studies

Case studies show the level of differences between individuals, and the importance of looking beyond aggregated data to discern meaningful differences between the daily experiences of individuals. P16 did not significantly differ from the control when comparing means, but did show a much wider variance. The heatmaps show how P16's experiences tended towards extremes along the diagonal, and clustered in two areas: the flow quadrant and unconsciousness quadrant. This bimodal plot of experiences was distinct from the control, as well as P20 and P25, while the clustering pattern suggests that P16 tends towards either a depressive state or a highly engaged flow-like state. P16 listed no mental health diagnoses.

P20 and P25 show similar distributions when compared with the control and P16, which may be mediated by their shared diagnoses of clinical depression and GAD, and sleep disorder. Beyond these diagnoses, P20 listed PTSD, while P25 listed suspected diagnoses of social anxiety, OCD, bipolar disorder and an eating disorder.

Correlations between the four groups were generally in line with the correlations between aggregated dimensions (above). Stable correlations which hold up at all levels of analysis are: moderate to strong positive correlation between X and Z, and weak to strong positive correlation between Z and SoS. These relationships are significant because they highlight the role valence plays in either determining or indicating both executive-cognitive functioning and the sense of self.

Predicting Mental Health Diagnoses

Mental health diagnoses could be predicted with considerable accuracy with demographics alone, and were bolstered with addition of the dimension means for each participant ($n = 14$; only participants with at least two experiences recorded were included). The high R-squared value for each of the 8 diagnoses assessed supports the idea that an experience sampling methodology like the one utilized for this study could be applied in a clinical setting to assist mental health professionals in their treatment of individuals with mental illness. This could allow individuals seeking mental health treatment to receive effective treatment sooner and more consistently over time, which supports the hypothesis that the CIF can use dimensional data along with demographic information to predict mental health diagnoses. However, the hypothesis that dimensional data alone could predict diagnosis was not supported.

In the case of psychiatric contexts this approach can be combined with information about any drugs, supplements, and psychoactive substances ingested by patients to target treatment and reduce the critical gaps where unwanted or dangerous drug effects are happening, but otherwise beyond the awareness of the individual or clinician. As covered in the section on psychoactive substances, this can reduce liability for clinicians, while also ensuring the best treatment for a highly at-risk population (Crump et al., 2013) making up more than 20% of the adult population of the United States (Canino et al., 2019). Practitioners of mental health are hampered/inhibited by the lack of definitive data regarding the day-to-day lived experience of their patients, and so must frequently make decisions without all the relevant information, risking malpractice (Ahuja, 2015; Dhadphale, 2019; Lindgren & Rozental, 2021). Current subjective rating scales are typically complex and long, containing dozens or hundreds of items making it difficult to implement them on a regular basis (Shiffman et al., 2008; Moskowitz, & Young, 2006; Balaskas et al., 2021), and therefore generally inefficient when implemented on a day-to-day basis (i.e. a 100-item assessment cannot be completed multiple times a day without becoming an impediment to the daily life experience it is meant to measure).

Limitations

A primary limitation was in recruiting and ensuring regular participation of the subjects. As the study had no funding for reimbursing participants, participation was insufficient to meet statistical power for many statistical and machine-learning models. Two-sample T-tests confirm in the majority of these cases with such limited datasets, the results aren't statistically significant. Thus, these results are merely exemplary/exploratory and support continued research with larger sample sizes.

An additional limitation is that the SoS single-item Likert scale is likely not generalizable. Future research should use the SoS Scale (SoSS) or comparable instruments to gauge the validity of such a single-item scale as used in this study.

An inherent limitation of the study is that the sampling methodology is only able to record experiences from the center of the framework; it is impossible to measure most of the transegoic experiences in real-time—only in retrospect. Future studies could be redesigned to allow for retrospective sampling of such experiences, paired with passive biometrics (Henriksen et al., 2018; Marín-Morales et al., 2021; Quintana & Heathers, 2014; Schaaf & Adam, 2013; Wang et al., 2018) such as heart-rate or sleep data to experimentally map the outer areas of the CIF.

Chapter 6: Conclusion

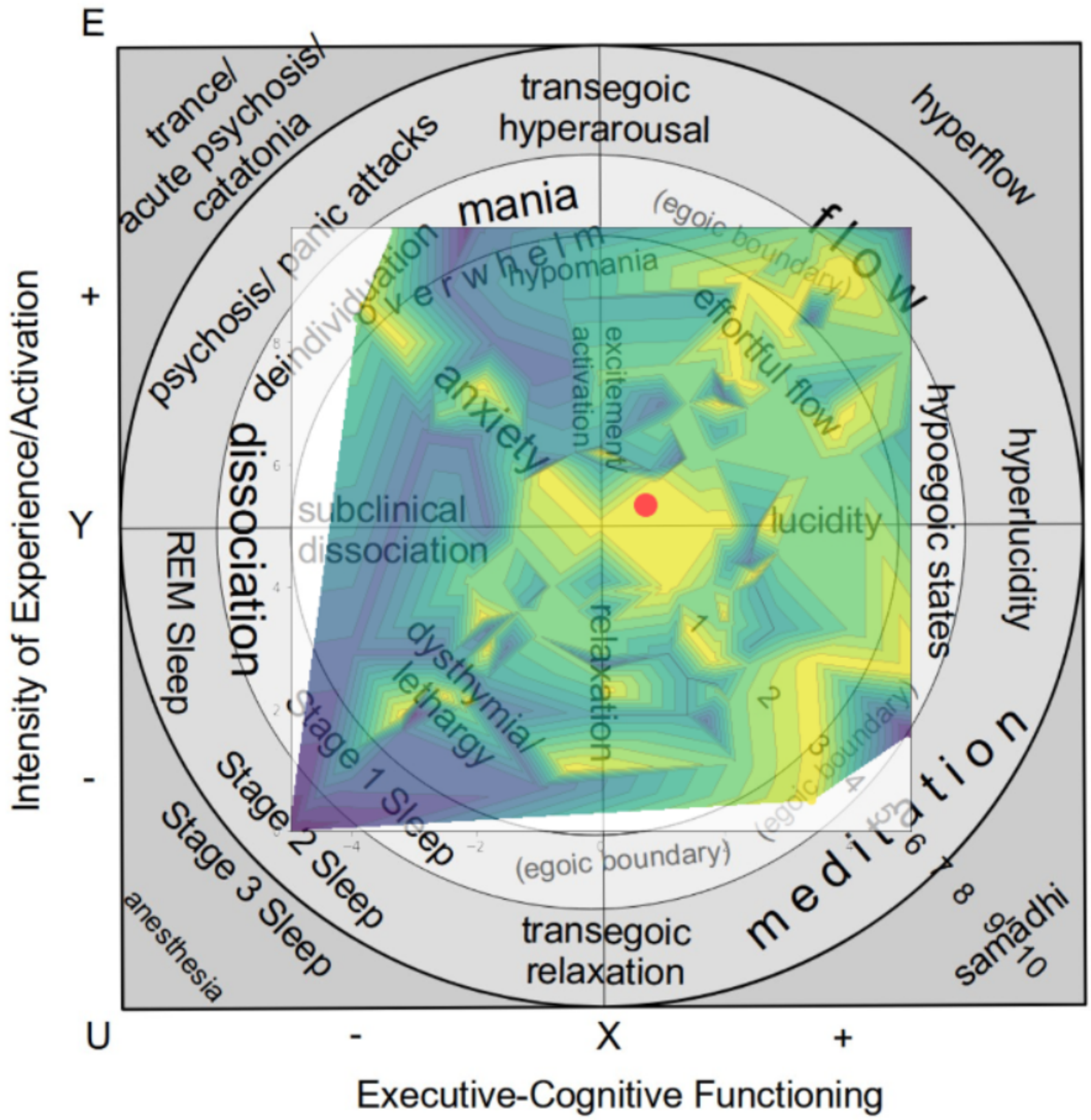


Figure 21: SoS contour plot superimposed on predicted XY plane (n = 204)

