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Behavioral Landscapes and Earth Mover's Distance: A New Approach for Studying Individual Differences in Density Distributions

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Abstract

Contemporary views of personality highlight intraindividual variability. We forward a general method for quantifying individual differences in behavioral tendencies based on Earth Mover's Distance. Using data from 150 individuals who reported on their and others' interpersonal behavior in 64,112 social interactions, we illustrate how this new approach can advance notions of personality as density distributions. Results provide independent confirmation and establish validity of existing representations of individual differences in interpersonal behavior, and identify new dimensions and profiles of personality and well-being. Benefits of the EMD method include freedom from assumptions about the shape and form of density distributions, generality of application to n-dimensional behavior captured in experience sampling studies, and natural integration of personality structure and dynamics.

Keywords

longitudinal analysis; ecological momentary assessment; intensive longitudinal data; interpersonal behavior

This article demonstrates a novel method for studying individuals' behavioral tendencies (including action, cognition, emotion, perception, physiology, etc.) – *personality*, and the individual differences therein. Making use of rich experience sampling data, wherein

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individuals provided many reports of their interpersonal behavior and their perceptions of their social interaction partners' interpersonal behavior *in situ* for about nine weeks, we explore how this new approach advances notions of personality as density distributions (Fleeson, 2001) or behavioral landscapes (Ram et al., 2013). We examine overlap with a variety of other metrics and procedures used to study individual differences in typical behavior (intraindividual mean) and within-person variability in interpersonal behavior across situations (e.g., intraindividual standard deviation, pulse, spin; Moskowitz & Zuroff, 2004). The findings are used to illustrate how the method recovers the individual differences captured by these metrics, and how it avoids existing metrics' preconceptions about the structure of individual behavior patterns (e.g., normally distributed) and the relevant features of the distribution (e.g., distance from origin).

Individual Differences in Behavioral Landscapes

Our presentation is placed within an interpersonal landscape characterized by two dimensions, *communion* and *agency*, that serves as a petri dish for methods development within a minimally multivariate space (e.g., Zimmerman & Wright, 2016). Our world-view prioritizes conceptualization of individuals (and the behavioral landscapes we use to represent them) as wholistic entities whose personality is better characterized by multiple characteristics than by any single characteristic in isolation (e.g., only communion or only agency; Bakan, 1966; Wiggins, 1997, 2003).

The Interpersonal Framework (a 2-d space)

Contemporary interpersonal theory (Pincus, 2005; Pincus & Ansell, 2013) proposes that (a) agency and communion are fundamental metaconcepts of personality, providing a superordinate structure for conceptualizing interpersonal situations, (b) explicatory systems derived from agency and communion can be used to understand, describe, and measure interpersonal dispositions and behaviors, and (c) such systems can be applied equally well to the objective description of contemporaneous interactions between two or more people (e.g., Sadler, Ethier, Gunn, Duoung, & Woody, 2009) and to interpersonal situations within the mind evoked via perception, memory, fantasy, and mental representation (e.g. Lukowitsky & Pincus, 2011). The typical operationalization of this framework is the Interpersonal Circumplex model, a formal geometric model of 2-d interpersonal space with a polar/circular representation that explicitly highlights the concurrent importance of both dimensions in accurately measuring, describing, and understanding interpersonal functioning (Fabrigar, Visser, & Browne, 1997; Shepard, 1978; Wiggins, 1991; Wiggins, Phillips, & Trapnell, 1989). This 2-d model has been successfully employed to examine interpersonal dispositions, interpersonal perceptions, and the dynamics of interpersonal behavior as it unfolds over time across multiple timescales (e.g., Pincus et al., 2014).

Experience Sampling Data

To understand how individuals conceptualize and behave in interpersonal situations, researchers have collected rich *repeated measures data* using event-contingent designs that ask people to rate, after each social interaction, their own and/or the other person's behavior along communion (distant ... friendly) and agency (submissive ... dominant) dimensions

(e.g., Ambwani, Roche, Minnick, & Pincus, 2015; Ansell, Laws, Roche, & Sinha, 2015; Fournier, Moskowitz, & Zuroff, 2009; Roche, Pincus, Hyde, Conroy, & Ram, 2014), or having trained coders rate individuals' behavior, second-by-second, throughout an (videotaped) interaction (e.g., Altenstein, Krieger, & Grosse Holtforth, 2013; Sadler, Woody, McDonald, Lizdek, & Little, 2015; Thomas, Hopwood, Woody, Ethier, & Sadler, 2014; Tracey, Bludworth, & Glidden-Tracey, 2012). Such studies produce rich repeated measures data about where in 2-d space individuals spend their interpersonal lives. For illustration, self-reports of an individual's interpersonal behavior during $T = 443$ social interactions he had over approximately 9 weeks are depicted in Figure 1, each panel highlighting a different analytical perspective. Looking first at Panel A, the black dots indicate the level of communion (x -axis) and agency (y -axis) for each social interaction. As an ensemble of scores, these measurements provide a robust characterization of how this individual behaves across multiple contexts.

Quantifying Intraindividual Variability

The *density-distributions approach* to personality (Fleeson, 2001) suggests that both the central tendency (i.e., average) and variability of behavior across situations are important aspects of personality. That is, the pattern of behavior a person exhibits or experiences across situations is an important individual difference in and of itself (Fiske & Rice, 1955). Some individuals may behave in a relatively consistent manner in many situations (black dots bunched together in a small portion of the space), while others' behavior may vary more dramatically from situation to situation (black dots spread out across the space). Researchers are making use of a number of summary statistics to describe the ensemble of reports (Ram & Gerstorf, 2009; Nesselroade, 1991). The density-distributions approach to personality typically uses the *intraindividual mean* (iMean) and *intraindividual standard deviation* (iSD, flux) as descriptors of person-level behavioral tendencies (Fleeson & Gallagher, 2009). Visual depictions of central tendency and variability on the communion and agency dimensions are shown in the Panel A of Figure 1 as the blue lines and blue rectangle, respectively. Within the interpersonal framework, researchers have introduced complementary quantifications of variability in the explicitly polar/circumplex space, namely *pulse* and *spin* (Moskowitz & Zuroff, 2004). These measures quantify variability in behavior in terms of distance from the origin of a radial vector, and variance of angular locations of behavior (or perception) around a circular mean. Visually, these metrics are represented by the length (pulse) and breadth (spin) of the "fan" in Panel B of Figure 1.

Following work in information theory (Shannon, 1948) and biological sciences (Magurran, 2004), multidimensional (and multicategory) forms of intraindividual variability are also sometimes operationalized as *entropy* (e.g., Hollenstein, 2013; Newell et al., 2009; Ram et al., 2012). In contrast to the iSD, pulse, and spin metrics, which all quantify spread in a specific direction (along x -axis or y -axis, away from origin, or around the circle), entropy metrics characterize spread across the entirety of possible behaviors or locations, without concern of direction, the location of an origin, or the shape of any underlying distribution. Conceptually, entropy describes the total size of the "island" shown in Panel C of Figure 1 – the area of the 2-d space that this individual tends to live. As with the other measures of intraindividual variability, individuals may differ in the extent of entropy.

Personality as Behavioral Landscapes

The density distributions approach is part of a “bottom-up approach to personality in which theorists start with the actual differences as they exist between individuals’ behaviors (including actions, cognitions, motivations, and emotions) and infer the personalities that produced those differences” (Fleeson & Nofle, 2008, p. 1358). For clarity, the density distributions approach to trait descriptions (Fleeson, 2001) proposes that traits are described by the *parameters* – and typically central tendencies – of individuals’ density distributions. Over time, as individuals encounter different situations, their behavioral tendencies will form a unique distribution. Each distribution, then can be described by its location (e.g., centroids shown by red dots in Figure 1), its size in terms of how wide it is, and its shape in terms of how much it corresponds to a normal distribution. Methodologically, these approaches acknowledge the within-person variation in individuals’ behaviors and perceptions and use iMeans, iSDs, pulse, spin, and entropy as measures of dispositional constructs that are indicators of personality and/or related to other individual difference characteristics (e.g., Five-factor model—FFM—of personality traits, well-being, and psychiatric diagnoses).

