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Individual and Joint-Level Properties of Personal Project Matrices: An Exploration of the Nature of Project Spaces

By

Travis Lloyd Gee

A thesis submitted to
the Faculty of Graduate Studies and Research
in partial fulfilment of the requirements
for the degree of
Doctor of Philosophy

Department of Psychology
Carleton University
Ottawa, Ontario
February 28, 1998

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submitted by

Travis Gee

in Partial fulfillment of the requirements for
the degree of Doctor of Philosophy

Chair

External Examiner

Thesis Supervisor

Carleton University
April, 1998

For Dad & Maury

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Abstract

Personal Projects Analysis (Little, 1983) is becoming an established measurement tool for the examination of the activities of everyday life, and has taken root in the field of personality. However, research to date has not taken full advantage of the information contained in PPA data matrices. Specifically, the Project Space is proposed as a subset of the general Personal Construct System (after Kelly, 1955). In this dissertation, methods which take advantage of multidimensional scaling techniques are proposed as a viable way to study single-case (often called "ipsative") PPA data. Indices from single-case analysis are related indirectly to enduring personality factors measured by the NEO-PI (Costa & McCrae, 1985; Costa & McCrae, 1997) by way of project content category. The reliability of individual Project Spaces is assessed and appears at first blush to be quite good. However, it is suggested that due to the very clear presence of a joint Project Space that is invariant across groups, time, choice of similarity coefficient and random re-arrangement of projects into "synthetic project systems," the reliability is an artefact, and broader generalizations can be made about the structure of the Project Space. These generalizations are discussed in the context of various theoretical models that have been proposed for PPA data at the normative, project-system level. We then return to three case studies which illustrate single-case methods. While it would appear that there is not much room for individual differences in Project Spaces, the clinical utility of the methods proposed for studying ipsative PPA data is an area for future research, which will be subject to constraints identified in the present work.

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Introduction

A fundamental problem for psychologists is knowing where exactly to start. Clinical psychologists may start with a single case, but in applying rules that are derived from their knowledge of people in general, they contradict the assertion that they are primarily concerned with that person. This is because their most reliable knowledge of people in general arises from research based on groups of people. Thus, when this knowledge is used to deal with a single case, we are left with the now-hidden assumption that this person is fundamentally like other people, and can be dealt with in ways that have been shown to be efficacious when applied to other people.

This assumption is probably partly true, and partly false. It is true to the extent that a person is similar to others, and false to the extent that he or she is truly unique. The vast majority of empirical literature in psychology has a habit of treating the former similarity as systematic variance, and the latter as error, due in large part to statistics that require us to do so. There are, however, other ways of conceptualizing data which permit a reversal of classical approaches. The widely-ignored “error variance” attributable to individuals’ uniquenesses may contain identifiable components of its own. Rather than starting with what is systematic across persons and discarding this component, we can start with what is unique about each individual, and worry about normative variance later. After all, if classical error variance is truly unrelated to classical systematic variance, then the study of the two phenomena should also be unrelated. What does it matter whether we identify “normative” sources first, or start with idiosyncratic sources, so long as they add up to 1.0?

These considerations are particularly important in the field of personality psychology which has traditionally been psychology’s Department of Adjectival Ascriptions, whose office it is to summarize the ways in which people differ and proffer labels for groups that differ in systematic ways. While recent work on the Big Five dimensions of Neuroticism, Extraversion, Openness, Agreeableness and

Conscientiousness (McCrae & Costa, 1996) has shown that people do vary along identifiable dimensions, the basic approach is no different than past approaches in terms of the way in which people are defined relative to others. Agreement or disagreement with various elements of a large set of common items establishes one's point in what amounts to a 5-dimensional space.

An alternative conceptualization is based on the ways in which people structure and interpret the events in their everyday lives. That conceptualization is Little's (1983, 1987, 1989) Personal Projects Analysis, the basics of which are sketched in Chapter 1, which presents a brief theoretical review of PPA and discusses its' deeper theoretical roots in the Personal Construct Theory of George Kelly. Chapter 2 covers general issues in reliability as classically defined, and with respect to newer definitions that suit single-case analysis. In Chapter 4 the results of some preliminary analyses are presented based on a single case. These results were obtained not only to provide some examples of the analytical approaches to be taken in the main study, but also to establish some of the parameters to which the main results must conform. Chapter 5 describes the data that are available for analysis, and presents a broad overview of the analytic strategy that was used in the main part of the study. Chapter 6 presents details of the approach taken in exploring the general properties of individual Project Spaces, and Chapter 7 establishes that these spaces appear to be reliable across time and over different projects, thereby making a very good case for the presence of a more general Project Space that is shared by English-speaking individuals (at the very least) and possibly people from other linguistic and cultural groups. The nature of this "joint space" is elucidated in Chapter 8, and its relationship with several theoretical models is detailed in Chapter 9. Chapter 10 returns to the analysis of single cases with an eye towards generating some more useful hypotheses for future research. A general discussion reviews the work, the significance of the results, flaws and possible future directions in Chapter 11.

Chapter 1: Towards an Integrative Model for Measurement

In this chapter, the theoretical basis of PPA is set forth, and the Kellian roots of this fruitful tree are laid bare. The idea of the “Project Space” as a subspace of Kelly’s (1955) “Personal Construct System” is delineated with reference to certain propaedeutic criteria that Little (1989) has set forth for the measurement of individuals.

Personal Projects Analysis

The most interesting and informative human narratives are almost invariably goal-driven. While fueled by the desire to attain (or maintain) some final state, these stories are as ships on a rough sea, tossed by the vagaries of the circumstances of the settings in which they unfold and steered by a more or less determined skipper. To navigate the social and ecological shoals of their particular civilization and make progress towards the distant harbour requires that one have some kind of map. That map may be one of the captain’s own design, one handed to him or her by an authority figure, or one made up along the way. It may be detailed or ambiguous, colourful or colourless, simple or complex. There may be no map at all or worse, the map may be of the wrong waterway, or of an indeterminate scale!

Working from a basis in Kellian theory (Kelly, 1991/1955), Little (1983, 1987, 1989) has evolved an approach to mapping out our “extended sets of personally relevant action” (Little, 1989, p. 15) which he terms ‘personal projects.’ In this definition, extension can be read as meaning both physical and temporal extension, but the extent of either kind of extension is not prescribed. Thus, a short trip to the grocery store and an afternoon spent reading a book both qualify as projects. Likewise, personal relevance merely implies that the project has found its way into the system of activities in which the person is engaged. It does *not* imply a great deal of importance, or that a given person likes or is rewarded by a given project. We can therefore subsume both climbing Mt. Everest and cleaning the neighbour’s cat’s litter box under the “personal projects”

heading, although the relative importance, attraction and reward of these two diverse examples will be a function of many other variables. As well, action can imply physical or cognitive action. "Obsessively thinking about X as a means of avoiding doing Y" is as much a project as "Compulsively doing A to avoid thinking about B."

The coherence (or lack thereof) within an individual's system of personal projects may not be immediately apparent to a researcher. However, it may well be clarified by examining the way that person construes the projects in the system. Understanding such regularities as may exist in an individual's way of construing his or her projects may well lead to valuable predictions about how that individual will respond to novel projects, or to deletion of existing projects, and how this individual might differ from others who face similar problems. Furthermore, understanding the extent to which individuals share common ways of construing may lead to practical methods for managing project systems which are more generally applicable. Of equal importance is our understanding as psychologists of the fact that dimensions that are salient to us may be irrelevant to the person in whom we are interested!