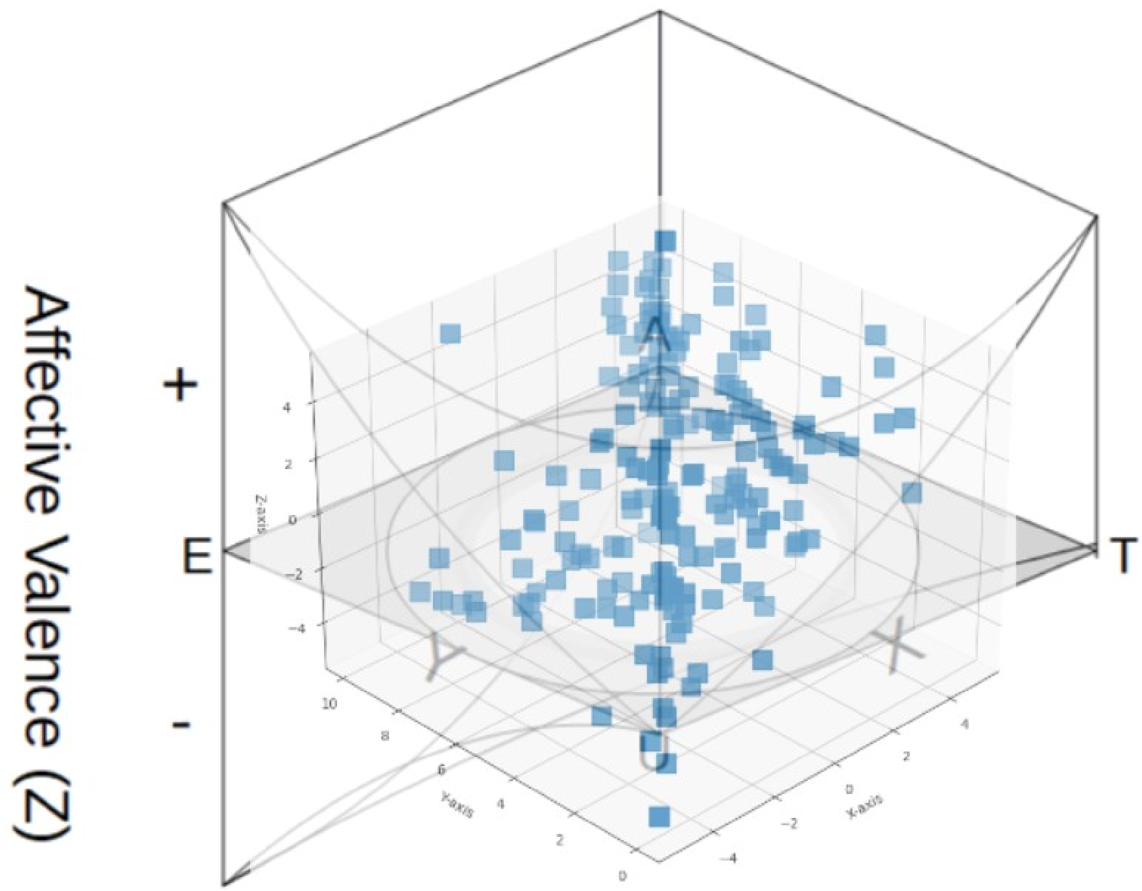


Figure 22: 3D scatterplot superimposed on predicted XYZ space (n = 204)

Overall, the conformity of the dataset to the hypothesized CIF structure was evident (Figures 21 and 22). The independence between the dimensions was supported by the inability to predict any individual dimensional value from the other three, although the incorporation of demographic variables was sufficient to do so. The moderate-to-high correlation between dimensions X and Z was evident at all levels of analysis, and along with the moderate correlation between Z and SoS warrants additional research to determine whether Z is a necessary variable to include in the framework.

Hypothesis 2 was supported by lexical and case study analyses, but unsupported by demographic analysis. The comparison of dimensional means and variances between demographic groups was insufficient to distinguish most groups, though the inclusion of other demographic variables in multivariate regression models were able to accurately predict more than 95% of variance in clinical depression or GAD diagnosis. Case studies and lexical analysis highlighted the utility of distinguishing between different individuals and experiential keywords on the basis of dimensional variables alone from the aggregated experiences respective of the phenomena being compared. Differences from average values for individuals with particular demographics could be readily applied in therapeutic/clinical settings, while phenomenological differences between lexical groups could be of interest to phenomenologists and psycholinguistic researchers who could build a searchable library of experiences.

Hypothesis 3 was supported by multiple OLS linear regression models when demographic variables were included with the dimensional variable means for each participant. However, mental health diagnoses could not be predicted with dimensional variables alone.

When taken together, a viable psychological model which can integrate the range of psychological phenomena appears to have several minimum requirements beyond validity and reliability. A model of the mind that is truly comprehensive must also be dimensional if it is to account for all possible psychological states across the diagnostic range from optimum health to severely disordered. Not only do boundaries between many disorders break down when the full picture of phenomenology, etiology, and ambiguous comorbidity are considered, but so do the boundaries between what is considered normal or healthy and what is abnormal or unhealthy. Without a taxonomic framework for the complete range of human experience—including well-being, happiness, and other positive aspects of psychology—researchers and clinicians risk not seeing the forest for the trees.

The most common mistake made by those endeavoring to integrate psychological research models is overemphasizing consideration of the biology, and insufficient consideration of the subjective experience itself. Phenomenal consciousness is what provides the context for the study of neuropsychology and the physiological bases that often take the center of focus in psychological and psychiatric research, and it must therefore be characterized to the same level of comprehensiveness as the biology if the hard problem of consciousness (Chalmers, 1996) is to be addressed. Similarly, computer science would languish as a field of study if the nature and potentials of software were disregarded for the study of hardware, or only the way in which binary code is encoded in that hardware.

While this study and literature review are only preliminary, they suggest a possible range of applications and implications of the CIF. First, taxonomic implications include a potential reconceptualization of the classification of psychiatric illness and treatment which is not beholden to diagnostic labels. Second, the CIF, as an additional psychometric tool for the individual assessment of the effects of psychoactives in the form of a spatial vector map is useful for clinicians, patients, and even independent psychonauts, in that it may allow for thorough and easy interpretation of the nature of a conscious mind with the specificity and individual uniqueness of a fingerprint. Thus, the CIF provides an answer to Moncrieff, Choen, and Porter's (2013) statement of clinical psychiatry that "the user's subjective experience should guide the use of psychiatric medications in a collaborative dialogue with the prescriber, rather than changes in designated symptoms or clusters of symptoms." (p. 413)

Moreover, the CIF can aid researchers and philosophers in the study of consciousness:

predictions of combined drug effects at the subjective level; understanding the relationships between different experiences (or psychoactives) with similar vector maps; predicting properties of uncharacterized, atypical vectors; and the use of the CIF in recording controlled administrations of different drugs for understanding atypical and altered states of consciousness generally.