Making the density-distribution perspective explicit, we have rendered our example individuals’ data as an actual density surface in Panel D of Figure 1. The density or probability of observation at each location in the 2-d space (which was equivalently represented by color in Panel C) is indicated by the height (*z*-axis) of the surface. The 2-d representations become 3-d. Conceptually, an individuals’ behavior “resides” within the hills. Depicted as such, personality, and the behavioral tendencies captured therein, can be represented as landscapes. Connections to the natural world – mountains, hills, and plains – are immediately apparent (e.g., Hooker, 2002; Waddington, 1957). Further, when depicted this way, one immediately sees that individuals’ behavioral tendencies do not conform to the idealistic statistical properties underlying calculation of iMean, iSD, pulse, spin. As noted by Sadler and colleagues in their examination of interpersonal behavior in psychotherapy sessions, “In their asymmetry, these patterns are strikingly unlike a bivariate normal distribution ... [and] unlike other patterns reported in the interpersonal literature [e.g., pulse and spin]. ... In short, further study of the particular patterns of variations ... should avoid preconceptions about the form these patterns may take” (Thomas et al., 2014, pp. 11–12). Rather than being symmetric and smooth, individuals’ behavioral landscapes are often filled with extra hills, sharp spires, and flat zones. Methods are needed to quantify these differences in an “assumption-free” manner.

Quantifying Individual Differences in Interpersonal Behavior Landscapes

Previously we proposed that the study of individual differences in *behavioral landscapes* and intraindividual *change in behavioral landscapes* could be accomplished using a landform classification approach (Ram et al, 2013). Specifically, procedures for classifying geographic landscapes into a topographic typology (e.g., irregular plains, flat plains, open hills, plains with hills; Gallant, Brown, & Hoffer, 2005; Hammond 1954/64) were adapted for classification of individual’s affective landscapes (2-d space defined by Positive Affect and Negative Affect). That method worked, but was somewhat lacking in its ability to capture

the range of individual differences and subtleties of intraindividual change that manifests in experience sampling data. Although the typology distinguished between very different kinds of landscapes (plains vs. mountains) and was useful in describing changes that were related to the “massive earthquakes” that occurred in some people’s lives, less dramatic differences and changes that accompanied less severe life events / development were completely missed. The typology was simply too coarse to track the more nuanced changes of life. In this paper we now propose a more general method for quantifying individual differences in behavioral landscapes.

How can we determine which landscapes are similar, which landscapes are different, and by how much? And, can we do this in a way that is relatively free of assumptions about the shape and form of the landscapes (Thomas et al., 2014)? If so, the method might be widely applied to many types of behavioral landscapes. That is, we do not want to presuppose the dimensionality, shape, and form of the density-distributions that may be derived from the plethora of multivariate repeated measures data now available (e.g., from diary and ecological momentary assessment studies). Fusing methods from behavioral and computer science, we forward an approach based on *Earth Mover’s Distance* (EMD), a metric used in multimedia databases for indexing and retrieving images.

Earth Mover’s Distance

Earth Mover’s Distance (EMD) was introduced by Rubner, Tomasi and Guibas (2000) as a method for retrieving similarly colored and textured images. The basic problem was to quickly and efficiently distinguish images of the same scene (i.e., same content) that may have been blurred or have local obstructions. Formally, the intensity and location of specific features (e.g., RGB color content) of an image are represented as a density distribution. Images are compared by quantifying the distance between them in terms of the amount of work (i.e., cost) needed to transform one image into another. EMD is a quantification of that work, and thus provides a way to quantify which images are similar, which images are different, and by how much.

We face a similar problem, in that we would like to quantify the distance between individuals’ behavioral landscapes. For illustration a subset of three (of 150) interpersonal behavior landscapes are shown along the diagonal of Figure 2. The intuitive interpretation of Earth Mover’s Distance, as the name implies, is the minimum amount of work needed to move the piles of earth that form one person’s behavioral landscape so that they resemble another person’s behavioral landscape—imagine a fleet of little bulldozers working inside of Figure 2 to transform the landscape of Person A into the landscape of Person B. EMD quantifies how much work the bulldozers must do. Conceptual visualization of the bulldozers’ work is shown in the off-diagonals of Figure 2. Each panel shows the geometric differences between a pair of landscapes. To transform one landscape into the other, the gray mass above the surface must be pushed over to fill in the empty spaces below the surface. The minimum work needed to make the ground flat is the EMD. As can be seen, the EMD metric captures much of our intuitive notions of similarities and differences between the landscapes. Persons A and C are relatively similar ($EMD_{A,C} = 3.23$) while Person B is relatively different ($EMD_{A,B} = 8.13$, $EMD_{B,C} = 7.37$).

EMD is used very widely in computer science applications, particularly in the indexing and retrieval of multimedia content (Ma, Sheng, Yao, Xu, & Shemshadi, 2014; Uysal, Beecks, Schmücking, & Seidl, 2014). For example, search engines (e.g., Google image search) use EMD-based similarity/dissimilarity metrics to produce a ranked list of documents/images similar to a user-provided document/image. Contemporary developments are mainly focused on design of algorithms that optimize speed/efficiency of calculation in high-dimensional spaces for big data applications (Pele & Werman, 2009; Shirdhonkar & Jacobs, 2008). Historically, EMD has formal links to 1st Mallows and 1st Wasserstein distance (Levina & Bickel, 2001), and thus was applied in a number of mathematical applications prior to its use for image retrieval. However, to our knowledge, this is the first study to employ EMD in psychological research. In this paper, we introduce EMD as a new approach for examining individual differences in aspects of individuals' personality – presently differences in interpersonal style, as captured through analysis of experience sampling data.

For clarity, we highlight a key difference in calculation of the more traditional weighted Euclidean Distance (wED) and EMD. The wED provides the distance between a pair of *points*. Individuals are represented as a single “particle” in multivariate space, the location of which is defined by a *vector* (with the weighting simply being a scaling that puts the distances into SD units). In contrast, EMD provides the distance between a pair of *distributions* (ensembles of points) defined by a multidimensional *matrix* of scores. Individuals are represented as “clouds” in a multivariate space (with the weighting defined by the ground-distance matrix D). Pushing further into the earth-moving analogy, wED quantifies how *much* earth there is above ground level relative to the size of the holes below ground, and ignores *where* the earth is. Mathematically, wED will subtract every value in vector A from the corresponding value in vector B, and calculate the root sum of squares of those difference scores. In contrast, EMD quantifies the difference in terms of transport costs, which are fully driven by *where* the earth is and where the holes are. For example, consider three 1d “hills” (each describing a person):

Person A: [3 0 0 0 0 0 0 0 3]

Person B: [3 0 0 0 0 0 0 3 0]

Person C: [3 3 0 0 0 0 0 0 0]

The Euclidean distance between A and B is the same as between A and C is the same as between B and C = $\sqrt{((3-0)^2 + (0-3)^2)} = 4.24$, and with weighting (which normalizes the 0 to 3 range to a 0 to 1 range), the wED between each pair of vectors becomes $\sqrt{((1-0)^2 + (0-1)^2)} = 1.41$. The relative location of the “hill” does not matter. In contrast, the (weighted) EMD between A and B = 0.5; between A and C = 4.0; and between B and C = 3.5. The relative location of the “hill” is important. As such EMD captures a character of the distribution that the wED does not.

The Present Study

To illustrate how EMD-based methods used in image analysis can be re-purposed to describe individual differences in behavioral landscapes, we analyze patterns of interpersonal behavior (and perceptions of others' interpersonal behavior) captured over ~9 weeks as part

of a community-based experience sampling study. Coupling the use of nonparametric density estimation, EMD, multidimensional scaling and cluster analysis, we derive the dimensional and/or categorical structure of individual differences in behavioral landscapes, and examine how dimensional differences compare to traditional intraindividual variability metrics and how categorical differences relate to measures of the FFM personality traits and psychological well-being. Although Extraversion and Agreeableness are often identified as the “interpersonal” dimensions of the FFM (McCrae & Costa, 1989), both theoretical perspectives (e.g., Wiggins & Trapnell, 1996) and empirical investigations (e.g., Ansell & Pincus, 2004; McCrae, 1996) support the view that all FFM trait dimensions have interpersonal characteristics and correlates. Our results provide independent confirmation of existing representations of individuals’ interpersonal behavior, and exploration into newly identified profiles of function based on EMD-based analysis of behavioral landscapes.