Little's (1976, 1983, 1987, 1989, 1993, in press) Personal Projects Analysis (PPA) assumes that such differences in construing are attributable to different understandings of the world which arise from different experiences. This assumption has lead to many productive lines of research on related Personal Action Construct (PAC) units such as Life Tasks (Cantor, 1990) and Personal Strivings (Emmons, 1986). Personal Projects have been linked to a number of other psychological constructs such as well-being (Omodei & Wearing, 1990; Salmela-Aro, 1992; Salmela-Aro & Nurmi, in press; Yetim, 1993), hypochondriasis and somatization (Karoly & Lecci, 1993), addictive behaviors (Karoly & McKeeman, in press) and emotion (Emmons & Diener, 1986).

PPA data typically consist of 10 projects in which the assessee is currently engaged, which are rated on approximately 17 features of projects (e.g., Importance, Stress, etc.) using an 11-point rating scale (from zero to 10). These features are commonly termed "dimensions" in standard PPA literature, but to avoid confusion with

the technical usage of “dimension” in multidimensional scaling (MDS) the term is reserved for the latter usage in this work.

The PPA methodology ordinarily produces a single 10x17 matrix of data, which may contain further qualitative information about the nature of the project, the usual place where the person works on it, the person or people with whom it is ordinarily carried out and nonstandard features that have been deemed relevant to the research question at hand. A sample PPA data collection form completed by myself is provided in the Appendix. In the correlation matrix derived from those data, the gross multivariate structure of the 17 features is laid bare, and cursory examination shows that the patterns are far from random. There is thus some kind of a “space” in which those features operate. At the very least, the process of completing the PPA form is assumed to tap into the basic underlying features which form the basis for an individual’s appraisal of his or her projects. It is plausible that there is even information about how the person generates hypotheses about new projects.

The Project Space

This latter question of whether the topography of this space guides an individual in the anticipation of aspects of their personal projects or merely reflects current appraisals is an interesting one. However, the issue of generativity versus reflection cannot begin to be answered until we have considered the structure and stability of what we shall term “Project Spaces.”

If a set of intercorrelations among project features for a given individual is relatively stable, then it can be argued that the way in which individuals anticipate their projects is a characteristic of that person on the same conceptual footing as other personality variables. The case for the generative Project Space would be supported (but not proved) by such a finding. If, however, it is *unstable*, then while it is arguable that the Project Space reflects current realities, it *cannot* function as a viable generator of hypotheses. If much of what we view as personality can be shown to be embedded in the way a person typically anticipates the ways of the world, then the fundamental reorganization of the Department of Adjectival Ascriptions is in order.

There are many sources of information about an individual's current perceptions of his or her present situation in the PPA matrix. An estimate of the total stress arising from projects can be obtained from the STRESS feature, as can measures of the level of ENJOYMENT involved in current projects, and so on. Means on these and many other project features have a distinctive factor structure across subjects (Little, 1988), and the qualitative variables offer direct clinical applications. However, while system-level patterns of association among the various features used in PPA have been explored, the study of within-case patterns has not. To redress this, I propose that we develop an integrative approach to measurement that exploits the ability of PPA to access a person's project system at different levels.

Personal Projects and Shared Meanings

The use of personal projects permits us to tap into many levels of meaning. Anyone who has ever had to explain a dissertation topic to an acquaintance not in his or her field is aware of the fact that one's most vital and interesting project may seem quite meaningless to at least *some* other people. At another level, the simplest of statements can carry a wealth of meaning. If a beleaguered graduate student responds to the question "How are you?" with a haggard expression and a simple "The kids are sick," knowing glances can convey the centrality and stressfulness of the implied projects, and their deleterious impact on other areas of concern. Thus, it is essential that we work from a model that can capture and integrate both broad generalities and peculiar idiosyncracies.

George Kelly's (1991/1955) Personal Construct Psychology is the key intellectual ancestor of PPA. His model of "man the scientist" implied directly the need to understand the systems of constructs that are applied by the individual in the guidance of everyday actions (see Wiggins, Renner, Clore & Rose, 1971). His model focused very heavily on the social world and the personal constructs that are used to anticipate the

The Eleven Corollaries of Kelly's Fundamental Postulate

1. The construction corollary: a person anticipates events by construing their replications.
 2. The individuality corollary: persons differ from each other in their construction of events.
 3. The organization corollary: each person characteristically evolves for his convenience in anticipating events, a construction system embracing ordinal relationships between constructs.
 4. The dichotomy corollary: a person's construction system is composed of a finite number of dichotomous constructs.
 5. The choice corollary: a person chooses for himself that alternative in a dichotomized construct through which he anticipates the greater possibility for extension and definition of his system.
 6. The range corollary: a construct is convenient for the anticipation of a finite range of events only.
 7. The experience corollary: a person's construction system varies as he successively construes the replications of events.
 8. The modulation corollary: the variation in a person's construction system is limited by the permeability of the constructs within whose range of convenience the variants lie.
 9. The fragmentation corollary: a person may successively employ a variety of construction subsystems which are inferentially incompatible with each other.
 10. The commonality corollary: to the extent that one person employs a construction of experience which is similar to that employed by another, his processes are psychologically similar to those of the other person.
 11. The sociality corollary: to the extent that one person construes the construction processes of another, he may play a role in a social process involving the other person.
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Figure 1: Corollaries of Kelly's Fundamental Postulate

actions of others. However, there was nothing in his approach that prohibits Kellian methods from being used to understand other constructs that are used for other purposes.

Kelly asserted his fundamental postulate thus: *"A person's processes are psychologically channelized by the ways in which he anticipates events."* (Kelly, 1991/1955, p. 32). From this postulate, he derived a set of corollaries which are summarized in Figure 1. In Kelly's view, they fail to successfully anticipate events. However, pathological situations can arise when the way in which people anticipate

events parallels the way in which scientists make predictions: a construct or set of constructs are used to make predictions about the world, and are then tested against experiences. The constructs are revised according to their utility in making good predictions. Ideally, unworkable construct systems are revised or rejected when individual clings to invalid or irrelevant constructs in the face of evidence that change is needed. Anxiety arises from the perception of the need for changes to the construct system - especially the core constructs of that system, and guilt lies in actions that are discrepant with the position that has been carved out for the self in the overall system.

From this very simple overview of some of the key features of Kelly's model, we can see that he appreciated the extent to which individuals continually interact with the immediate environment to create ever-deeper understandings. Cognitions, in the form of personal constructs operate to apprehend the full complexity of the ecological setting, and are applied when required. Experience informs the conclusion about the usefulness of the construct for prediction. Affective reactions to changes are assumed to operate at one level in giving valence to the outcomes of predictions, and at another level where they may block necessary changes to the construct system.

Kelly (1991/1955) relied upon the elicitation of personal constructs through the comparison of individuals known to the respondent (who comprised the "elements" in a Repgrid). "Triadic elicitation" involved the generation of two poles of a dichotomous construct by identifying some way in which two elements differed from a third. For example, Joe and Dad might be "hard-nosed" and Alicia might be "a softie." The methods used made it rather unlikely that any two people would generate a comparable set of either elements or constructs.