Future research can build on the results of this preliminary study by consolidating the website, notification system, and Stroop test into an integrated smartphone app to improve compliance. This methodological change would support larger datasets that can surpass the threshold of broad statistical power with multilevel modeling and other machine learning models. Another important augmentation of this study would take more regular samples in shorter intervals over periods of one to several days to provide increased resolution in the measurement of how individuals change over time and in response to environmental or physiological changes. Biometrics from wearable instruments could track heart-rate, sleep, and physical activity, which can be paired with experience samples (i.e. heart-rate is a good approximator of Y (Henriksen et al., 2018; Marín-Morales et al., 2021; Quintana & Heathers, 2014; Schaaf & Adam, 2013; Wang et al., 2018)). This could potentially expand to include pairing experience data with neuroimaging techniques to explore the relationship between brain activity and subjective experience.

Future research should also address how to measure complex experience (multivectored states), as well as to compare results of CIF sampling with established psychometric instruments like the five-factor model of personality (McCrae & John, 1992), the Minnesota Multiphasic Personality Inventory (Sellbom, 2019), the Sense of Self Scale (Flury, 2004), the Altered States of Consciousness (OAV; Studerus et al., 2010) rating scale, etc.

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Appendix A: Participant Consent Form

HOOD COLLEGE
INFORMED CONSENT FORM

Common Integrative Framework – Experience Sampling Study Consent Form

1. INTRODUCTION

You are invited to be a participant in a research study about the nature and structure of the mind. We ask that you read this document and ask any questions you may have before agreeing to be in the study by making your account. We require that participants in this study be at least 18 years old.

This study is being conducted by Jacob Abuhamada, a graduate student at Hood College.

2. BACKGROUND AND PURPOSE OF THE STUDY

Resarchers in the psychological sciences have long searched for unifying theories, models, and frameworks to improve the understanding of the human mind for both research and clinical applications. The general purpose of this study is to understand the nature of the mind by tracking experiences over time from many individual participants along a few basic qualities of subjective experience. The specific goals of the study include understanding differences of experience across demographic categories, predicting psychiatric diagnosis, and validating a general framework of the mind: the Common Integrative Framework (CIF).

3. **DURATION**

This study will continue until July 1st, 2022. The length of time you will be participating is at your discretion, although a minimum of 3 months participation is preferable. You will receive two randomized prompts daily between the hours of 8am and 9pm for as long as you wish to participate. Simply uninstall or silence the Samply app or ignore the prompts when you no longer wish to participate.

4. **PROCEDURES**

If you agree to be in this study, we will ask you to do the following:

- First, you will create an account on the CIF DB site: cifdb.org (this will be the link sent in the two daily prompts).
- Next, you will be prompted to complete demographic and basic psychiatric questions.
- When prompted via reminder once or twice per day using the Samply Research mobile app or an email reminder, (circumstances permitting) you will click the link in the reminder to log in to the CIF DB site and record your current experience on the website, generally taking no more than 2 to 3 minutes.
- If you are unable to respond to all prompts, there is no need to submit the incomplete current experience—either respond in full when you have a moment to safely do so or skip that entry (please do not answer questions when in a situation where doing so is unsafe, i.e. while driving). Skipping entries is not a problem for the study (as the study's focus is on aggregating this data over an

extended period of time), so do not hesitate to ignore the prompt if completing it feels at all stressful/unsafe given your present situation.

- Additionally, you are encouraged to do the EncephalApp Stroop Test immediately afterwards and follow the instructions for submitting the completed tests as often as possible to have an objective measure of cognition/processing speed, but this is not required to submit your experiences.

5. **RISKS/BENEFITS**

Given that the respondent has control over the choice to respond, this study has minimal or no anticipated risks associated with participating. The two daily prompts may be distracting, but do not hesitate to ignore them if this is ever the case.

The benefits of participation are:

1) A .csv file/s containing all of your data will be available upon request.
2) When the study is completed you will receive a report detailing the conclusions of the study, and access to a copy of the final thesis manuscript upon request.
3) If you are an undergraduate student enrolled in a psychology course at Hood College, you may receive extra credit for participating in this student-led research.

6. **CONFIDENTIALITY**

The records of this study will be kept private on Hood College's password-protected server and your name will not be recorded at any point. Birthdate, ID, login and contact information will all be encrypted. In any sort of report that is published or presentation that is given, we will not include any information that will make it possible to identify a participant.

7. VOLUNTARY NATURE OF THE STUDY

Your participation in this study is completely voluntary. Your decision whether or not to participate will not affect your current or future relations with Hood College or any of its representatives. If you decide to participate in this study, you are free to withdraw from the study at any time without affecting those relationships. You are also free to simply stop participating at any time. If you wish to formally withdraw, send an email request to abuhamada@cifdb.org, and you will be sent a copy of your data before it is deleted.

8. CONTACTS AND QUESTIONS

The researcher conducting this study is Jacob Abuhamada. If you have questions, you may contact the researcher at abuhamada@cifdb.org.

If you have questions or concerns regarding this study and would like to speak with someone other than the researcher, you may contact Dr. Jolene Sanders, Institutional

Review Board Chair, Hood College, 401 Rosemont Ave., Frederick, MD 21701, sandersj@hood.edu.

9. **STATEMENT OF CONSENT**

You will be sent a copy of this form to your email, to keep for your records.

The procedures of this study have been explained to me and my questions have been addressed. The information that I provide is confidential and will be used for research purposes only. I am at least eighteen years old. I understand that my participation is voluntary and that I may withdraw or cease to participate at anytime without penalty. If I have any concerns about my experience in this study (e.g., that I was treated unfairly or felt unnecessarily threatened), I may contact the Chair of the Institutional Review Board or the Chair of the sponsoring department of this research regarding my concerns.