Method

Our illustration makes use of data from the Intraindividual Study of Affect Health and Interpersonal Behavior (iSAHIB), a multiple time-scale experience sampling study (Ram et al., 2014). A brief overview of details relevant to the present analysis is given below.

Participants

The iSAHIB (Ram et al., 2014) worked with 150 adults recruited from the Pennsylvania State University and surrounding community. Purposefully stratified by gender and across the adult life span in 18–24 ($n=22$), 25–34 ($n=27$), 35–49 ($n=30$), 50–64 ($n=41$), 65+ ($n=30$) year age-bins, participants were between 19 and 89 years of age ($M_{Age} = 47.64$, $SD_{Age} = 18.85$), had obtained between 2 and 24 years of formal education ($M_{Educ} = 16.36$, $SD_{Educ} = 3.90$), and had between 0 and 6 children ($M_{Children} = 1.5$, $SD_{Children} = 1.41$). Participants self-identified as Caucasian (91%), African American (4%), Asian American (1%), and Mixed or Other (4%) ethnicity; and as heterosexual (93%) or bisexual, gay, or lesbian (6%), with less than 1% of the participants declining to indicate sexual orientation. Participants’ yearly family income ranged from ‘under \$20,000’ to ‘\$200,000 and over’ ($Median_{Income} = \$50,000 - \$74,999$, $Mode_{Income} = \$20,000 - \$49,999$), with 8.7% declining to answer.

Of the 150 participants, 136 (90.7%) completed the entire intensive protocol, and 14 withdrew after completing between a third ($n = 11$, 7.3%) and two-thirds ($n = 3$; 2.0%) of the total protocol. Reasons for withdrawal included relocation or loss of contact ($n = 10$), health problems ($n = 1$), and loss of interest or inability to complete protocol ($n = 3$). Participants who withdrew did not differ systematically from those who completed the entire protocol with respect to the measured demographics (p s > .05).

Procedure

After recruitment, receipt of information about the intensive nature of the assessments, and self-selection into the study, participants completed a series of three 21-day “measurement bursts” spaced at approximately 4.5-month intervals ($M_{Interval} = 5.25$ months between Bursts 1 and 2; $M_{Interval} = 4.25$ months between Bursts 2 and 3). During each 21-day burst, individuals went about their normal daily lives, reporting about their social interactions and

providing end-of-day reports about their feelings, thoughts, and behaviors using a study-provided smartphone (Verizon XV6900) with a customized ‘iSAHIB Surveys’ application. At the beginning and end of each 21-day burst, individuals visited the laboratory, received training or debriefing, picked-up or dropped-off smartphones, and completed web-based batteries of demographic, health, personality, and other questionnaires. Participants were compensated \$500 for completing the entire protocol.

Throughout each day (~9 weeks total), participants provided event-contingent reports of face-to-face social interactions that lasted longer than five minutes by completing 27 items on the smartphone survey application. These reports included descriptions of when and where the interaction occurred, whom the interaction was with, what their perceptions of their and their partner’s behavior was, and how they felt after. To facilitate compliance, the smartphones were programmed to chime a prompt if the participant did not provided a report for any two hour span between 8 am and 8 pm. Data flow was monitored in real-time, a process that enabled the research staff to make periodic “check-in” calls to solve technical issues, instill support and motivation in participants, and help produce high quality reports. Over the entire study period, the 150 participants provided reports on a total of 64,112 social interactions ($M_{numobs} = 427.4$, $SD = 145.7$, range = 88 to 869).

Measures

Interpersonal Behavior (Communion and Agency)—After each social interaction individuals indicated how they (self) and their interaction partner (other) behaved with respect to *communion* and *agency*. Specifically, after answering questions about where they were and who they were with, participants were prompted with the items “Rate how THE OTHER PERSON acted” and “Rate how YOU acted”, each of which was followed by a ‘touch-point continuum’ (slider-type interface) with end-point anchors of “Distant ... Friendly” and “Submissive ... Dominant”. Responses on each of the continua were digitally coded on a –50 to +50 scale (numbers not visible to participants) to locate each interaction within two 2-dimensional spaces that describe individuals’ *interpersonal behavior* and *perception of others’ interpersonal behavior* in terms of communion and agency (see Ansell et al, 2015; Ambwani et al., 2015; Horowitz et al., 1991; Moskowitz & Zuroff, 2009; Roche et al., 2014 for discussion of benefits of using uni-dimensional or two-dimensional grid ratings that simplify presentation, increase the sensitivity to small changes, and reduce participant burden). As shown in Table 1, across all social interactions, individuals rated their own interpersonal behavior as relatively high in communion ($M = 31.92$, $SD = 9.23$ on the –50 to +50 scale) and mid-range in agency ($M = 5.26$, $SD = 8.80$), and perceived their partners’ interpersonal behavior as relatively high in communion ($M = 30.24$, $SD = 8.87$) and mid-range in agency ($M = 6.85$, $SD = 9.44$).

Personality—Trait-like demographics and dispositions were measured periodically throughout the study using web-based questionnaires (and paper-pencil versions for a few persons who preferred that format). The FFM personality traits were measured once at the conclusion of the study using the NEO-FFI (Costa & McCrae, 1992). Individuals’ level of Neuroticism ($M = 2.39$, $SD = 0.73$), Extraversion ($M = 3.59$, $SD = 0.58$), Openness ($M = 3.49$, $SD = 0.63$), Agreeableness ($M = 3.91$, $SD = 0.50$) and Conscientiousness ($M = 3.95$,

$SD = 0.58$) were each indicated by the average of responses (1 = strongly disagree to 5 = strongly agree) to 12 items.

Psychological Well-being—Prior to and after each burst, participants completed the 20-item Center for Epidemiologic Studies Depression scale (CESD; Radloff, 1977). A person-level *depressive symptoms* score was calculated as the average of responses across all assessments ($M = 9.94$, $SD = 7.26$). Similarly, *emotional well-being* was assessed calculated as the average across six assessments of the 5-item emotional well-being subscale of the sf-36 Health Survey (Ware & Sherbourne, 1992; $M = 23.57$, $SD = 2.60$). Individual differences in overall *life satisfaction* scores were calculated as the average of responses to item, “All things considered, how satisfied are you with your life?” from the Satisfaction with Life Scale (Diener, Emmons, Larsen, & Griffin, 1985; $M = 5.63$, $SD = 0.90$). Trait-level perceptions of *control* were assessed prior to and after each burst using nine items (adapted from Lachman & Weaver, 1998) asking about both domain-related control beliefs (“How would you rate the amount of control you have over your [relationships/finances/health/work/leisure/life] these days?”) and general control beliefs (“I often feel helpless in dealing with the problems of life,” “What happens in my life is often beyond my control,” and “I have little control over the things that happen to me.”). Ratings (1 = no control at all to 7 = Very much control) were averaged to obtain person-level control scores ($M = 5.16$, $SD = 0.90$).

Data Analysis

The first stage of analysis was to summarize each individual’s reports of their own and their partners’ interpersonal behavior as behavioral landscapes (using nonparametric density estimation) and develop a framework for examining differences between those landscapes based on EMD. In the second stage of analysis, individual differences were examined in relation to more traditional univariate density distribution metrics (iMean and iSD), circumplex-based measures of intraindividual variability (e.g., pulse and spin), and the set of personality and well-being measures.

Intraindividual Landscapes

We considered each individual’s ensemble of interpersonal behavior ratings as behavioral landscapes (ratings of self and perceptions of others separately). To obtain the landscape representation, each individual’s raw data was re-represented as a density surface where the height/elevation indicates the proportion of observations that have particular x , y coordinates (Panel D of Figure 1). Formally, the conversion of the raw data into a “behavioral landscape” makes use of tools that build an estimate of the underlying probability density function (Scott, 1992; Silverman, 1986). In particular, nonparametric density estimators obtain what is essentially a smoothed histogram by centering a kernel function at each point, estimating the density at that location, working across the data step-by-step and summing. The result is a smooth surface, the height of which indicates the density of observations in a local neighborhood. The benefit of using a nonparametric method is that it allows for flexibility in what the surface of the resulting landscape can look like – here, free of assumptions about the structure of individual’s interpersonal lives. However, as always, there are caveats.