It is apparent that this approach is very general, and incautiously followed, may devolve into a solipsistic constructivism in spite of Kelly's insistence on the reality of the events we are trying to predict (McCoy, 1975). However, Kelly never excluded any manner of construable entities (such as personal projects) from the Repgrid, nor did he insist that constructs are intrinsically personal and unshareable amongst many people. He realized that communication is only possible to the extent that people are able to

partake of the constructs used by others. Indeed, current Personal Construct Theory (PCT)-based research on knowledge acquisition depends on the ability to order various interpretations of events according to their usefulness in generating predictions about the world (Bradshaw, Ford, Adams-Webber & Boose, 1993). Assuming an objective universe around which individuals construe with greater or lesser degrees of accuracy permits us talk simultaneously about both common and idiosyncratic elements and constructs. With these distinctions in mind, we may re-construe some existing research, and place PPA in relation to PCT as part of a 2x2 table (see Figure 2).

		Elements	
		Idiosyncratic	Common
Constructs	Idiosyncratic	Personal Construct Theory, following Kelly (1991/1955)	Repeated measures studies, e.g., Widom (1976).
	Common	PPA as developed by Little (1987)	PCT as used by Krackhardt (1990)

Figure 2: PPA in relation to PCT

Kelly's focus was on idiosyncratic construct systems, derived from the construal of idiosyncratic sets of elements. Other researchers (e.g., Krackhardt, 1990) have looked for constructs which are shared among members of a particular setting by exploring common elements of their setting. Furthermore, an important part of cognitive modeling research is the unique perspectives on shared elements that each individual brings to an area (Gaines & Shaw 1992). In the upper right cell, idiosyncratic construing of 30 common situations (i.e., elements) under two different instruction sets to the same "psychopath" has been used to examine discrepancies from how other people are perceived to construe the same situations (Widom, 1976).

Conventional PPA falls into the remaining cell of our 2x2 table, that of common constructs applied to idiosyncratic elements. Projects are the elements of the grid, and

are equally idiosyncratic and personal. However, a set of common constructs is used in place of idiosyncratically generated ones. As well, dichotomous polar opposites are abandoned in favour of features that have an assumed underlying (at least) monotonically ordered continuum. This makes it possible to access multiple levels of analysis in a way which is not possible when both constructs and elements are free to vary. We thus find it necessary to underscore that the Personal Construct System is a much larger space than what Kelly was able to explore in his lifetime¹. We can widen our scope by extending the elements from other people to our own projects, and yet at the same time we can narrow our focus to constructs commonly used by many people when construing their personal projects. It is in this sense that we consider the Project Space as a sub-region of the Personal Construct System. However, this study is the first to explore the extent to which that sub-region is genuinely idiosyncratic.

The study of subsets of constructs that are common to many, and whose range of convenience extends beyond the construal of other people may also afford us insight into the patterns of interaction that arise among people. One individual might find, for instance, that important projects tend to generate a lot of stress, while less important projects are less stressful. Another individual may construe the world in the opposite direction, and mutual understanding amongst these people may well be impaired by this (see Corollary 10 in Fig. 1). Understanding the nature of these differences among individuals could well set us on a path towards explaining many of the difficulties that can arise in various settings.

A Social Ecological Model

Kelly's appreciation for the settings in which individuals find themselves and the sense that they make of those settings is reflected in the work of Little & Ryan (1979), who asserted their own fundamental proposition: "*Human development comprises a series of interdependent adaptations between persons and their environments, involving both contemporaneous and delayed effects.*" (p. 274). Their second proposition, that environments comprise social and material aspects which act individually and as systems to influence human development, leads to an explicitly Kellian third proposition: that

personal systems (including Project Spaces) arise out of “canalization” that is attributable (to some degree) to the effect of environmental systems. Thus, while personal processes may be channelized in a Kellian way, the processes themselves are subject to the canalizing influences of the local ecosystem. These factors may be social, legal, economic, climatological or from any of a broad array of other sources of influences.

This perspective has implications for measurement. From a social ecological perspective, it is clear that the units of traditional psychometric approaches fail to capture certain basic facts about human reality. Little (1989) has argued that if we assume human conduct to be “*subject to systemic influences of both an intentional and contextual nature*,” there are clear implications for the units that are selected to operationalize facets of personality (1989, p.16). These implications have led to the formulation of a set of propaedeutic criteria for measurement, several of which are centrally related to the present study.

Propaedeutic Criteria for Measurement

Little (1989) outlines a set of ten propaedeutic measurement criteria which underlie personal projects analysis. Of these, six are detailed in this section, as they are of particular importance to the present study. They are personal saliency, ecological representativeness, the need for ipsative and normative levels of measurement, integrative units, temporal extension, and modularity.

PERSONAL SALIENCY

The personal saliency criterion requires that the units be expressed in the idiosyncratic language of the respondent, instead of such language as the researcher sees fit to use. This may or may not result in discernible differences of project content. However, it will have marked impact on the ratings for the project. Consider a familiar example. Jane and Evelyn are taking an advanced-level statistics course. They may even sit next to each other every week. Both might list the cryptic course code “PSY49.300” as a project when asked what they are doing. However, Jane is taking the stats course to get a credit and graduate, hoping never to see sigma notation again, while Evelyn plans

on a career in multivariate behavioral research. The apparent similarity of their projects is extremely superficial, and will not necessarily be reflected in the ratings given to the projects. Consider that the meaning of PSY49.300 to each woman may be entirely different in spite of the fact that both labeled it as such on their PPA rating forms. This illustration underscores how the loss of precision in the expression of the unit is exchanged for a gain in fidelity of measurement on the various features to which the unit is analytically subjected. This is, of course, a logical problem at this point which may be moot if project content actually does not vary as markedly as is possible.

PPA nevertheless deviates from the Kellian perspective in that by supplying features along which projects are rated, the researcher effectively provides of a set of personal constructs on which elements are rated. This is inconsistent with the Kellian construct-elicitation philosophy. Fortunately, a comparison of correlations between personally-generated constructs and those provided has shown the standard PPA features to map highly onto self-generated personal constructs. Cameron (1984) had a group of 78 people generate both projects and constructs that described those projects using standard Repgrid methods. The projects were rated on self-generated features and 17 features which have come to be standard in many PPA studies. Of these features, Stress, Difficulty, Challenge Importance stood out most clearly as common to all subjects, and most "mappable" onto the personal construct system. However, even the least mappable features (e.g., Progress, Self-Identity) were fairly well-represented in terms of being correlated with the personal constructs generated by subjects. We must not forget, however, that the use of within-case Pearson r 's on 15 projects gives a power of .462 to detect a correlation of .5 with a two-tail alpha of .05, and so a fair number of associations may still be missed. The power drops to .297 when only ten projects are collected (as is more common in PPA research; power calculations done using STPLAN; Brown, et al., 1993). As well, while the probability of a Type II error is high, we must recall that genuine relationships will distribute non-centrally around zero in a manner that is at least somewhat consistent with the true population parameter. Importantly, the pattern of these relationships should emerge over a large number of replications.