Appendix B: Scripts for Analysis (Python 3)

```
#load libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import sklearn

stroops = pd.read_csv("stroops.csv")
vectors = pd.read_csv("vectors.csv")
profile = pd.read_csv("profile.csv")
vectors.describe()
stroops.describe()
profile.describe()
vectorstroop = pd.read_csv("vectorstroop.csv")
VS = vectorstroop.dropna()
dimensions = vectors[['X', 'Y', 'Z', 'SoS']].copy()

pairplot = sns.pairplot(dimensions, hue="SoS")
pairplot.fig.suptitle("Pairplot of 4 Experiential Dimensions", y=1.05,
fontsize = 18)

scatterXY = sns.jointplot(x="X", y="Y",
              kind = "scatter", data = vectors)
scatterXY.fig.suptitle("Scatterplot of X and Y", y=1.05, fontsize = 18)
plt.show()

scatterXZ = sns.jointplot(x="X", y="Z",
              kind = "scatter", data = vectors)
scatterXZ.fig.suptitle("Scatterplot of X and Z", y=1.05, fontsize = 18)
plt.show()

scatterZY = sns.jointplot(x="Z", y="Y",
              kind = "scatter", data = vectors)
scatterZY.fig.suptitle("Scatterplot of Z and Y", y=1.05, fontsize = 18)
plt.show()

scatterZSoS = sns.jointplot(x="Z", y="SoS",
              kind = "scatter", data = vectors)
scatterZSoS.fig.suptitle("Scatterplot of Z and SoS", y=1.05, fontsize =
18)
plt.show()

ax = sns.regplot(x="Z", y="SoS", data=vectors)

scatterYSoS = sns.jointplot(x="Y", y="SoS",
              kind = "scatter", data = vectors)
scatterYSoS.fig.suptitle("Scatterplot of Y and SoS", y=1.05, fontsize =
18)
plt.show()
```

```
scatterXSoS = sns.jointplot(x="X", y="SoS",
              kind = "scatter", data = vectors)
scatterXSoS.fig.suptitle("Scatterplot of X and SoS", y=1.05, fontsize =
18)
plt.show()

XYkde = sns.jointplot(data=vectors, x="X", y="Y", kind="kde")
XYkde.fig.suptitle("Kernel Density Estimation of X and Y", y=1.05,
fontsize = 18)

lat = vectors["X"]
long = vectors["Y"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title('X-Y Heatmap', fontsize = 18)

XYhist = sns.jointplot(data=vectors, x="X", y="Y", kind="hist")
XYhist.fig.suptitle("Histogram of X and Y", y=1.05, fontsize = 18)

cgram_4D = sns.heatmap(dimensions.corr(), cmap="YlGnBu", annot = True)
plt.title('Correlogram of Experiential Dimensions', fontsize = 18, y =
1.05)
sns.set(rc = {'figure.figsize':(6,6)})
plt.show()

VS_dimensions = vectorstroop[['X', 'Y', 'Z', 'SoS', 'OffTime+OnTime',
'Ontime minus Offtime']].copy()
sns.heatmap(VS_dimensions.corr(), cmap="YlGnBu", annot = True)
plt.title('Correlogram of Experiential Dimensions and Stroop', fontsize
= 16, y = 1.05, x = .55)
sns.set(rc = {'figure.figsize':(7,6)})
plt.show()

ax = sns.regplot(x="SoS", y="OffTime+OnTime", data=VS_dimensions)
ax = sns.regplot(x="X", y="Z", data=vectors)
ax = sns.regplot(x="X", y="OffTime+OnTime", data=VS)
ax = sns.regplot(x="X", y="Ontime minus Offtime", data=VS)

lat = VS["Z"]
long = VS["Y"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of Z-Y (Circumplex) Vectors", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

#scatterplot of all recorded vectors for all subjects w/ centroid
fig, ax = plt.subplots(figsize=(8,8))
ax.scatter(vectors['X'], vectors['Y'], c=vectors['SoS'])
ax.set_xlabel('X (Executive-Cognitive Functioning)', fontsize = 15)
ax.set_ylabel('Y (Intensity of Exp/Activation)', fontsize = 15)
```

```
plt.title('Projection of Sense of Self Over X-Y Plane of All
Experiences', fontsize = 18, y = 1.04)

#centroid point (red)
X_mean = vectors['X'].mean()
Y_mean = vectors['Y'].mean()
ax.plot(X_mean, Y_mean, 'ro', markersize=16)

x = vectors['X']
y = vectors['Y']
z = vectors['SoS']
plt.tricontour(x, y, z, 14, linewidths=0.2, colors='k')
plt.tricontourf(x, y, z, 14)

plt.show()

#scatterplot of all recorded vectors for all subjects w/ centroid
fig, ax = plt.subplots(figsize=(8,8))
ax.scatter(vectors['X'], vectors['Z'], c=vectors['SoS'])
ax.set_xlabel('X (Executive-Cognitive Functioning)', fontsize = 15)
ax.set_ylabel('Z (Affective Valence)', fontsize = 15)
plt.title('Projection of Sense of Self Over X-Z Plane of All
Experiences', fontsize = 18, y = 1.04)

#centroid point (red)
X_mean = vectors['X'].mean()
Z_mean = vectors['Z'].mean()
ax.plot(X_mean, Z_mean, 'ro', markersize=16)

x = vectors['X']
y = vectors['Z']
z = vectors['SoS']
plt.tricontour(x, y, z, 12, linewidths=0.2, colors='k')
plt.tricontourf(x, y, z, 12)
plt.show()

#scatterplot of all recorded vectors for all subjects w/ centroid
fig, ax = plt.subplots(figsize=(8,8))
ax.scatter(vectors['X'], vectors['Y'], c=vectors['Z'])
ax.set_xlabel('X (Executive-Cognitive Functioning)', fontsize = 15)
ax.set_ylabel('Y (Intensity of Exp/Activation)', fontsize = 15)
plt.title('Projection of Valence Over X-Y Plane of All Experiences',
fontsize = 18, y = 1.04)

#centroid point (red)
X_mean = vectors['X'].mean()
Y_mean = vectors['Y'].mean()
ax.plot(X_mean, Y_mean, 'ro', markersize=16)

x = vectors['X']
y = vectors['Y']
z = vectors['Z']
```

```
plt.tricontour(x, y, z, 10, linewidths=0.2, colors='k')
plt.tricontourf(x, y, z, 10)
plt.show()

VS_dimensions.describe()
dimensions.describe()

#distributions of dimensions
ax = sns.boxplot(data=dimensions)
plt.title("Boxplots of Experiential Dimensions", fontsize = 18, y =
1.04)
plt.ylabel("Participant Scores", fontsize = 15)

sns.histplot(data=vectors, x="SoS", discrete=True, shrink=0.8)
plt.title("Histogram of SoS Response Counts", fontsize = 18, y = 1.04)
plt.xlabel("Sense of Self Response (1-5)", fontsize = 15)
plt.ylabel("Number of Vectors With SoS Response", fontsize = 15)
plt.show()

#take average vector values for each participant
centroids = vectors.groupby('ID').mean()

centroid_dims = centroids[['X', 'Y', 'Z', 'SoS']].copy()
sns.heatmap(centroid_dims.corr(), cmap="YlGnBu", annot = True)
sns.set(rc = {'figure.figsize':(6,6)})
plt.title("Correlogram of Dimensions (Centroids)", fontsize = 16, y =
1.04, x = 0.57)
plt.show()

centroid_dims.describe()

pairplot_centroids = sns.pairplot(centroid_dims, hue="SoS")
pairplot_centroids.fig.suptitle("Pairplot of 4 Experiential Dimensions",
y=1.05, fontsize = 18)

ax = sns.regplot(x="Z", y="SoS", data=centroid_dims)
ax = sns.regplot(x="X", y="Z", data=centroid_dims)

#scatterplot of all participant centroids
fig, ax = plt.subplots(figsize=(8,8))
ax.scatter(centroid_dims['X'], centroid_dims['Y'],
c=centroid_dims['SoS'])
ax.set_xlabel('X (Executive-Cognitive Functioning)', fontsize = 15)
ax.set_ylabel('Y (Intensity of Exp/Activation)', fontsize = 15)
plt.title("Projection of SoS Over X-Y Plane of All Experiences
(Centroids)", fontsize = 17, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

#centroid of centroids point (red)
X_mean = centroid_dims['X'].mean()
Y_mean = centroid_dims['Y'].mean()
```

```
ax.plot(X_mean, Y_mean, 'ro', markersize=16)

x = centroid_dims['X']
y = centroid_dims['Y']
z = centroid_dims['SoS']
plt.tricontour(x, y, z, 15, linewidths=0.2, colors='k')
plt.tricontourf(x, y, z, 15)
plt.show()

plt.title("Heatmap of X-Y Centroids", fontsize = 18, y = 1.04)
lat = centroid_dims["X"]
long = centroid_dims["Y"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.xlim([-5, 5])
plt.ylim([0, 10])

lat = centroid_dims["X"]
long = centroid_dims["Z"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of X-Z Centroids", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([-5, 5])

lat = centroid_dims["Z"]