Flexibility is bounded by the sizing of the grid (i.e., bin size of a histogram), the shape of the locally applied kernel function (e.g., uniform, triangle, Gaussian) and the bandwidth, h , defining the boundaries of the local neighborhood (and thus governing the smoothness of the resulting landscape surface). In practice, a variety of methods are used to select an optimal bandwidth, for example by minimizing the integral of the squared error (MISE, Scott 1992). In the present analysis, we sought landscapes that retained individual-specific features, but that were also comparable across persons. As such, we imposed a form of measurement invariance (see e.g., Widaman, Ferrer, & Conger, 2010) by using the same grid size (30 x 30), local kernel (Gaussian) and bandwidth ($h = 5$, selected as a common width near the individual-specific optimal bandwidths obtained using a “direct plug-in” selection method; Park & Marron, 1990; Sheather & Jones, 1991) to generate all 150 individuals’ density surfaces.

Following performance-based recommendations (Deng & Wickham, 2011) our implementation of the nonparametric density estimation was done using the `bkde2d` function in the `KernSmooth` package in R (Wand & Ripley, 2010; Wand & Jones 1995; Wand, 1994). A selection of the resulting behavioral landscapes is shown along the diagonal of Figure 2. As can be seen, the surfaces are different in shape, size, and orientation. Each landscape provides a picture of a person’s interpersonal life, with the hills created from the intensive experience sampling data indicating where, in the interpersonal space defined by communion and agency, the individual reported spending his/her time during the 9 weeks of assessment.

Earth Mover’s Distance

Individual differences in the behavioral landscapes were quantified using EMD. The calculation of EMD is formalized as a transportation problem and solved using linear programming. Following Rubner and colleagues (2000), let $P = \{(p_1, w_{p1}), \dots (p_m, w_{pm})\}$ be the signature for Individual A represented as the mass (hills), w_j , at m specific locations, p_j (which are, in our case the x,y coordinates attached to each section of the grid). In parallel, let $Q = \{(q_1, w_{q1}), \dots (q_n, w_{qn})\}$ be the signature for Individual B represented as the mass, w_k , at n specific locations, q_k . We define a *ground distance* metric $\mathbf{D}$, where d_{jk} is the ground distance between locations p_j and q_k . In our case, the distance is defined by the Cartesian coordinate axes of the communion, agency space. The calculation task is to find a flow, $\mathbf{F} = [f_{jk}]$, where f_{jk} is the flow between p_j and q_k , that minimizes the overall cost

$$WORK(P, Q, \mathbf{F}) = \sum_{j=1}^m \sum_{k=1}^n d_{jk} f_{jk}$$

subject to the following constraints:

$$\begin{aligned}
 f_{jk} &\geq 0 & 1 \leq j \leq m, 1 \leq k \leq n, & \text{(allows moving “earth” from } P \text{ to } Q \text{ and not vice versa);} \\
 \sum_{k=1}^n f_{jk} &\leq w_{pj} & 1 \leq j \leq m, & \text{(limits the amount of “earth” being moved from } P); \\
 \sum_{j=1}^m f_{jk} &\leq w_{qk} & 1 \leq k \leq n, & \text{(limits the amount of “earth” being received by } Q); \\
 \sum_{j=1}^m \sum_{k=1}^n f_{jk} &= \min \left(\sum_{j=1}^m w_{pj}, \sum_{k=1}^n w_{qk} \right), & & \text{(forces movement of the maximum amount of “earth” possible)}
 \end{aligned}$$

Once the transport problem is solved, we have the optimal flow $\mathbf{F}$. Earth Mover’s Distance is defined as the resulting work normalized by the total flow (as constrained by the smaller signature):

$$EMD(P, Q) = \frac{\sum_{j=1}^m \sum_{k=1}^n d_{jk} f_{jk}}{\sum_{j=1}^m \sum_{k=1}^n f_{jk}}$$

EMD can be computed (or approximated) using a variety of algorithms, the most prominent being the transportation simplex method (Hillier & Lieberman, 1990). In brief, the simplex algorithm transforms the feasible region into a nonnegative surface that is concave, so that any local minimum is also a global minimum. The region is then systematically searched to determine the minimum value. Although sometimes computationally expensive, the simplicity of the search process provides for efficiency of evaluation and it has been implemented within a number of easy to use software packages. Our use of EMD to examine individual differences in behavioral landscapes was facilitated by the *emd* package in R (Urbaneck, 2012; based on Rubner et al’s, 1998, original implementation), and visualization of those differences by the *GA* (Scrucca, 2013) and *ggplot2* (Wickham, 2009) packages.

Individual Differences in Intraindividual Variability

In preparation for the second stage of analysis we calculated traditional person-level summaries of the interpersonal behavior reports (*self* and perceptions of *others* separately). Given the theoretical conceptualization of interpersonal behavior as situated in a circumplex space, we converted the agency and communion reports for each social interaction from Cartesian coordinates (x, y) to polar coordinates (r, Θ) using Pythagorean theorem, where the vector length $r_{it} = \sqrt{communion_{it}^2 + agency_{it}^2}$ and angular position $\Theta = \tan^{-1}(agency_{it} / communion_{it})$, with adjustment for quadrant (typically invoked using an *atan2* function in most software). Person-level characteristics were then calculated for both Cartesian (x, y ; Figure 1 Panel A) and circumplex (r, Θ ; Figure 1 Panel B) coordinates.

Average interpersonal behavior—In the Cartesian space, individuals’ average interpersonal behavior was operationalized as the arithmetic mean of all communion scores and the arithmetic mean of all agency scores,

$$\begin{aligned}
 imean.communions_i &= \frac{1}{T_i} \sum_{t=1}^{T_i} communion_{it}, \text{ and} \\
 imean.agency_i &= \frac{1}{T_i} \sum_{t=1}^{T_i} agency_{it}.
 \end{aligned}$$

Variability in interpersonal behavior—Variability in individuals' interpersonal behavior across social interactions in the Cartesian space was operationalized as the intraindividual standard deviation of all agency scores and the intraindividual standard deviation of all communion scores,

$$iSD_{communion_i} = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (communion_{ti} - \overline{communion_i})^2}, \text{ and} \\ iSD_{agency_i} = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (agency_{ti} - \overline{agency_i})^2}.$$

Similarly, variability of individuals' interpersonal behavior in the circumplex space was operationalized as the intraindividual standard deviation of vector lengths and angles (*pulse* and *spin*, Moskowitz & Zuroff, 2004). *Pulse* is calculated straightforwardly as

$$pulse_i = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (r_{ti} - \bar{r}_i)^2}.$$

Spin is calculated as the circular standard deviation of the angles, Θ_{it} (see Jammalamadaka & SenGupta, 2001; Mardia & Jupp, 2000). First, the circular variance is calculated as

$CVar_i = \sqrt{MCos_i^2 + MSin_i^2}$, where $MCos_i^2$ and $MSin_i^2$ are the mean of the cosines of the angles and the mean of the sines of the angles, respectively. With $CVar_i$ ranging from 0 to 1, the standard deviation is calculated as.

$$spin_i = \sqrt{-2\ln(1 - CVar_i)}.$$

The general measure of dispersion across the landscape was quantified using Shannon's (1948) *entropy* metric,

$$entropy_i = - \sum_{j=1}^m \pi_j \ln \pi_j$$

where π_j is the proportion of the density mass at each of m locations (each cell of the grid used to produce the density distribution; proportions calculated after Laplacian correction, i.e. adding the minimum machine precision to the density at each location so that no cells would have $\ln(0) = \infty$).

Individual Differences in Behavioral Landscapes

In the second stage of our analysis we examined the differences between individuals' behavioral landscapes and how those differences align with the more traditional metrics and/or provide for identification of a typology of persons. We identified the underlying structure of individual differences embedded in the EMDs in two ways: using

multidimensional scaling, implemented in the R base package using *cmdscale* function (R Core Team, 2015), and *vegan* package (Oksanen, Blanchet, Kindt, Legendre, Minchin, O'Hara, ..., & Wagner, 2015); and (b) using *cluster analysis*, implemented in R using the *cluster* package (Maechler, Rousseeuw, Struyf, & Hornik, 2014) and *fpc* package (Hennig, 2014).