ECOLOGICAL REPRESENTATIVENESS

This criterion is an obvious consequence of the assumption that systemic influences are at work. The embeddedness of an individual in a local ecosystem makes ecologically representative units necessary. This is because the social ecological model asserts that ecological factors are a key source of variance. Different settings may give rise to different construct systems that do not withstand transplantation. Individuals in different settings may or may not construe their projects in similar fashion. The importance of this criterion is a function of the extent to which different construct systems exist in different social ecologies. Large factor-analytic studies have thus far only examined mean-level data within the same study, and so the extent to which between-study differences at the project-system level exist has not been mapped out.

IPSATIVE AND NORMATIVE LEVELS OF MEASUREMENT

Theoretically, the need to have access to both individual-level and aggregate-level information is a vital concern to the Personal Projects analyst. The recognition of systemic influences of both a subjective and objective nature (Little & Ryan, 1979) has clear implications for psychometric evaluation. One of the implications that flows from this reasoning is that a successful unit of measurement should allow access to both idiographic and normative levels of measurement, permitting not only global statements to be made about a group of subjects, but also allowing a window to be opened on the immediate subjective reality of the individual subject. PPA has the capability to do precisely this.

This criterion has a long history. Kelly's (1991/1955) Rep Grids responded to the then-dominant nomothetic approach with a uniquely ipsative tool. Little (1975) bemoaned the unidimensional and crudely nomothetic views of the then-current research on environmental perception and attitudes. He proposed that we study not just *"discrete, unorganized and decontextualized blips of information,"* but rather the *"system of organized constructs used by an individual in guiding his environmental predictions and actions."* However, despite some two decades of research, surprisingly

little work has been done towards a full understanding of the individual system of constructs (but see Cameron, 1984; Palys, 1979; Palys & Little, 1979).

Part of this problem may stem from the fact that statistics for ipsative and idiographic research are in their infancy (Lamiell, 1981; Little, 1986, p. 606; Zimmerman & Little, 1982). Thus, the focus of PPA research to date has been on normative levels of project system-level characteristics. Factor-analytic studies of project system-level structure (Little, 1987, 1988, 1989) and longitudinal analysis of stability of ratings (Little, 1988) have established the basic properties of feature means for sets of projects. These general theoretical factors and the PPA features that load on them are summarized in Figure 3.

Standard PPA Features on their Five Theoretical Factors (Little, 1993)

Meaning*: Importance, Enjoyment, Value Congruency, Self-Identity

Structure: Initiation, Control, Time Adequacy, Positive Impact,
Negative Impact

Community: Visibility, Others' View of Importance

Efficacy: Progress, Outcome

Stress: Stress, Difficulty, Challenge

* Note: Although not listed here, Absorption has commonly been considered a "Meaning" feature.

Figure 3: The Theoretical Factors of PPA based on System-Level Factor Analysis

In 1986, Little pointed out the possibilities inherent in the ipsative analysis of PPA features, and noted that individual correlations within a matrix do not necessarily follow the pattern that obtains normatively. This problem is analogous to one known more generally as the ecological fallacy (Richards, 1990) or Simpson's paradox (Yarnold, 1996), wherein generalizations made on the basis of data analyzed at one level

of aggregation are invalid at different levels of aggregation (such as when positive correlations between scores on scales are taken to imply that people are ordering the items identically; see Neabel, 1998 for an study that addresses this problem in nursing research). The extent of the problem in PPA is as yet unknown. An scatterplot wherein

Figure 4 Example of Mean-Level Positive and Project-Level Negative Correlations

analysis at the mean level provides a positive correlation while analysis at the individual project level would provide a pair of negative correlations (for cases A and B) and a positive one for case C is provided in Figure 4.

INTEGRATIVE UNITS

Anyone who has seen a toddler search frantically for a lost teddy bear knows that not only do we think about the things in our environment, but we have feelings about them as well. Thus, units that contain information about affect, thought processes and behavioral components of the system in which the individual is currently embedded are required for truly social-ecological assessment. Projects are ideal units because they contain information about all of these components. They carry information both about what is happening in the environment and how the person is generating hypotheses about what will happen next on the basis of current actions. Thus, while projects may differ across individuals and within a given case over time, such similarities as exist across cases, within cases and over studies are arguably very generalizable features of people in general.

TEMPORAL EXTENSION

This criterion requires that a unit contain information about time periods that extend to either side of the point of measurement. Projects, as units, capture some of the less immediate circumstances of the individual and so are not restricted to a "snapshot of human conduct" (Little, 1989, p.17). However, since such longitudinal data as exist have not been thoroughly analyzed, inferences about the nature of structural stability of Project Spaces over time remain unresolved. This interesting question will be explored as part of the present research.

MODULARITY

While Repgrid were so adaptable that often no two could easily be compared within the same study, PPA grids remain modular, but only *across* studies. The modularity criterion demands that an instrument to be flexible enough to adapt to a given research situation, but it neither implies nor precludes the possibility that it can be ex-

tended to the individual case. Features that are not salient to one study may be central to another, and vice-versa. However, this flexibility is not without a price. Many studies have excluded some features, thus limiting some cross-study comparisons to those features that the studies all share. For example, in Dr. Little's Social Ecology Assessment Databank (known as SEABank), there are currently over seven hundred cases which have values on all 17 of the "standard" PPA features summarized in Figure 3.

Review: the Propaedeutic Criteria

It is useful at this point to reconsider these propaedeutic criteria as they pertain to both the rows and columns of the PPA matrix. Projects as units are row variables, and the features along which these units are rated form the columns. The ecological representativeness criterion refers primarily to units, which must reflect the local ecosystem. However, the modularity criterion refers to features, which can be modified to tap into locally-useful constructs that are applied to projects in a given ecology. In a sense, it is just the ecological representativeness criterion applied to the columns. By extension from ecological representativeness, they are both thus tied to the idea of personal saliency. However it is assumed that the personal meaning of a feature is common throughout a given social ecology, and thus is not subject to the vagaries of idiosyncratic construing.

A problem arises at this point. While it is assumed that features differ in terms of their relevance to social ecologies, the lack of truly idiosyncratic expression of the features seems to imply that they do not differ in terms of their relevance across persons in the setting of interest. This is because in order to obtain commensurable variables from disparate objects, the PPA method achieves a compromise by deviating from the Kellian practice of eliciting constructs. On the one hand, in order to meet the ecological representativeness criterion, personal projects provide units that tap into the situation in which the assessee finds himself or herself. These units are analogous to the "elements" of a Repgrid. On the other hand, it is assumed (not without some fairly good evidence; Cameron, 1984) that there exist some fairly standard features which function as

“constructs” that many people (or at least, the people in the setting being studied) apply when construing their projects. Thus, while the constructs assumed to operate in any individual construct system are constrained², the elements being construed are allowed an infinite possible range.

The net effect of this trade-off is that while personal salience might be lost at the feature level, comparability across individuals is obtained. However, the validity of this comparability depends in part on the extent to which the various features are *used* in similar fashion. By implication, this means that their relationships to other constructs do not vary markedly across cases, at least within a given setting and possibly across a range of settings. Thus, while the presumed constructs seem to be common, the interrelationships among them may or may not be much the same from person to person.