long = centroid_dims["Y"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of Z-Y (Circumplex) Centroids", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

lat = centroid_dims["X"]
long = centroid_dims["SoS"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of X-SoS Centroids", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])

lat = centroid_dims["Z"]
long = centroid_dims["SoS"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of Z-SoS Centroids", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])

#distributions of dimensions (centroids)
ax = sns.boxplot(data=centroid_dims)
```

```
plt.title("Boxplots of Experiential Dimensions (Centroids)", fontsize =
18, y = 1.04)
plt.ylabel("Participant Scores", fontsize = 15)

#3D plot
from mpl_toolkits import mplot3d
fig = plt.figure()
ax = plt.axes(projection='3d')
ax.scatter3D(vectors['X'], vectors['Y'], vectors['Z'], c=vectors['SoS'])
ax.set_xlabel('x')
ax.set_ylabel('y')
ax.set_zlabel('z')

# 3D Heatmap in Python using matplotlib

# to make plot interactive
get_ipython().run_line_magic('matplotlib', '')

# importing required libraries
from mpl_toolkits.mplot3d import Axes3D
from pylab import *

# creating a dummy dataset
x = vectors['X']
y = vectors['Y']
z = vectors['Z']
colo = vectors['SoS']

# creating figures
fig = plt.figure(figsize=(10, 10))
ax = fig.add_subplot(111, projection='3d')

# setting color bar
color_map = cm.ScalarMappable(cmap=cm.gray)
color_map.set_array(colo)

# creating the heatmap
img = ax.scatter(x, y, z, marker='s',
                 s=200, color = 'gray')
plt.colorbar(color_map)

# adding title and labels
ax.set_title("3D Heatmap")
ax.set_xlabel('X-axis')
ax.set_ylabel('Y-axis')
ax.set_zlabel('Z-axis')

# displaying plot
plt.show()

# # Lexical Analysis
```

```
wordlist = pd.Series(np.concatenate([x.split() for x in
vectors.description])).value_counts()
wordlist2 =
vectors.description.str.split(expand=True).stack().value_counts()
pd.DataFrame(data=wordlist)
wordlist.describe()

#load lexical dataframes
coffee = pd.read_csv("coffee_vecs.csv")
relationships = pd.read_csv("relationship_vecs.csv")
relax = pd.read_csv("relax_vecs.csv")
tired = pd.read_csv("tired_vecs.csv")
work = pd.read_csv("work_vecs.csv")

coffee.describe()
relationships.describe()
relax.describe()
work.describe()
tired.describe()

X = coffee["X"]
Y = coffee["Y"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
plt.title("X-Y Heatmap of 'Coffee' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

X = coffee["Z"]
Y = coffee["SoS"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
plt.title("Z-SoS Heatmap of 'Coffee' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])

coffee_dims = coffee[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_coffee = sns.pairplot(coffee_dims, hue="SoS")
pairplot_coffee.fig.suptitle("Pairplot of 4 Experiential Dimensions
(Coffee)", y=1.05, fontsize = 18)

X = tired["X"]
Y = tired["Y"]
plt.title("X-Y Heatmap of 'Tired' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
```

```
X = tired["Z"]
Y = tired["SoS"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
plt.title("Z-SoS Heatmap of 'Tired' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])

tired_dims = tired[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_tired = sns.pairplot(tired_dims, hue="SoS")
pairplot_tired.fig.suptitle("Pairplot of 4 Experiential Dimensions
(Tired)", y=1.05, fontsize = 18)

X = relax["X"]
Y = relax["Y"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.title("X-Y Heatmap of 'Relax' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
plt.rcParams["figure.figsize"] = (5,5)

X = relax["Z"]
Y = relax["SoS"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
plt.title("Z-SoS Heatmap of 'Relax' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])

relax_dims = relax[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_relax = sns.pairplot(relax_dims, hue="SoS")
pairplot_relax.fig.suptitle("Pairplot of 4 Experiential Dimensions
(Relax)", y=1.05, fontsize = 18)

X = work["X"]
Y = work["Y"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
plt.title("X-Y Heatmap of 'Work' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

X = work["Z"]
Y = work["SoS"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
plt.title("Z-SoS Heatmap of 'Work' Vectors", fontsize = 18, y = 1.04)
```

```
plt.xlim([-5, 5])
plt.ylim([1, 5])

work_dims = work[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_work = sns.pairplot(work_dims, hue="SoS")
pairplot_work.fig.suptitle("Pairplot of 4 Experiential Dimensions
(Work)", y=1.05, fontsize = 18)

X = relationships["X"]
Y = relationships["Y"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
plt.title("X-Y Heatmap of 'Relationship' Vectors", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

X = relationships["Z"]
Y = relationships["SoS"]
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
plt.title("Z-SoS Heatmap of 'Relationship' Vectors", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])

relationship_dims = relationships[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_relationship = sns.pairplot(relationship_dims, hue="SoS")
pairplot_relationship.fig.suptitle("Pairplot of 4 Experiential
Dimensions (Relational Terms)", y=1.05, fontsize = 18)

# # Demographic Analysis
profile_clean = pd.read_csv("profile_clean.csv")

profile_clean = profile_clean.loc[:,
~profile_clean.columns.isin(['ID'])]

sns.heatmap(profile_clean.corr(), cmap="YlGnBu", annot = True)
plt.title("Correlogram of Participant Profile Features", fontsize = 18,
y = 1.01)
plt.show()

## Code source: https://www.geeksforgeeks.org/convert-birth-date-to-age-
in-pandas/
from datetime import datetime, date
dob = {'DOB': profile["DOB"]}
df = pd.DataFrame(data = dob)
def age(born):
    born = datetime.strptime(born, "%Y-%m-%d").date()
    today = date.today()
```

```
    return today.year - born.year - ((today.month,
                                      today.day) < (born.month,
                                                    born.day))
df['Age'] = df['DOB'].apply(age)
display(df)
##

df.sort_values(by=['Age'])

ages_hist = plt.hist(df['Age'], bins=50)
plt.title("Histogram of Participant Ages", fontsize = 18, y = 1.03)
plt.xlabel("Participant Age", fontsize = 15)
plt.ylabel("Number of Participants", fontsize = 15)
plt.rcParams["figure.figsize"] = (6,4)

#Comparison of Experiences by Gender (cis vs trans)
trans_vectors = centroids.query('ID in [10, 15, 16, 18, 34, 49]')
cis_vectors = centroids.query('ID not in [10, 15, 16, 18, 34, 49]')
cis_vectors.describe()
trans_vectors.describe()

#find variance for each group
print(np.var(trans_vectors), np.var(cis_vectors))

#perform two sample t-test with equal variances
stats.ttest_ind(a=trans_vectors, b=cis_vectors, equal_var=True)

#perform two sample t-test with equal variances
stats.ttest_ind(a=trans_vectors, b=cis_vectors, equal_var=False)

trans_vecs = vectors.query('ID in [10, 15, 16, 18, 34, 49]')
trans_dims = trans_vecs[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_trans = sns.pairplot(trans_dims, hue="SoS")
pairplot_trans.fig.suptitle("Pairplot of 4 Experiential Dimensions
(transgender participants)", y=1.05, fontsize = 18)

cis_vecs = vectors.query('ID not in [10, 15, 16, 18, 34, 49]')