In brief, the 150 x 150 dissimilarity matrices obtained using EMD (*self* and perceptions of *others* separately) were fit using a classic multidimensional scaling model (Kruskal & Wish, 1978) with a small number of orthogonal coordinates (number of dimensions determined through examination of stress plots and goodness of fit criteria). The resulting scores indicating where each individual's landscape is located in the parsimonious coordinate space were then correlated with the intraindividual variability metrics (iMean, iSD, etc.) to interpret the meaning of the coordinates. In parallel, the dissimilarity matrices (*self* and perceptions of *others* separately) were used to identify a "typology" of landscapes – clusters with distinct landscape types. Specifically we used agglomerative hierarchical clustering based on Ward's method to identify groups of relatively homogeneous landscapes (number of clusters chosen based on dendrogram, assessment of possible cut points, and examination of solutions for interpretability). Cluster assignment groups were then examined with respect to our array of personality and well-being measures to confirm that the groups were different in substantively meaningful ways. Together the multidimensional scaling and cluster analysis serve to illustrate different ways to make use of the EMD-based methods for study of individuals' behavioral landscapes.

Results

Results are presented in two sections, working first through the findings from analysis of the behavioral landscapes describing each individual's reports of their own interpersonal behavior (*self*), and then the landscapes describing each individual's perceptions of their interaction partners' interpersonal behavior (perceptions of *others*). Multidimensional scaling and cluster analyses were conducted on both measures. However, for brevity of illustration regarding how the EMD-based method can be used, we only elaborate the cluster analysis results for perception of *others*.

Interpersonal Behavioral Landscapes: Self

Following the procedures described above, the full 150 x 150 matrix of EMDs was fit using a classic multidimensional scaling model. Examination of the eigenvalues (825.66, 710.46, 442.57, 98.32, 73.86 and associated scree plot) suggested consideration of three (goodness of fit = .589, stress = .097, Mardia's goodness of fit = .945, linear fit $R^2 = .940$) and four coordinate solutions (goodness of fit = .618, stress = .086, Mardia's goodness of fit = .951, linear fit $R^2 = .950$). With the four coordinate model providing good fit to the data (based on shape of the scree and the better stress and goodness of fit statistics; Kruskal, 1964), locations for each person's landscape in the MDS coordinate space (MDS_{1s} , MDS_{2s} , MDS_{3s} , MDS_{4s}) were then examined in relation to the traditional individual-level summaries of interpersonal behavior reports (iMeans, iSDs, pulse, spin, entropy). Correlations shown in the upper triangle of Table 1 provide for straightforward interpretation of each coordinate

axis, and how the individual differences among the interpersonal behavior landscapes are organized. Shown in bold, MDS_{1s} closely tracks individual differences in mean level of agency ($r_{MDS1s,imean.agency} = .91$); MDS_{2s} closely tracks individual differences in mean level of communion ($r_{MDS2s,imean.communio} = .80$); and MDS_{3s} closely tracks individual differences in spin ($r_{MDS3s,ispin} = .80$), intraindividual variability in agency ($r_{MDS3s,isd.agency} = .78$), and intraindividual entropy ($r_{MDS3s,ientropy} = .72$). These purely data-driven findings confirm the utility of the EMD-based procedure. The approach identifies the primary differences among individuals' interpersonal behavior reports projected by both Cartesian and circumplex theoretical models, and measured using standard quantifications of intraindividual central tendency and dispersion. This is good news in that the prominence of mean levels of agency and communion and interpersonal spin as the major features of individuals' interpersonal style is confirmed using a method that is free of assumptions about the direction, shape, and structure of the interpersonal landscape.

Going a step further, we see that the fourth coordinate, MDS_{4s} , does not map so strongly onto any of the traditional metrics. To interpret what this dimension of individual differences may be capturing, we ordered the landscapes using the MDS_{4s} scores and looked for a pattern. Although this dimension may be a catch-all for residual noise, this dimension appears to capture something that might be described as "multidirectionality". Displayed on the diagonal in Figure 2, Persons A, B, and C have high, medium, and low scores (respectively) on MDS_{4s} . Person A's landscape is characterized by a ridge that runs parallel to the agency axis (unidirectional); Person B's landscape is characterized by a mountain with clear slopes outward; and Person C's landscape is characterized by slopes that point inwards and outwards without ridges (multidirectional). Following Moskowitz and Zurroff's (2004) introduction of spin, we speculate that the next intraindividual variability metric that could emerge for description of differences in interpersonal landscapes will be one that captures the multidirectionality quantified by MDS_{4s} .

Interpersonal Behavior Landscapes: Perception of Others

As with the interpersonal self landscapes, the eigenvalues (956.52, 597.60, 413.26, 88.70, 84.27) and associated scree plot of the full 150 x 150 matrix of EMDs for the perception of others landscapes suggested a classic multidimensional scaling model with four orthogonal coordinates (60.66% of the total variance, stress = .086, Mardia's goodness of fit criteria = .948, linear fit $R^2 = .951$). Similar to the MDS of the interpersonal self landscapes, the first three MDS dimensions of perceptions of partners' behavior have straightforward interpretations shown in bold in the lower triangle of Table 1; MDS_{1o} closely tracks individual differences in mean level perceptions of others' agency ($r_{MDS1o,imean.agency} = .93$); MDS_{2o} closely tracks individual differences in mean level perceptions of others' communion ($r_{MDS2o,imean.communio} = .83$); and MDS_{3o} closely tracks differences in variability of perceived agency ($r_{MDS3o,isd.agency} = .80$), spin in the circumplex space ($r_{MDS3o,ispin} = .75$), and intraindividual entropy ($r_{MDS3o,ientropy} = .68$); all again confirming the utility of the EMD-based procedure. The fourth dimension, MDS_{4o} , seems to have the same "multidirectionality" interpretation found for interpersonal behavior of self.

To illustrate additional utility provided by the EMD-based procedure for identifying typologies, we further explored the structure of individual differences in the landscapes of perceptions of others' interpersonal behavior using a clustering approach. Using an agglomerative hierarchical method, the 150 landscapes were clustered into relatively homogeneous landscapes based on the EMDs. As shown in the top panel of Figure 3, the dendrogram (based on Ward's single linkage method; Ward, 1963) suggested presence of 3 or 9 clusters. Given our purposes here (which are in part didactic) we present the more parsimonious 3-cluster solution. The three clusters of size $n_1 = 80$, $n_2 = 32$, and $n_3 = 38$ were somewhat, but not completely, distinct (average silhouette width = 0.28, within/between ratio = 0.64). Qualitative differences among clusters can be discerned from the medoid landscapes shown in the middle panel of Figure 3. *Cluster 1* is characterized by a *slightly constrained* landscape – with a density distribution that is relatively multivariate normal, sloping outward with quick tails from a centroid that is placed near the sample-level means for communion ($M = 80.24$) and agency ($M = 56.85$). *Cluster 2* is characterized by a *dispersed* landscape – with more extensive variability, particularly along the agency axis. They appear to be particularly attuned to differences in others' behavior along the submissive—dominant continuum. In contrast, *Cluster 3* is characterized by a *tightly constrained* landscape – with mass centered near the sample-level means for communion and agency, but with a much more limited range of differences in perceived behavior than the other cluster medoids.