Access to both joint individual and normative levels of measurement is needed because each level provides different kinds of information. A demonstration that the constructs do not covary in markedly idiosyncratic fashion would be an argument for the validity of generalizations about PPA features, at least within the ecological setting where they are used. The lack of development of PPA research on approaches to the study of individual cases needs to be redressed through the development of idiographic and ipsative approaches to the extant data.

Idiographic and Ipsative Approaches

It is necessary at this point to distinguish between idiographic and ipsative analysis. Popularized by Allport (1955), “idiographic” analysis is a general term for the analysis of a single case and was used by Kelly (1955/1991) to refer to the selection of facts about an individual case for the purpose of abstracting principles which *may* apply beyond the individual case. These facts do not *need* to so generalize in order to qualify as scientific. This reasoning flows from Kelly’s original model: if an individual acts as a scientist in comprehending the world, then a scientific understanding of that individual’s model of the world must be possible, even if the model is based on bad or incomplete science. After all, scientists routinely find flaws in each others’ work, but this does not mean that science as an enterprise is impossible.

In PPA, idiographic information about project content, means and inter-correlations among features constitutes potentially valuable information for the clinician (Little, 1986, 1989) and the researcher who is interested in a particular individual and his or her experience of the world. PPA features have been shown to have counterparts in the personal construct systems of many university students (Cameron, 1984; Lelacheur, 1993), emphasizing the validity of the features. Studies of the stability of the means have also been done (e.g., Little, 1988), revealing some degree of stability at the system level. However, the stability of the intercorrelations, and the degree to which individuals differ in terms of the structure and stability of these coefficients remains uncharted territory.

	Raw	Standardized
Semi-ipsatized	all persons brought to the same mean	all tests standardized by columns, before bringing to same mean by rows
Fully ipsative	all persons brought to the same mean and standard deviation	scores standardized across cases, then brought to same mean and standard deviation.

Figure 5: The varieties of ipsatization (based on Cattell, 1994).

Ipsative measures are behavioral data that have been referred to a population of measurements within the individual case (Cattell, 1944). Importantly, in his discussion of ipsative and normative measures, Cattell (1944, p. 294) indicates that *"there are ...derivatives possible...e.g., measures relative to the self may secondarily be used as a basis for measures relative to a group."* Cattell and Brennan (1994) point out that there are several kinds of ipsatization available. These are summarized in Figure 5.

Much of the work on the varieties of ipsative scores has focused on the ipsatization of scores obtained on individual cases, and these measures have come under fire lately in the context of forced-choice items where mathematical interdependence is unavoidable (see Bartram, 1996; Saville & Willson, 1991; Tenopir, 1988). PPA uses rating, rather than ranking, scales, and so this fundamental problem is avoided.

Following Cattell's (1944) definition of ipsative measurement, the statistical tools for the analysis of single cases that exist have been predicated upon the idea of what a person does relative to the range of options that are available to them. Rankin (1967; see also Zimmerman & Little, 1982) developed the idea of maximum possible variance, and defined reliability as $1 - (\text{observed variance}) / (\text{maximum possible variance})$. Similarly, Lamiell (1981) developed an idiographic definition of a person on an attribute by defining a functional zero point from which the individual deviates relative to how much he or she *could have* deviated given the imposed constraints of the measurement procedure.

This latter line of reasoning seems to be counterfactual. However, there is a profound analogy between these novel techniques and more well-established statistical procedures. The assumption of maximum possible variance is based on a consideration of what could have happened, just as the probability of rolling a 3 on a fair die is assigned $1/6$ in view of the range of *possible* outcomes of the roll. Likewise, statistical bootstrapping methods that are used *across* individual cases such as those described by Efron & Tibshirani (1993) are also counterfactual. The latter authors indicate that resampling with replacement (i.e., bootstrapping) many times can produce accurate empirical estimates of population parameters such as means, standard deviations and regression coefficients, because the relevant information about those parameters is contained even in small samples. In a deep sense, this too is counterfactual, because in the process of resampling we pretend that we are sampling from the population at large in a way which was not done when the sample was taken, and thus that the error estimates around the parameters are those that would have been obtained in any event by sampling from the larger population. The success of the bootstrap paradigm suggests

that referring observed to potential variability is not illegitimate. Thus individual-level analyses (not ipsative in the technical Cattellian sense) may be conducted which take advantage of the same kind of counterfactual reasoning. In fact, I suggest that bootstrapping procedures may provide a solid foundation for estimating the parameters of single-case data.

Ipsative Scores

The notion of an ipsative score as expressed in the literature to date is somewhat different from that used in PPA research thus far. The fact that multiple projects are obtained on an individual implies that classical ipsatization could be done *at the project level* within a single matrix on rows, columns or both. As well, within the single case, a matrix of intercorrelations could be derived which reflect patterns of covariation among the columns on either raw or standardized project data. Palys (1979) used the term “zipsative” with reference to the conversion of intercorrelations amongst PPA features by way of a Fisher *r*-to-*z* transformation (see endnote 3). Since correlation coefficients are themselves a form of standardization, the comparison of matrices across a group of cases results in what we may term fully ipsatized standardized multivariate data.

Summary

PPA moves away from the classical Kellian model in that the constructs that respondents are asked to use in rating their projects are provided by the researcher. This is because the propaedeutic criterion of joint individual and normative measurement requires that both levels of analysis be meaningful, and comparability at the normative level requires consistent measures. While comparing Simon's apple project to Marion's orange project and Gunther's prune project is not likely to result in overly broad generalizations, the stress that each of these projects brings into their respective systems must be comparable at some common level. Thus, an integrative model of measurement is required which permits not only an idiographic understanding of the nature of the single case, but a common framework for comparing across cases.

Of course, if we are to derive clinically useful tools for idiographic research, we need analytic tools that can provide some insight into the structure and stability of certain

key properties of single PPA matrices. These tools are well-defined for classical individual differences approaches, but we are interested in a variety of different levels of analysis, for which different approaches will be required. To revisit the idea of maps that was introduced at the outset, we may consider some ideas from Mandelbrot's (1983) presentation of topology. A coastline may seem to be 1 kilometre long, when measured at the level of the odometer of an automobile following a coastal road. Measured with a metre stick following the waterline of the beach on a still day, it may be considerably longer. Examined with an electron microscope and measured in nanometers, it may approach infinity as we wind around massive grains of sand between vast inter-electron distances. The shape may seem like a smooth curve on the road, a jagged array of lines when applying the metre stick, and an asteroid belt in interstellar space from the microscopic perspective. There is no necessary similarity of topology from one level of analysis to another, although the possibility of self-similarity exists, as in static bursts during radio transmission (Eiser, 1994). The presence of such a topological crossing of levels of analysis would be a fascinating as well as aesthetically pleasing result.

The study of individual differences can proceed only from measures that make reliable and valid statements about the single case, and this is where we shall begin. In the next chapter we will explore the fundamental notions of reliability and between-person differences with an emphasis on reliability as it may be defined for an individual case.

Chapter 2: The Measurement of Single Cases: Expanding Conceptions of Reliability and Individual Differences

In this chapter we will consider the issue of normative and ipsative reliability coefficients with respect to Project Space data. Issues surrounding the magnitude of within- and between- subject variability will be discussed. Some subsidiary problems of Project Space dimensionality are considered, and the basic comparisons needed to determine the relative magnitude of intra- and inter- individual differences are laid out, along with some ancillary hypotheses that can be tested to elucidate the degree of impact of personality and other factors on Project Spaces.