cis_dims = cis_vecs[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_cis = sns.pairplot(cis_dims, hue="SoS")
pairplot_cis.fig.suptitle("Pairplot of 4 Experiential Dimensions
(cisgender participants)", y=1.05, fontsize = 18)

#Comparison of Experiences by Mental Illness (has(15)/might
have(3)/doesn't have(8))
no_diagnoses = centroids.query('ID in [16,24,27,30,31,33,42,43]')
no_diagnoses.describe()
diagnoses = centroids.query('ID not in [16,24,27,30,31,33,42,43]')
diagnoses.describe()

#find variance for each group
print(np.var(no_diagnoses), np.var(diagnoses))
```

```
#perform two sample t-test with equal variances
stats.ttest_ind(a=diagnoses, b=no_diagnoses, equal_var=True)

#perform two sample t-test with equal variances
stats.ttest_ind(a=diagnoses, b=no_diagnoses, equal_var=False)

#GAD as point of comparison
GAD = centroids.query('ID in [3,6,10,18,20,25,28,34,37,41,49]')
no_GAD = centroids.query('ID not in [3,6,10,18,20,25,28,34,37,41,49]')
GAD.describe()
no_GAD.describe()

#find variance for each group
print(np.var(GAD), np.var(no_GAD))

#perform two sample t-test with equal variances
stats.ttest_ind(a=GAD, b=no_GAD, equal_var=True)

#perform two sample t-test with equal variances
stats.ttest_ind(a=GAD, b=no_GAD, equal_var=False)

GAD_vectors = vectors.query('ID in [3,6,10,18,20,25,28,34,37,41,49]')
GAD_vectors = GAD_vectors[['X', 'Y', 'Z', 'SoS']].copy()

no_GAD_vectors = vectors.query('ID not in
[3,6,10,18,20,25,28,34,37,41,49]')
no_GAD_vectors = no_GAD_vectors[['X', 'Y', 'Z', 'SoS']].copy()

#find variance for each group
print(np.var(GAD_vectors), np.var(no_GAD_vectors))

#perform two sample t-test with equal variances
stats.ttest_ind(a=GAD_vectors, b=no_GAD_vectors, equal_var=True)

X = GAD_vectors["X"]
Y = GAD_vectors["Y"]
plt.title("X-Y Heatmap of 'GAD' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = GAD["X"]
Y = GAD["Y"]
plt.title("X-Y Heatmap of 'GAD' Centroids", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)
```

```
X = GAD_vectors["Z"]
Y = GAD_vectors["SoS"]
plt.title("Z-SoS Heatmap of 'GAD' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = GAD["Z"]
Y = GAD["SoS"]
plt.title("Z-SoS Heatmap of 'GAD' Centroids", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

GAD_dims = GAD_vectors[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_GAD = sns.pairplot(GAD_dims, hue="SoS")
pairplot_GAD.fig.suptitle("Pairplot of 4 Experiential Dimensions (GAD)",
y=1.05, fontsize = 18)

X = no_GAD_vectors["X"]
Y = no_GAD_vectors["Y"]
plt.title("X-Y Heatmap of 'Non-GAD' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = no_GAD["X"]
Y = no_GAD["Y"]
plt.title("X-Y Heatmap of 'Non-GAD' Centroids", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = no_GAD_vectors["Z"]
Y = no_GAD_vectors["SoS"]
plt.title("Z-SoS Heatmap of 'Non-GAD' Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = no_GAD["Z"]
Y = no_GAD["SoS"]
```

```
plt.title("Z-SoS Heatmap of 'Non-GAD' Centroids", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

no_GAD_dims = no_GAD_vectors[['X', 'Y', 'Z', 'SoS']].copy()
pairplot_no_GAD = sns.pairplot(no_GAD_dims, hue="SoS")
pairplot_no_GAD.fig.suptitle("Pairplot of 4 Experiential Dimensions
(non-GAD)", y=1.05, fontsize = 18)

#depression
depression = centroids.query('ID in [10,15,18,20,25,34,37,40,41,49]')
no_depression = centroids.query('ID not in
[10,15,18,20,25,34,37,40,41,49]')
depression.describe()
no_depression.describe()

#find variance for each group
print(np.var(depression), np.var(no_depression))

#perform two sample t-test with equal variances
stats.ttest_ind(a=depression, b=no_depression, equal_var=True)

depression_vectors = vectors.query('ID in
[3,6,10,18,20,25,28,34,37,41,49]')
depression_vectors = depression_vectors[['X', 'Y', 'Z', 'SoS']].copy()
no_depression_vectors = vectors.query('ID not in
[3,6,10,18,20,25,28,34,37,41,49]')
no_depression_vectors = no_depression_vectors[['X', 'Y', 'Z',
'SoS']].copy()

#find variance for each group
print(np.var(depression_vectors), np.var(no_depression_vectors))

#perform two sample t-test with equal variances
stats.ttest_ind(a=depression_vectors, b=no_depression_vectors,
equal_var=True)

X = depression_vectors["X"]
Y = depression_vectors["Y"]
plt.title("X-Y Heatmap of 'Depression' Vectors", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = depression["X"]
```

```
Y = depression["Y"]
plt.title("X-Y Heatmap of 'Depression' Centroids", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = no_depression_vectors["X"]
Y = no_depression_vectors["Y"]
plt.title("X-Y Heatmap of 'Non-Depression' Vectors", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = no_depression["X"]
Y = no_depression["Y"]
plt.title("X-Y Heatmap of 'Non-Depression' Centroids", fontsize = 18, y
= 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = depression["Z"]
Y = depression["SoS"]
plt.title("Z-SoS Heatmap of 'Depression' Centroids", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = depression_vectors["Z"]
Y = depression_vectors["SoS"]
plt.title("Z-SoS Heatmap of 'Depression' Vectors", fontsize = 18, y =
1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = no_depression["Z"]
Y = no_depression["SoS"]
```

```
plt.title("Z-SoS Heatmap of 'Non-Depression' Centroids", fontsize = 18,
y = 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

X = no_depression_vectors["Z"]
Y = no_depression_vectors["SoS"]
plt.title("Z-SoS Heatmap of 'Non-Depression' Vectors", fontsize = 18, y
= 1.04)
plt.xlim([-5, 5])
plt.ylim([1, 5])
ax = sns.kdeplot(X, Y, cmap="Blues", shade=True, shade_lowest=False,
cut=0)
plt.rcParams["figure.figsize"] = (5,5)

#PTSD
PTSD = centroids.query('ID in [15,18,19,20,34,39,40,49]')
no_PTSD = centroids.query('ID not in [15,18,19,20,34,39,40,49]')
PTSD.describe()
no_PTSD.describe()

#find variance for each group
print(np.var(PTSD), np.var(no_PTSD))

#perform two sample t-test with equal variances
stats.ttest_ind(a=PTSD, b=no_PTSD, equal_var=True)

profile_w_centroids = pd.read_csv("profile_clean_w_centroids.csv")
profile_w_centroids = profile_w_centroids.drop(['ID'], axis=1)

sns.heatmap(profile_w_centroids.corr(), cmap="YlGnBu", annot = True)
sns.set(rc = {'figure.figsize':(22,17)})
plt.title("Correlogram of Participant Profile Features And Centroids",
fontsize = 18, y = 1.01)
plt.show()

# # Analyzing Individuals - 3 Exemplary Participants

#Analyzing 16
Participant_16 = pd.read_csv("16.csv")
P16_dims = Participant_16[['X', 'Y', 'Z', 'SoS']].copy()
P16_dims.describe()

sns.heatmap(P16_dims.corr(), cmap="YlGnBu", annot = True)
sns.set(rc = {'figure.figsize':(6,6)})
plt.title("Correlogram of Participant 16's Vectors", fontsize = 18, y =
1.04)
plt.show()
```

```
pairplot16 = sns.pairplot(P16_dims, hue="SoS")
pairplot16.fig.suptitle("Pairplot of 4 Experiential Dimensions (P16)",
y=1.05, fontsize = 18)

#scatterplot of all recorded vectors for P16 w/ centroid
fig, ax = plt.subplots(figsize=(8,8))
ax.scatter(P16_dims['X'], P16_dims['Y'], c=P16_dims['SoS'])
ax.set_xlabel('X (Executive-Cognitive Functioning)', fontsize = 15)
ax.set_ylabel('Y (Intensity of Exp/Activation)', fontsize = 15)
plt.title("Projection of SoS Over X-Y Plane P16's Experiences", fontsize
= 18, y = 1.04)

#centroid point (red)
X_mean = P16_dims['X'].mean()
Y_mean = P16_dims['Y'].mean()
ax.plot(X_mean, Y_mean, 'ro', markersize=16)

x = P16_dims['X']