To further validate and profile the clusters we examined whether and how the cluster groups differed with respect to our array of personality and psychological well-being variables. Results of a series of ANOVAs testing for group differences are shown in Table 2, along with indication of which group means differed significantly in follow-up TukeyHSD corrected pair-wise tests (indicated by the bold subscripts). Interpretation is facilitated by the cluster-level profile plots in the bottom panel of Figure 3. *Cluster 1 (slightly constrained)* might be further considered as “introverted”, with all scores hovering around the sample-level averages for the personality and well-being variables except for Extraversion, on which this group was significantly lower than both the other groups ($F_{2,133} = 7.95$, $p < .001$). *Cluster 2 (dispersed)* might be considered “conventional” as this group generally exhibited a profile of scores hovering around the sample-level averages. A notable characteristic is that this cluster's most distinctive score is for low Openness and it is the only cluster to score below the sample mean. Thus this cluster might be considered “conventional.” *Cluster 3 (tightly constrained)* might be described as “happy campers”. They were significantly lower than Cluster 1 in Neuroticism ($F_{2,133} = 3.46$, $p = .03$), lower than both other groups in Depressive Symptoms ($F_{2,147} = 4.64$, $p = .01$), and significantly higher than Cluster 1 in Agreeableness ($F_{2,133} = 4.08$, $p = .02$), Emotional Well-being ($F_{2,147} = 3.83$, $p = .02$), and Perceived Control (also higher than Cluster 2, $F_{2,147} = 9.76$, $p < .001$). The clusters' personality and well-being profiles generally confirm the interpretations of the interpersonal behavior landscapes. The cluster with *slightly constrained* perceptions of interpersonal behavior is a bit introverted; the cluster with *dispersed* perceptions is relatively conventional; and the cluster with *tightly constrained* perceptions is relatively warm and satisfied, if not overly in control. In sum, we hope to have demonstrated that the clustering of the EMDs of

individuals' perceptions of others interpersonal behavior landscapes provides an opportunity to identify subgroups of perceivers with distinct psychological profiles.

Discussion

In this paper, we attempted to describe individual differences in behavioral tendencies and personality – by fusing methods from social science and the study of intraindividual variability with methods from computer science and the indexing of multimedia databases. The density distribution approach to personality has promoted the use of intensive repeated measures data from daily diary and experience sampling designs to describe and quantify individuals' typical behavior *and* the range of behaviors they exhibit across multiple situations and/or occasions (Fleeson, 2001). Across domains (e.g., emotion, cognition, motivation), quantification of intraindividual variability has promoted consideration of a wide set of dynamic constructs (e.g., stability, inconsistency, flexibility, lability) as viable descriptors of individuals' personal characteristics (see Ram & Gerstorf, 2009). Generalizing from the standard description of univariate density distributions (e.g., using iSD), description of bivariate density distributions has focused on circumplex-based measures of intraindividual variability (e.g., pulse, spin, Moskowitz & Zuroff, 2004). Here, we proposed that individual differences in density distributions be quantified and studied using a more general approach based on *behavioral landscapes* and *Earth Mover's Distance (EMD)*.

We illustrated the method through analysis of intensive repeated measures data collected from 150 individuals over ~9 weeks, specifically, event-contingent self-reports of individuals' and their social partners' interpersonal behavior (communion and agency) in 64,112 face-to-face social interactions. Analysis consisted of three steps. First, each individual's ensemble of reports was collected into behavioral landscapes using nonparametric density estimation (see Figure 1). Second, individual differences between landscapes were quantified using EMD (Rubner et al., 2000; see Figure 2). Third, the resulting dissimilarities were analyzed using multidimensional scaling and cluster analysis to identify the underlying structure of individual differences in interpersonal behavior and perceptions of others' interpersonal behavior. The resulting dimensional differences were then validated with respect to traditional quantifications of intraindividual variability (e.g., imean, iSD, pulse, spin, entropy; see Table 1), and the group differences were profiled with respect to FFM personality traits and psychological well-being (see Table 2, Figure 3).

Individual Differences in Interpersonal Landscapes

The empirical results provided independent confirmation of existing representations of individuals' interpersonal behavior. We found that individual differences in the behavioral landscapes describing individuals' own interpersonal behavior and their perceptions of others' interpersonal behavior were well-captured by four orthogonal dimensions. The three most prominent dimensions map closely onto differences in individuals' (1) average level of agency ($r_s = .90$), (2) average level of communion ($r_s = .80$), and (3a) interpersonal spin ($r_s = .75$) and (3b) intraindividual variability in agency ($r_s = .75$). Key is that these dimensions emerged from a method that is relatively free of assumptions about the shape and form of the landscapes. Thus, the results add to the growing body of validity evidence supporting

these three specific features of individuals' interpersonal lives as important aspects of "interpersonal style" (e.g. Gurtman & Balakrishnan, 1998; Markey et al., 2015, Sadikaj et al., 2015, Wiggins et al., 1989).

Consistent with other experience sampling studies (e.g., Rappaport, Moskowitz, & D'Antono, 2014; Roche, Pincus, Hyde, Conroy, & Ram, 2013), differences in the extent of angular dispersion and/or dispersion along the agency dimension are features of intraindividual variability that differentiate individuals' interpersonal behavior and perceptions. Specifically, after locating differences with respect to overall levels of behavior (i.e., MDS_1 and MDS_2 map closely to iMean of agency and iMean of communion), the third coordinate in the multidimensional space also provided meaningful description of the between-person differences in iLandscapes describing individuals' own others' interpersonal behavior. In a way this suggests that the emergence of flux (in agency) and spin in the interpersonal literature is exactly right.

Of note, working from a circumplex perspective, Moskowitz and Zuroff (2004) suggested pulse and spin (intraindividual variability in distance from origin and around the circle, respectively) as a feature of individuals' interpersonal behavior. Generally, however, they have found that spin carries much more explanatory power than pulse (Côté, Moskowitz, & Zuroff, 2012; Sadikaj et al., 2015). Consistent with this trend, none of the four dimensions we identified as organizing features of individual differences among interpersonal landscapes mapped to pulse. Rather, the dimensions identified here are consistent with interpersonal theories of development and attachment (Benjamin, 2003, Florsheim & McArthur, 2009; Horowitz, 2004; Pincus, 2005) which argue that Western culture socializes children to be rather consistently warm and kind (communion) and to vary in terms of leading, sharing power, and following (as would be captured by iSD of agency and spin).

The results of our EMD-based analysis of individual differences in interpersonal landscapes point towards the potential importance of a not-yet described feature of intraindividual variability of interpersonal behavior and perception. Although the fourth coordinate of the multidimensional scaling solutions may just be residual noise, we also speculate that the dimension may capture a kind of "multidirectionality". As shown along the diagonal in Figure 2, individuals with high scores on this dimension have landscapes that are characterized by "ridges" (unidirectional) while individuals with median scores have landscapes characterized by a "single hill" (outward directionality) and individuals with low scores have rough landscapes with slopes that run inward, outward, and parallel to both x and y axes (multidirectional). While additional data and analyses are needed to confirm the presence and utility of this dimension of individual differences, our speculative hypothesis is that the newly identified "multidirectionality" dimension of interindividual differences may describe the extent of differentiation in individuals' interpersonal lives – either through deployment of behavioral sets across situations (see Gurtman, 1999), or exposure to an array of qualitatively different social situations. It will be informative to check its relation to markers of pathoplasticity (Wright et al., 2009) and social diversity (Ram et al., 2012) as indicators of enactment of many qualitatively different behavioral sets or exposure to many qualitatively different social situations. In sum, we identified four dimensions underlying differences in interpersonal behavior landscapes. Three of these dimensions map to features

already being elaborated in the literature – average level of agency, average level of communion, and interpersonal spin. The fourth dimension may provide for additional description and understanding of how interpersonal processes contribute to whole trait theory and the explanation of personality traits (Fleeson & Jayawickreme, 2015).

In addition to illustrating the utility of EMD for obtaining the dimensions along which individual differences in behavioral landscapes are organized, we also illustrated how the EMDs can be used to identify a typology of landscapes. Cluster analysis of the landscapes based on perceptions of others' interpersonal behavior revealed three somewhat distinct types of landscapes that we described as *slightly constrained*, *dispersed*, and *tightly constrained*. To validate and profile these clusters we examined how they differed on the FFM personality traits and well-being variables. Notably, the *slightly constrained* group was distinguished by lower average Extraversion, a dimension with clear interpersonal relevance (McCrae & Costa, 1989; Wiggins & Trapnell, 1996). In line with the propositions of whole trait theory, the identification of this cluster using EMD-based, “bottom-up” procedures clearly provides a window for exploring how interpersonal processes manifesting in daily social interaction contribute to the explanation of personality traits (Fleeson & Jayawickreme, 2015). Similarly, the cluster with tightly constrained perceptions of others' interpersonal behavior had a profile distinguished from the other groups by lower depressive symptoms, lower neuroticism, higher perceived control. This profile matches known associations between neuroticism and constrained variability (e.g., Block, 1961), and also implies that individuals who can, or believe they can, control their lives indeed perceive almost all their interaction partners as warm and not particularly submissive or dominant. It is not clear whether this cluster of people are good at selecting or creating prototypically healthy interpersonal relations, are lucky in rarely being confronted with difficult interpersonal situations, or consistently see others through rose-colored glasses. Regardless, the findings illustrate how the EMD-based approach may be used to identify distinct groups of individuals with interesting and meaningful profiles. The illustration here highlights the potential for using the approach to understand of how daily behaviors accumulate to influence long-term health and well-being, as well as to develop tailored behavioral interventions.