Reliability: Normative or Ipsative Measures?

Palys (1979) has discussed the issue of reliability of ipsative indices in PPA. Working with 13 features, among which were early versions of some of the modern 17 standard PPA features, he examined the stability of 78 ipsative indices over a period of two weeks. These indices were termed 'zipsative' indices, meaning that the inter-feature Pearson r correlation was transformed (via Fisher's formula³) to a Z score. He found them to be somewhat less stable than the nomothetic indices such as feature means. However, this stability was based on a normative comparison, correlating Z at time 1 to Z at time 2 across subjects, and did not take into account the overall pattern of intercorrelations in the matrices. This is important because of the theoretical structure of PPA, which asserts that conceptually, there are a number of factors at work. This implies that there will be clusters of variables that "go together," which are distinct from elements of other clusters that do not share the same space. Thus, those features which should not exhibit much reliability are lumped in with those that should exhibit reliability.

Furthermore, Palys also analyzed data on 13 features, only seven of which have survived in some form or another as standard PPA features. With the benefit of 20/20 hindsight, we may reconsider his data in light of what has been learned in the intervening time. Of the 78 indices he computed, a somewhat disheartening 15 (or 19%) had reliability coefficients of .4 or higher. However, when we consider only the seven surviving features that are in some way comparable to the common features in SEABank, we find that 10 of the 21 (or 48%) had values in excess of .4 - in fact, the median value is .38 (Fisher $z/sd = 1.12$). This is actually quite remarkable if we consider the degree of attenuation that these coefficients would suffer from the fact that the standard error of the Z-scores is in large part due to the sampling of only 10 projects. For the transformed values, this would mean a 95% confidence interval of $1.96 * (1/(10-3)) = .28$ on the Z's. The power to detect a population correlation of .38 with 10 projects (2-tail $\alpha = .05$) is only .178 and so the proportion observed is several times what would be expected.

It would be of interest to see if the modern PPA features suffer from unreliability. However, it will be necessary to address some weaknesses in the method. Specifically, Palys' approach addresses isolated item pairings, and does not look at global similarities of individuals' matrices over time. This conflates expected unreliability with true unreliability in the sense described above. In addition, it does not address the relative magnitude of intra-individual differences as compared to between-individual differences.

The relative magnitude of between- and within- individual differences in project spaces is important to personality theory. If project spaces are well-differentiated between individuals, and stable over time within individuals, then personality variables may be linked to these differences. If, on the other hand, there is a strong similarity between most individuals' individual project spaces, then there would likely be insufficient variability between individual matrices to correlate personality variables (e.g., "Big Five" measures such as those of the NEO-PI; McCrae & Costa, 1996) with ipsative indices.

Within-Individual Stability and Between-Individual Differences

Classical conceptions of reliability and individual differences assume that individuals differ from one another in measurable ways, and retain these characteristics over time. These are ideas on which claims of longitudinal stability of psychological characteristics (e.g., Costa & McCrae, 1997) are based. Typically, a score on a test is the measured, and the stability of that score over time is the gold standard for reliability. Ideally, the test itself does not change or, if it does, the changes are not such that the accuracy of the measurement is impaired through conflation with other factors. With ecologically representative units that mirror factors that may change over time, changes to the “items” are *expected* to occur, and changes in the evaluation of them are assumed to follow suit. However, the idea of the Project Space is that the way the evaluations are performed is stable, and that this stability is reflected in the individual matrix.

In terms of an ipsative index (such as the correlation between Importance and Stress), stability could be measured on the same set of projects or different sets of projects at two or more points in time, and the variability of the correlation coefficient, if small, indicates reliability. Reliability obtained under the sampling of variable projects would be more convincing as an argument for a Project Space than reliability obtained under sampling of the same projects at two points in time. Nevertheless, even with the same set of projects, changes in stage of completion of the various projects from time 1 to time 2 should add variability that will tend to produce conservative estimates of reliability.

This idea runs in parallel to the classical conception of the reliability coefficient, which involves a relationship between the average variation within subjects' scores and the overall variation across individuals. Williams and Zimmerman (1984) point out that the classical reliability coefficient $\rho_{xx} = 1 - \sigma_E^2 / \sigma_{xx}^2$ “has meaning only with respect to an entire group” (p. 232). This is because it has been based on the estimate of error variance σ_E^2 which is derived normatively. To the extent that error variance is small, relative to population variance, reliability is high. In other words, small intra-individual variability (on average) relative to more substantive individual differences implies

reliability. This allows us to conceive of a general approach to reliability that compares between-subject differences defined in some manner to within-subject differences defined in the same way.

However, Zimmerman and Little (1982) indicate it is possible to define a reliability coefficient ipsatively. With a small correction to the reasoning presented in their paper this is both possible and appropriate (Gee, 1997a). As noted above in the discussion of ipsative measurement, the idea of maximum possible variance is substituted for normative variability, and within-subject variability is referred to this standard. Thus, reliability may be defined as small variability relative to maximum possible variability. As Zimmerman and Little (1982) point out, this avoids a key problem in assessing the reliability of homogeneous groups, where the classical reliability coefficient can seriously underestimate the actual reliability inherent in the data (see also Williams and Zimmerman, 1984).

Longitudinal Data and the Test-Retest Coefficient

Another way to assess reliability is the test-retest method. Some PPA data has been collected longitudinally, and thus affords the opportunity to look at stability of Project Spaces over time. Assuming that it is possible to compare one matrix to the other, it then becomes possible to compare paired matrices of correlations to matrices of correlations from different individuals. The extent to which intra-individual variation is smaller than inter-individual variation thus opens a window on the multivariate reliability of Project Spaces as measured by PPA.

Analytic methods discussed in the next chapter can provide insight into such longitudinal data. However, another way of comparing the between-to-within case similarity would be to derive a global index of matrix similarity for a given case, at time 1 and time 2 (or even time 3 where available) and examine the relative magnitude of the similarity index computed on two matched matrices as compared to the magnitude of the same index computed on that subject's first matrix and a randomly selected matrix from another subject. Across a large number of replications, an estimate of the relative magnitude of between- to within- subject variability could be obtained. If and only if

individual differences between matrices were substantial and individual matrices tend to be stable over time would the difference between paired observations be greater than the difference between one individual's matrix and that of another person, randomly selected from the databank. However, this is only one possible state of the world. There are several other possible scenarios that must be considered.

The Four Possible States of the World

The central problem that the proposed research will address is the relative magnitude of individual differences among Project Spaces, and the stability of these spaces over time. Consideration will also be given to the subsidiary problem of their dimensionality.

THE CENTRAL PROBLEM

While there is some evidence that Big Five personality factors tend to be stable over time (Costa & McCrae, 1997), individual differences in Project Spaces may be large or small, and matrices may be stable over time or unstable. These two distinctions allow us to create Figure 6, wherein the case of stable and substantial individual differences constitutes Cell A. It is of course necessary to consider the implications of *not* finding sufficient stability in PPA matrices to state that individual spaces exist. This may be attributable to any of the three remaining states of the world outlined in Figure 6. In Cell B, where there is great variability both between and within subjects in terms of the Project Space, there appears to be a good *prima facie* case against ipsative analyses. This is not necessarily true. While stable trait measures (such as those tapped by the NEO-PI; McCrae & Costa, 1996; Costa & McCrae, 1997) should not be strongly related to unstable measures, dynamic fluctuations in project space may well be linked to other measures that are temporally unstable. For instance, if the Stress/Challenge/ Difficulty triad may dominate the construals of projects when one is not on vacation, but fade into the background when construing a large set of recreational projects.