y = P16_dims['Y']
z = P16_dims['SoS']
plt.tricontour(x, y, z, 14, linewidths=0.2, colors='k')
plt.tricontourf(x, y, z, 14)
plt.show()

lat = P16_dims["X"]
long = P16_dims["Y"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of P16's Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

#Analyzing 20
Participant_20 = pd.read_csv("20.csv")
P20_dims = Participant_20[['X', 'Y', 'Z', 'SoS']].copy()
P20_dims.describe()

sns.heatmap(P20_dims.corr(), cmap="YlGnBu", annot = True)
sns.set(rc = {'figure.figsize':(6,6)})
plt.title("Correlogram of P20's Vectors", fontsize = 18, y = 1.04)
plt.show()

pairplot20 = sns.pairplot(P20_dims, hue="SoS")
pairplot20.fig.suptitle("Pairplot of 4 Experiential Dimensions (P20)",
y=1.05, fontsize = 18)

#scatterplot of all recorded vectors for P20 w/ centroid
fig, ax = plt.subplots(figsize=(8,8))
ax.scatter(P20_dims['X'], P20_dims['Y'], c=P20_dims['SoS'])
ax.set_xlabel('X (Executive-Cognitive Functioning)', fontsize = 15)
ax.set_ylabel('Y (Intensity of Exp/Activation)', fontsize = 15)
```

```
plt.title("Projection of SoS Over X-Y Plane P20's Experiences", fontsize
= 17, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

#centroid point (red)
X_mean = P20_dims['X'].mean()
Y_mean = P20_dims['Y'].mean()
ax.plot(X_mean, Y_mean, 'ro', markersize=16)

x = P20_dims['X']
y = P20_dims['Y']
z = P20_dims['SoS']
plt.tricontour(x, y, z, 14, linewidths=0.2, colors='k')
plt.tricontourf(x, y, z, 14)
plt.show()

lat = P20_dims["X"]
long = P20_dims["Y"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of P20's Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

#Analyzing 25
Participant_25 = pd.read_csv("25.csv")
P25_dims = Participant_25[['X', 'Y', 'Z', 'SoS']].copy()
P25_dims.describe()

sns.heatmap(Participant_25.corr(), cmap="YlGnBu", annot = True)
sns.set(rc = {'figure.figsize':(9,7)})
plt.title("Correlogram of P25's Vectors", fontsize = 18, y = 1.04)
plt.show()

sns.heatmap(P25_dims.corr(), cmap="YlGnBu", annot = True)
sns.set(rc = {'figure.figsize':(6,6)})
plt.title("Correlogram of P25's Vectors", fontsize = 18, y = 1.04)
plt.show()

pairplot25 = sns.pairplot(P25_dims, hue="SoS")
pairplot25.fig.suptitle("Pairplot of 4 Experiential Dimensions (P25)",
y=1.05, fontsize = 18)

#scatterplot of all recorded vectors for P25 w/ centroid
fig, ax = plt.subplots(figsize=(8,8))
ax.scatter(P25_dims['X'], P25_dims['Y'], c=P25_dims['SoS'])
ax.set_xlabel('X (Executive-Cognitive Functioning)', fontsize = 15)
ax.set_ylabel('Y (Intensity of Exp/Activation)', fontsize = 15)
plt.title("Projection of SoS Over X-Y Plane P25's Experiences", fontsize
= 18, y = 1.04)
plt.xlim([-5, 5])
```

```
plt.ylim([0, 10])

#centroid point (red)
X_mean = P25_dims['X'].mean()
Y_mean = P25_dims['Y'].mean()
ax.plot(X_mean, Y_mean, 'ro', markersize=16)

x = P25_dims['X']
y = P25_dims['Y']
z = P25_dims['SoS']
plt.tricontour(x, y, z, 14, linewidths=0.2, colors='k')
plt.tricontourf(x, y, z, 14)
plt.show()

lat = P25_dims["X"]
long = P25_dims["Y"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of P25's Vectors", fontsize = 18, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

#Everyone else as control
control = vectorstroop[vectorstroop["ID"] != 16]
control = control[control["ID"] != 20]
control = control[control["ID"] != 25]
control_dims = control[['X', 'Y', 'Z', 'SoS']].copy()
control_dims.describe()

sns.heatmap(control_dims.corr(), cmap="YlGnBu", annot = True)
sns.set(rc = {'figure.figsize':(6,6)})
plt.title("Correlogram of Control Group's Vectors", fontsize = 18, y =
1.04, x = .55)
plt.show()

pairplot_control = sns.pairplot(control_dims, hue="SoS")
pairplot_control.fig.suptitle("Pairplot of 4 Experiential Dimensions
(Controls)", y=1.05, fontsize = 18)

#scatterplot of all recorded vectors for controls w/ centroid
fig, ax = plt.subplots(figsize=(8,8))
ax.scatter(control_dims['X'], control_dims['Y'], c=control_dims['SoS'])
ax.set_xlabel('X (Executive-Cognitive Functioning)', fontsize = 15)
ax.set_ylabel('Y (Intensity of Exp/Activation)', fontsize = 15)
plt.title("Projection of SoS Over X-Y Plane of Experiences (excluding
P16, P20, and P25)", fontsize = 16, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])

#centroid point (red)
X_mean = control_dims['X'].mean()
Y_mean = control_dims['Y'].mean()
```

```
ax.plot(X_mean, Y_mean, 'ro', markersize=16)

x = control_dims['X']
y = control_dims['Y']
z = control_dims['SoS']
plt.tricontour(x, y, z, 10, linewidths=0.2, colors='k')
plt.tricontourf(x, y, z, 10)
plt.show()

lat = control_dims["X"]
long = control_dims["Y"]
ax = sns.kdeplot(lat, long, cmap="Blues", shade=True,
shade_lowest=False, cut=0)
plt.title("Heatmap of Control (excluding P16, P20, and P25)", fontsize =
15, y = 1.04)
plt.xlim([-5, 5])
plt.ylim([0, 10])
plt.grid()
plt.show()

#perform two sample t-test with equal variances
stats.ttest_ind(a=P16_dims, b=P25_dims, equal_var=True)

#perform two sample t-test with equal variances
stats.ttest_ind(a=P25_dims, b=control_dims, equal_var=True)

#perform two sample t-test with equal variances
stats.ttest_ind(a=P20_dims, b=control_dims, equal_var=True)

#perform two sample t-test with equal variances
stats.ttest_ind(a=P16_dims, b=control_dims, equal_var=True)

#perform two sample t-test with equal variances
stats.ttest_ind(a=P16_dims, b=P20_dims, equal_var=True)

#perform two sample t-test with equal variances
stats.ttest_ind(a=P20_dims, b=P25_dims, equal_var=True)

# # Machine Learning for Predicting Mental Illness
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)
import statsmodels.formula.api as smf

from sklearn.model_selection import train_test_split
from sklearn import metrics

from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import svm
from sklearn.neural_network import MLPRegressor
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.decomposition import PCA

#define scaler
scaler = StandardScaler()
#create copy of DataFrame
scaled_df=dimensions.copy()
#created scaled version of DataFrame
scaled_df=pd.DataFrame(scaler.fit_transform(scaled_df),
columns=scaled_df.columns)
#define PCA model to use
pca = PCA(n_components=4)
#fit PCA model to data
pca_fit = pca.fit(scaled_df)

PC_values = np.arange(pca.n_components_) + 1
plt.plot(PC_values, pca.explained_variance_ratio_, 'o-', linewidth=2,
color='blue')
plt.title('Scree Plot')
plt.xlabel('Principal Component')
plt.ylabel('Variance Explained')
plt.show()

print(pca.explained_variance_ratio_)

from statsmodels.multivariate.manova import MANOVA
fit = MANOVA.from_formula('X * Y * Z ~ SoS', data=dimensions)
print(fit.mv_test())

from statsmodels.multivariate.manova import MANOVA
fit = MANOVA.from_formula('X * Y * Z ~ SoS', data=centroids)
print(fit.mv_test())

from statsmodels.multivariate.manova import MANOVA
fit = MANOVA.from_formula('X * Y * Z ~ SoS', data=scaled_df)
print(fit.mv_test())

profile_columns = list(profile_clean.columns.values)
columns = list(vectors.columns.values)
data = profile_clean.merge(vectors, how = 'left')

from sklearn.neural_network import MLPClassifier

# The independent variables are X, Y, and Z. The dependent variable is
SoS.
X = vectors[['X', 'Y', 'Z']]
y = vectors[['SoS']]

# Splitting the data into training and test data
X_train, X_test, y_train, y_test = train_test_split(X, y,
train_size=0.75, test_size=0.25, random_state=10)