The Earth Mover's Distance Based Approach

Detailed mathematically above, density distributions are often described by calculation of distributional parameters that are person-specific, including iMean, iSD, pulse, spin, and iEntropy. However, many researchers have noted that empirical density distributions rarely conform to the statistical assumptions on which these calculations are based (Ram et al., 2013; Sadler et al., 2015; Thomas et al., 2014). Thus, these metrics may not be able to capture some of the most interesting features of the rich data now flowing in from digital interfaces (e.g., experience sampling studies). Taking the “personality as density distributions” conception literally, we have worked from the bottom up to identify individual differences in personality directly from the raw data. In particular, we obtained each individual's density distribution using smoothing methods that retain many of the hills and valleys in the raw data. The result is *asymmetric* landscapes that resemble real-world

geography and our journey into methods that might be used to describe and quantify the innumerable differences in the location, size, and shape of the “landforms”.

EMD is General—Dissatisfied with the transfer of basic geographic classification systems to behavioral landscapes (see Ram et al., 2013), we happened upon the intriguingly named *Earth Mover’s Distance* metric that is used for fast indexing and retrieval of images in multimedia databases. EMD is a very general quantification that can be used to obtain distance between single elements (e.g., scores on a single variable), sets (e.g., scores on multiple variables), histograms (e.g., raw data), and multivariate distributions (e.g., RGB color distributions), has a bounded minimum, and allows for partial matches (Rubner et al., 2000). The generality of the metric is what has made it so popular in computer science applications.

In this initial exploration of the utility of EMD for study of individual differences in behavioral landscapes we applied the procedure to intensive repeated measures data (~425 observations per person) obtained using modern, smartphone-based experience sampling methods. EMD provided quantification of between-person differences among 150 well-defined density distributions located in the 2-d interpersonal circumplex space (communion x agency), and facilitated examination of how those differences were related to traditional intraindividual variability metrics, FFM personality traits, and psychological well-being. We note explicitly, that although the interpersonal framework considers agency and communion as a minimally multivariate space with two orthogonal dimensions, this is not a requirement for application of EMD. EMD generalizes to n -dimensional space (with orthogonal or oblique dimensions), and thus can be applied in settings where behaviors are measured in relation to many dimensions. For example, EMD might be used to quantify differences in the density distributions of 5+ dimensional density distributions available in studies that have obtained many moment-to-moment or day-to-day assessments of personality (emotional, interpersonal, cognitive, etc.) states (e.g., Baird et al., 2006; Borkenau & Ostendorf, 1998; Fournier et al., 2009).

From what we can tell so far, EMD-based analyses will provide a general method that can support empirical integration of personality structure and dynamics (Hopwood, Zimmerman, Pincus, & Krueger, 2015), or, as outlined in the presentation of whole trait theory (Fleeson & Jayawickreme, 2015), more holistic and precise description of traits (as multivariate density distributions). Contemporary advances in the computational efficiency of EMD provide the ability to describe individual differences in n -dimensional landscapes for large samples of persons. Monitored in real-time, one can imagine experimental and observational designs that track how EMD-based differences result from direct manipulation or observation of the interpretative, motivational, stability-inducing, temporal, and random error processes that make up the explanatory part of traits. For example, EMD-based differences may be useful to empirically test the evocation and impact of an array of cognitive-affective units (CAUs) on situation feature detection and behavioral activation based on the Cognitive-Affective Processing System (Eaton, South, & Krueger, 2009; Mischel & Shoda, 2008; Wang et al., 2014). The possibilities are endless, and of course reach across many types of behavioral tendencies.

Cautionary Notes—Our articulation of behavioral landscapes was facilitated by a study design that obtained many reports from each individual ($M_{numobs} = 427.4$, $SD = 145.7$) using a slider-type interface that converted responses to -50 to $+50$ scale. The density of data and continuous scale provide for robust description of the bivariate distribution of interest, without having to make assumptions on the functional form of the distribution. That is, the sampling design provides for a wide variety of irregular shapes to emerge in the behavioral landscapes. In contrast, designs with relatively few assessments and with categorical response scales (e.g., 5-point scales) would severely limit description of the distributions and discovery of individual differences. For example, with less than 100 repeated measures it may be necessary to make an a priori assumption about the shape of the density distribution (e.g., that the distribution is Gaussian). Introducing assumptions allows for use of “smaller” data, but constrains discovery. Similarly, the extent of smoothing used in the nonparametric kernel density estimation matters. When and how person-level and/or group-level standardization of band-width and bin-size parameters are incorporated into the analysis implicitly make assumptions about how much “noise” is in the data.

We introduced “measurement invariance” into the assessment and estimation of the density distributions by using a single item for each dimension and applying the same level of smoothing to each person’s data. Alternative procedures will prioritize different types of individual differences. For example, we could have centered each individual’s data (iMean of communion = 0; iMean of agency = 0) before estimating the density distributions – a “pre-processing” step that would remove individual differences in location of the landscapes and shift priority towards differences in size and shape. Working from a conceptual framework that considers relative levels communion and agency as important between-person differences (Pincus & Ansell, 2013; Wiggins, 1991) we chose to retain the original scaling, but highlight that analysis of pre-centered data would start interpretation of the MDS solutions at a different place (with a dimension very close to what was labeled here as MDS_3).

Of note, EMD requires explicit definition of the ground distance, $\mathbf{D}$, which is essentially the cost associated with moving “earth”. We tethered these costs directly to the original -50 to $+50$ scale; a decision that implicitly placed equivalent weight on movement in the horizontal direction (along x -axis) and in the vertical direction (along y -axis). However, this need not be the case. Different kinds of moves could be paired with different costs. For instance, changes in warmth may be easier to evoke than changes in submissiveness (e.g., Cain et al., 2012; Maling, Gurtman, & Howard, 1995; Ruiz et al., 2004). Pushing further, we could formulate the ground distance so as to use EMD to prioritize quantification of specific types of individual differences (e.g., by defining complementarity of dominance/submissiveness (Sadler, Ethier, & Woody, 2011) directly into the structure of $\mathbf{D}$). From a methodological perspective, specification of ground distance, cost structures, and similarity transforms (e.g., replacing bulldozer pushes with a different action) within an EMD-based approach is wide open and ripe for elaboration (see e.g., recent work on finger-EMD; Ren, Yuan, & Zhang, 2011).

Behavioral Landscapes to Dynamic Systems

The behavioral landscapes we have presented are quite similar to the graphical representations used by dynamical systems theorists to represent the “flow” of behavior over time (e.g., Thelen & Smith, 1994). Of note, the construction of density distributions and behavioral landscapes typically treats all the repeated measures obtained from any given individual as independent observations. For example, note that the formulas for calculation of iMean, iSD, pulse, spin, and entropy make no claims about, or accommodation for, time-dependencies. All these metrics are based on an assumption that the repeated measures are independent and identically distributed (see Ram & Gerstorf, 2009 for further elaboration of this point). As such, the metrics do not describe the *dynamics* of behavior, only the *distribution* of behavior. The ensemble of assessments (black dots in Figure 1) indicate where people live, but provide very little information about how the distributions form. A next step in the examination of behavioral landscapes is to explicitly incorporate how a person moves from one area of the space to the next.