	Matrices tend to be stable over time.	Matrices tend to be unstable over time.
Individual differences large	A) Time1-Time2 difference smaller than Time1-Random Matrix difference.	B) Time1-Time2 difference not different from Time1-Random Matrix difference. Reliability coefficients low.
Individual differences small	C) Time1-Time2 difference not different from Time1-Random Matrix difference. Reliability coefficients high.	D) Time1-Time2 difference not different from Time1-Random Matrix difference. Reliability coefficients low.

Figure 6: Outcomes under possible states of the world for between/within comparisons

If the overall reliability is good, and individual differences are small (Cell C), then the most plausible explanation is that people tend to have a common way of viewing their projects, which may or may not reflect the factor structure that has been reported for system-level measurements (Little, 1988). Knowledge of the norm would permit a clinical comparison to be made. Forensic use of PPA might turn up intriguing “signature” problems in the project spaces of individuals exhibiting particular pathologies, although more general variables (such as personality and well-being measures) may not be strongly related to the differences due to the general similarity of most cases.

If the matrices tend to be unstable over time (Cell D), then it is hard to believe that individual differences would be small, because it is improbable that so many

different subjects, sampled over a substantial time frame and across a variety of settings, would by chance exhibit similar project spaces. Thus, it is extremely unlikely that apparent temporal instability will be present while individual differences remain small. Nevertheless, situational variables may induce consistencies across subjects *within* a given setting (e.g., Fleeson & Cantor, 1995) to produce such an effect. If the randomly-selected matrices are drawn from a study done at a different time, under different circumstances, with a different population, then in the event that structures are seen to be constant, the situational-consistency hypothesis is not very tenable. If, on the other hand, subjects paired on the basis of being in the same study are more similar than subjects paired on the basis of being in different studies, then the effect of general social ecological similarities would be apparent.

A SUBSIDIARY PROBLEM: DIMENSIONALITY

A key problem in the analysis of individual cases is the dimensionality that is to be expected to best describe each case. If individual differences in project spaces are not marked, then a single optimal dimensionality should be discoverable. However, there is nothing in the theory of PPA to imply that a single dimensionality *should* best describe everyone. While factor analysis of column means has told us much about project *systems* (Little, 1988), the results obtained at one level of aggregation may or may not be informative at a different level of aggregation (Little, 1986; this is the statistical problem of “Simpson’s Paradox” noted above). Specifically, while the 5-dimensional factor solution summarized in Figure 3 has been suggested as the optimal way of viewing project system-level information, individual project spaces may be better described by the operation of a few major factors, although residual traces of the theoretical factors may remain. A three-dimensional structure has been offered by Little (1993), but it is still based on the analysis of mean-level data. Nevertheless, if similarity of structure persists across levels of analysis, it may yet account for individuals’ structures to a greater or lesser degree.

As an example, Stress, Challenge and Difficulty have (at the nomothetic level) consistently formed a distinct cluster. Life experience tells us that the various activities

in which we engage tend to vary along these three features in a systematic way, and a comparison of project-level and system-level scores found that level of analysis was essentially irrelevant to this structure (Little, 1988). Nevertheless, there may exist sets of projects for which there are one or more zero-to-negative correlations within this set of variables, or between these variables and other ones in the project space. We may even anticipate the presence of some personality differences between the people who report such project systems and those who exhibit more typical construals. However, on the whole, it seems reasonable to expect positive correlations amongst these variables at both the project system and Project Space levels, thus reflecting self-similarity across levels.

Little (1988) suggests that for project-level ratings there may only be two broadly evaluative dimensions, with the Stress triad just described forming one of them. Even with two such dimensions, orthogonality is not assured, because of the way Challenge may load on personal meaning. Nevertheless, individuals may well differ from this value in the dimensionality of their Project Spaces, with a single dimension being most unlikely, but two a plausible dimensionality, or even three. As part of this study I will establish the relative degree of individual differences in the dimensionality of Project Spaces. From related analyses, it may be possible to establish the goodness-of-fit between normative-level analysis of PPA data, and individual matrices. A good fit would rule out the operation of Simpson's Paradox, while a poor fit would serve as a cautionary note against generalization from the normative case to the individual case. Furthermore, the existence of a general Project Space shared by most people would present a limitation on the extent to which classical individual difference measures may relate to Project Space indices as a result of restriction of range effects due to homogeneity of construing. In the strongest form, a stable structure that is independent of individuals, but which depends more on the projects reported, would not be expected to form a centre of gravity, where deviations are related to personality factors. Under these circumstances it would be surprising if trait measures were found to be related to distortions relative to the joint Project Space.

Generalized Reliability of Multidimensional Project Spaces.

If we are willing to construe the test-retest reliability coefficient as a measure of the stability of a score over time, then two consequences emerge. First, by a mathematical generalization, we may consider the canonical correlation between two *sets* of numbers to be an index of multivariate stability between two instances of a set of vectors that may have any degree of interrelationship among themselves. Quite simply put, if a 17x17 Project Space can be reduced to three dimensions at one point in time using MDS procedures, the canonical correlation between the vectors that define those dimensions at time 1 and vectors derived on the basis of data collected at a second point in time (or on the basis of some theoretical model) can be considered as a set of indices of goodness-of-fit.

Secondly, an element-wise comparison between the entries of two Project Space matrices produces a correlation coefficient in a test known as the Quadratic Assignment Procedure (QAP; Hubert, 1987). This coefficient is tested against row- and- column permutations of the elements of one of the matrices to approximate a sampling distribution against which the original correlation may be compared. Both of these approaches are discussed in the next chapter and are compared as part of this research.

Beyond Reliability: Some Interesting Hypotheses

The views set forth in the preceding sections lead to some hypotheses that can be answered with existing data, given viable procedures for single-case analysis. One: To the extent that the individual's method of processing information through the Project Space is idiosyncratic, one would expect more similarity between two measures of a single individual's project system than exists between individuals. This is the basic reliability proposition of the preceding section, and it is fundamental to advanced questions that are broader in scope.

Two: To the extent that differences exist among social ecologies, individuals within one setting (e.g., high school students) will be more similar among themselves than they are to individuals from another setting (e.g., adults in the workforce).

Differences among projects that arise from project category (e.g., leisure vs. work) are

among these sources of variation. Three: If individuals differ markedly in their Project Spaces, then personality differences among subjects may be linked either directly or indirectly to differences in individual Project Spaces. And lastly, if individuals do not differ markedly, then it is possible that a restriction of range effect precludes the detection of relationships between personality measures and deviations from the joint space. However, in this case we may ask other questions, such as “Does the joint space produce solutions that are different from those obtained by factoring mean-level data or factoring project-level data?” Similarly, “Can the joint space be recovered by resampling project category profiles?” In other words, is Simpson’s Paradox at work or do normative data reflect the lower level of aggregation? If the normative data reflect the lower level of aggregation, then the importance of the extent to which interdependence among projects is at work may be tested by factoring mean-level data from intact project systems and comparing the solution to that obtained by randomly agglomerating sets of ten projects and obtaining a joint solution for these “synthetic” data.