print('The shape of training features is:', X_train.shape)
```

```
print('The shape of testing features is:', X_test.shape)

neuralNetworkMLP = MLPClassifier(random_state = 1)
neuralNetworkMLP.fit(X_train, y_train)
y_pred = neuralNetworkMLP.predict(X_test)

accuracy = metrics.accuracy_score(y_test, y_pred)
print('The overall accuracy of the Neural Network classifier is:',
round(accuracy*100,2), '%')

#SoS as dependent variable
m1 = str('SoS ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status + X + Y + Z')
fittedModel = smf.ols(m1, data = data).fit()
print(fittedModel.summary())

#SoS as dependent variable - centroids + demographics
m1 = str('SoS_mean ~ Age + gender + trans + econ_stance +
cultural_stance + education + soc_class + dis_status + Z_mean + Y_mean +
X_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#SoS as dependent variable - centroids
m1 = str('SoS_mean ~ Z_mean + Y_mean + X_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#SoS as dependent variable - profile data only
m1 = str('SoS_mean ~ Age + gender + trans + econ_stance +
cultural_stance + education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#X as dependent variable
m1 = str('X ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status + SoS + Y + Z')
fittedModel = smf.ols(m1, data = data).fit()
print(fittedModel.summary())

#X as dependent variable - centroids
m1 = str('X_mean ~ SoS_mean + Y_mean + Z_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#X as dependent variable - centroids + demographics
m1 = str('X_mean ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status + SoS_mean + Y_mean + Z_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#X as dependent variable - profile data only
```

```
m1 = str('X_mean ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#Y as dependent variable
m1 = str('Y ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status + SoS + X + Z')
fittedModel = smf.ols(m1, data = data).fit()
print(fittedModel.summary())

#Y as dependent variable - centroids + demographics
m1 = str('Y_mean ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status + SoS_mean + X_mean + Z_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#Y as dependent variable - centroids
m1 = str('Y_mean ~ SoS_mean + X_mean + Z_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#Y as dependent variable - profile data only
m1 = str('Y_mean ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#Z as dependent variable
m1 = str('Z ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status + SoS + Y + X')
fittedModel = smf.ols(m1, data = data).fit()
print(fittedModel.summary())

#Z as dependent variable - centroids + demographics
m1 = str('Z_mean ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status + SoS_mean + Y_mean + X_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#Z as dependent variable - centroids
m1 = str('Z_mean ~ SoS_mean + Y_mean + X_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#Z as dependent variable - profile data only
m1 = str('Z_mean ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#depression as dependent variable - centroids + demographics
```

```
m1 = str('maj_depression ~ Age + gender + trans + econ_stance +
cultural_stance + education + soc_class + dis_status + Z_mean + Y_mean +
X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#depression as dependent variable - centroids
m1 = str('maj_depression ~ Z_mean + Y_mean + X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#depression as dependent variable - demographics
m1 = str('maj_depression ~ Age + gender + trans + econ_stance +
cultural_stance + education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#GAD as dependent variable - centroids + demographics
m1 = str('GAD ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status + Z_mean + Y_mean + X_mean +
SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#GAD as dependent variable - centroids
m1 = str('GAD ~ Z_mean + Y_mean + X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#GAD as dependent variable - demographics
m1 = str('GAD ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#PTSD as dependent variable - centroids + demographics
m1 = str('PTSD ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status + Z_mean + Y_mean + X_mean +
SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#PTSD as dependent variable - centroids
m1 = str('PTSD ~ Z_mean + Y_mean + X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#PTSD as dependent variable - demographics
m1 = str('PTSD ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())
```

```
#Social Anxiety as dependent variable - centroids + demographics
m1 = str('social_anx ~ Age + gender + trans + econ_stance +
cultural_stance + education + soc_class + dis_status + Z_mean + Y_mean +
X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#social_anx as dependent variable - centroids
m1 = str('social_anx ~ Z_mean + Y_mean + X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#social_anx as dependent variable - demographics
m1 = str('social_anx ~ Age + gender + trans + econ_stance +
cultural_stance + education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#OCD as dependent variable - centroids + demographics
m1 = str('OCD ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status + Z_mean + Y_mean + X_mean +
SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#OCD as dependent variable - centroids
m1 = str('OCD ~ Z_mean + Y_mean + X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#OCD as dependent variable - demographics
m1 = str('OCD ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#bipolar as dependent variable - centroids + demographics
m1 = str('bipolar ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status + Z_mean + Y_mean + X_mean +
SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#bipolar as dependent variable - centroids
m1 = str('bipolar ~ Z_mean + Y_mean + X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#bipolar as dependent variable - demographics
m1 = str('bipolar ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status')
```

```
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#sleep as dependent variable - centroids + demographics
m1 = str('sleep ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status + Z_mean + Y_mean + X_mean +
SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#sleep as dependent variable - centroids
m1 = str('sleep ~ Z_mean + Y_mean + X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#sleep as dependent variable - demographics
m1 = str('sleep ~ Age + gender + trans + econ_stance + cultural_stance +
education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#eating as dependent variable - centroids + demographics
m1 = str('eating ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status + Z_mean + Y_mean + X_mean +
SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#eating as dependent variable - centroids
m1 = str('eating ~ Z_mean + Y_mean + X_mean + SoS_mean')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())

#eating as dependent variable - demographics
m1 = str('eating ~ Age + gender + trans + econ_stance + cultural_stance
+ education + soc_class + dis_status')
fittedModel = smf.ols(m1, data = profile_w_centroids).fit()
print(fittedModel.summary())
```