Consider again the landscapes along the diagonal of Figure 2. Flipping them upside-down, we obtain a surface like those often used to illustrate behavioral tendencies in the dynamic systems literature (see e.g., figures in Nowack & Vallacher, 1998; van Geert, 1998). If one dropped a marble on the upside-down landscape it would roll around and eventually settle into deepest wells – the “attractors” and equilibriums where behavior tends to go (Gernigon, Vallacher, Nowak, & Conroy, 2015; Thelen & Smith, 1994). The implication is that, when we can supplement the density distributions with information about the direction, velocity, and acceleration with which a person is traveling, an EMD-based approach might provide for easy identification and quantification of individual differences in *behavioral dynamics* – for instance interaction-to-interaction changes as individuals engage complementary interpersonal behavior (Carson, 1969; Kiesler, 1983; Sadler et al. 2009). Further, recall that the calculation of EMD provides us with both the distance between two landscapes and the pattern of flows that transform one landscape to another with minimum cost. In a clinical setting that means we have the possibility to identify the specific actions needed to “move” a problematic behavioral repertoire towards a desirable one (e.g., Anchin & Pincus, 2010; Cain & Pincus, 2016; Callahan, 1982; Hopwood, Pincus, & Wright, in press). To the extent that individuals’ behavioral landscapes are changeable, the EMD flows might be used to design interventions that transform unhealthy landscapes into healthy landscapes efficiently, and with the least cost. Certainly, much work must be done before we can predict when and how specific behavioral and cognitive levers will change an individual’s behavioral landscape, and why some of those changes will be temporary and some permanent. Optimistically, as we hope to have demonstrated here, the data collection and analytical infrastructures for that work are emerging.

The use of intensive longitudinal, diary, and ecological momentary assessment designs to collect time-series data is in full swing (Mehl & Conner, 2012). We can now obtain detailed and context-specific descriptions of individuals’ behavioral landscapes. This paper introduced and illustrated a new analytical approach, based on *Earth Mover’s Distance*, to quantify and examine individual differences in behavioral landscapes without presupposing their shape and form. We confirmed the relevance of the traditional quantifications of

intraindividual variability that have served as the core of the density distributions approach to personality, and identify possible avenues for further inquiry – namely metrics that capture “multidirectionality”. As the density of available data increases we hope that the EMD-based approach forwarded here might contribute to the integration of personality structure and dynamics, an area of much needed development in personality and clinical science (Hopwood et al., 2015; Krueger, 2013; Revelle & Condon, 2015).

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Figure 1. Self-reports of one individual’s interpersonal behavior across $T = 443$ social interactions. Panel A depicts the Cartesian-space measures of *iMean* and *iSD* (flux) on the communion and agency dimensions. Panel B depicts the Circular/Polar-space measures of *pulse* (variability in distance from origin) and *spin* (variability in angular space). Panel C depicts the location-based measure of *entropy* as the size of the “island”. Panel D depicts the *behavioral landscape* as a nonparametric density surface where the height indicates the density of observations at each location.

Figure 2. Earth Mover's Distance

is the minimum amount of work needed to transform one behavioral landscape into another. Three individuals' behavioral landscapes are shown on the diagonal. The EMD between each pair of landscapes is depicted in the off-diagonals, numerically, and as the amount of mass that must be moved from the "piles" above the surface into the "holes" below the surface.

Figure 3. Cluster analysis of EMDs for landscapes based on perception of others' interpersonal behavior. Top panel: Dendrogram of agglomerative process (Ward's method) indicating parsimonious 3-cluster solution. Middle panel: Contour plots of the behavioral landscapes for the medoid person for each of the three clusters (1 = *slightly constrained*, 2 = *dispersed*, 3 = *tightly constrained*). Bottom panel: Cluster group profiles on FFM personality and psychological well-being variables. (1 = *average but introverted*, 2 = *average*, 3 = *very healthy*).

Descriptives and interrelations among the intraindividual summaries, and EMD-based quantifications of the behavioral landscapes – Interpersonal Behavior: Self (upper triangle) and Perception of Others (lower triangle).

Table 1

Interpersonal Behavior: Self												
	iMean, Communion	iMean, Agency	iSD, Communion	iSD, Agency	iPulse	iSpin	iEntropy	MDS1	MDS2	MDS3	MDS4	Sample Mean, Self
												Sample SD, Self
iMean, Communion	--	0.01	-0.40	0.17	-0.36	-0.56	-0.41	0.36	0.80	-0.21	0.11	81.92
iMean, Agency	0.05	--	0.05	0.08	0.13	-0.06	0.07	0.91	-0.37	0.04	0.04	55.26
iSD, Communion	-0.29	0.10	--	0.42	0.84	0.81	0.77	-0.11	-0.22	0.62	0.40	11.00
iSD, Agency	0.12	0.24	0.53	--	0.44	0.58	0.67	0.18	0.44	0.78	-0.08	13.41
iPulse	-0.28	0.14	0.78	0.48	--	0.71	0.77	-0.02	-0.22	0.58	0.21	9.50
iSpin	-0.62	-0.01	0.76	0.54	0.63	--	0.85	-0.24	-0.22	0.80	0.18	0.48
iEntropy	-0.45	0.12	0.77	0.67	0.77	0.82	--	-0.05	-0.09	0.72	0.02	5.04
MDS1	0.33	0.93	0.04	0.36	0.08	-0.12	0.07	--	0	0	0	0
MDS2	0.83	-0.3	-0.2	0.27	-0.23	-0.40	-0.24	0	--	0	0	0
MDS3	-0.14	-0.07	0.66	0.80	0.51	0.75	0.68	0	0	--	0	0
MDS4	0.09	0.06	0.40	0.01	0.32	0.07	0.11	0	0	0	--	0
Sample Mean, Other	80.24	56.85	12.84	14.58	10.06	0.56	5.21	0	0	0	0	0
Sample SD, Other	8.87	9.44	4.68	6.61	2.75	0.25	0.52	2.53	2.00	1.67	0.77	0.77

Note: N = 150. iMean = intraindividual mean, iSD = intraindividual standard deviation (flux). MDS1, MDS2, MDS3, MDS4 are coordinate scores from multidimensional component solutions. Relations with highly similar intraindividual variability metrics shown in bold.

Table 2

Mean Differences Among 3 Clusters Identified for Interpersonal Landscapes: Perception of Others.

	<i>F</i> (2,147)	<i>p</i> -value	Cluster 1 (<i>n</i> = 80)		Cluster 2 (<i>n</i> = 32)		Cluster 3 (<i>n</i> = 38)	
			<i>mean</i> (<i>sd</i>)		<i>mean</i> (<i>sd</i>)		<i>mean</i> (<i>sd</i>)	
Neuroticism [#]	3.46	.034	2.49 (0.74) ₃		2.48 (0.67)		2.12 (0.72)₁	
Extraversion [#]	7.95	.001	3.41 (0.54)_{2,3}		3.73 (0.59) ₁		3.82 (0.54) ₁	
Openness [#]	1.70	.186	3.52 (0.62)		3.30 (0.64)		3.57 (0.61)	
Agreeableness [#]	4.08	.019	3.82 (0.47) ₃		3.87 (0.53)		4.11 (0.51)₁	
Conscientiousness [#]	1.88	.157	3.87 (0.56)		3.97 (0.63)		4.10 (0.57)	
Depressive Symptoms	4.64	.011	10.76 (7.15) ₃		11.44 (8.11) ₃		6.95 (5.94)_{1,2}	
Emotional Well-being	3.83	.024	23.19 (2.50) ₃		23.35 (2.80)		24.55 (2.46)₁	
Life Satisfaction	2.49	.087	5.57 (0.83)		5.46 (1.10)		5.90 (0.83)	
Perceived Control	9.76	.001	4.97 (0.84) ₃		5.01 (0.91) ₃		5.68 (0.80)_{1,2}	

Note: *N* = 150. *F*- and *p*-values from overall ANOVA test. Significant group contrasts with Tukey HSD correction are indicated by **1,2,3** for each cluster group; subscript indicates which groups the current group is different from. Pattern of group differences also shown in Figure 3. *sd* = standard deviation for group.

[#] overall ANOVA of the FFM personality variables with *F*(2,133) due to reduced sample size at the single-occasion NEO-FFI administration (cluster sizes of 72, 28, and 36, respectively). Prominent differences in group profiles shown in bold.