The need for an ipsative approach to the Project Space (which we assume to be reflected in the individual PPA matrix) should be apparent. The intercorrelations of the features *within* an individual matrix may reflect the well-replicated factor structure that is obtained at the normative level (i.e., by factoring projects’ column means), or they may not. Either way, they constitute an intrinsically interesting and potentially valuable source of information. However, in some (or perhaps many) cases, unique patterns may exist which account for other observed differences between individuals. Given the fact that a need for units that permit this kind of analysis has been put forward as a criterion for assessment (Little, 1989) a study which taps into the potential mine of rich information that lies in the intrinsic multidimensionality of ipsative Project Spaces is long overdue.

In the next chapter, the analytical tools discussed above are explored in more detail. In the subsequent chapter, the results of preliminary analyses are presented to familiarize the reader with some of the approaches taken. Following this introductory exploration, the results of both separate and simultaneous analyses of Project Spaces

drawn from SEABank are presented which take full advantage of these methods. Taking cases separately, it will be shown that ratings of the same projects over a short period produce more stable estimates of the Project Space than do ratings of different projects over a longer period of time. However, this difference is not so great as would be expected under a substantial-individual-differences hypothesis. Rather, the joint analysis of a large number of cases will reveal a stable common structure, or “joint space” which describes Project Spaces in general. This structure is invariant across several transformations that, under a strong individual differences model would be expected to perturb it markedly.

With these basic ideas in mind, we may now proceed to a more detailed examination of the methods to be used to address these issues. Chapter 3 will discuss the basic analytical tools that were used in this research, and provide a basis for understanding the studies that follow in Chapters 4 through 9.

Chapter 3: Analytic Methods

This chapter discusses the analytical tools mentioned above that will be used to study the properties of Projects Spaces over time and across cases, as well as within the single case. In order to establish the reliability of individual configurations over time, some measure of the similarity of one Project Space to another is required which permits comparisons. For complex multivariate data this is not a simple task. The novelty of the present approach is such that two analytic approaches will be taken, in the hope that a convergence of results will strengthen the conclusions that are drawn, or at the very least elucidate differences between the procedures. These methods are multidimensional scaling (MDS) and its' near relative Individual Differences Scaling (INDSCAL), as well as the quadratic assignment procedure (QAP; Hubert, 1987). It was expected that the convergence of MDS and QAP would provide a solid basis for the analysis of PPA data at the single-case level. However, some differences in the results that were obtained highlights the relative strength of the MDS/Canonical correlation method relative to QAP. To establish the similarity of two sets of vectors (e.g., dimension coefficients derived by MDS) canonical correlation was used, and where assumptions may have been violated, asymptotic results have been supplemented with results from simulated or permuted data.

An additional section on Poisson regression has been provided for readers who are unfamiliar with generalized linear models. This brief description has been supplemented reflections on the analogy between nonmetric MDS methods and the these models in so far as untestable assumptions are concerned.

Determining Structure

Two techniques are discussed here that can reduce a matrix of (dis)similarity data to a small number of dimensions. Multidimensional scaling (MDS) obtains a spatial representation of the structure of a single matrix, and Individual Differences Scaling

(INDSCAL) obtains a similar representation of the joint space based on a two or more matrices that are solved simultaneously. The latter technique also provides subject weights, commonly known as “weirdness coefficients” that are indices of the relative emphasis or “salience” (Davison, 1992) of a given dimension to a given individual.

MULTIDIMENSIONAL SCALING

In PPA, the analysis of a single case results in a 17x17 correlation matrix derived from ten projects. Traditional factor-analytic methods fail when the number of variables exceeds the number of subjects (Schiffman, Reynolds & Young, 1981). However, if a structure *is* present within a given matrix, multidimensional scaling methods may be able to provide a good picture of what is happening in an individual project space, despite the fact that few studies have sampled more than 10 projects from any given individual. Nonmetric methods have been shown to be more stable and resistant to the effects of outliers (Spence & Lewandowsky, 1989), and the solutions obtained by several different programs have shown to differ very little in Monte Carlo simulations (Spence, 1972). Given the potential for unusual observations in matrices of the type obtained in PPA, the leveling effect of nonmetric approaches is to be preferred.

Davison (1985) indicated that a components solution would contain up to a maximum of one dimension more than an MDS solution for the same data, and that the “lost” first component is probably due to uninteresting psychological variables. Kop and Tournois (1995, 1996) have shown that a MDS solution may *appear* to be of lower dimensionality than a factor-analytic solution under some circumstances, but that the apparent disappearance of the first principal component is an illusion. It is still present, in the overall distance of points from the origin defined as $d(A, 0) = \sqrt{\sum_k C_{ak}^2}$ (Kop & Tournois, 1995, p. 4). Their main conclusions are worth quoting verbatim:

The location of the first component depends on the structure of the correlation matrix:

- when there is no general factor, the first component matches the first dimension of the scaling solution;*
- when there is one general factor, the loadings along the first component have to be searched in the distances from the origin of the configuration.*

(Kop & Tournois, 1995, p. 10).

These findings are interesting in that personality differences may exist between people who have a coherent, perhaps rigid way of construing projects (whatever that way may be), and people whose system of anticipation is more differentiated (i.e., of higher dimensionality). For instance, what amounts to a Kellian “hardening of the construct system” may well account for some of the differences between neurotic introverts and well-adjusted extraverts.

INDSCAL

Standard multidimensional scaling approaches can be applied to single cases. However, if we wish to examine the “shared” space of a group of individuals who may differ to some degree in that space, individual differences multidimensional scaling (INDSCAL; Carroll & Chang, 1970) is a related technique which is capable of identifying a “joint space” while providing coefficients that reveal the relative importance of the derived dimensions to individuals. “Weirdness” coefficients are also provided. These coefficients exist for each dimension of the solution obtained, and are indicative of the extent to which the case deviates from the joint space. They are non-negative and have no simple interpretation other than as indices of what Davison (1992) terms the “salience” of the dimension to the individual.

A method for testing the goodness-of-fit of multidimensional scaling solutions to theoretical models (and to other MDS solutions) has been provided by Carroll & Chang (1964). Property fitting (PROFIT) provides multiple R^2 values for the various dimensions. Substantial correlations indicate a good fit between the solution and a given attribute. However, a general principle has been stated that running separate regressions

for attributes is less informative than obtaining the global fit of a hypothesized set of attributes (Cooley & Lohnes, 1971). The mathematics of canonical regression have been suggested as a more general technique for the simultaneous assessment of goodness-of-fit between an MDS solution and a set of attributes (Schiffman, Reynolds & Young, 1981). The latter authors strongly advocate a very conservative approach to significance testing due to the probable violation of assumptions of the canonical model. However, a purely descriptive approach using redundancy analysis may be taken with individual cases, and an aggregation of individual cases can give a picture of the empirical distribution of goodness-of-fit between a theoretical model and observed data.

BASIC MDS MODELS

The MDS and INDSCAL solutions are obtained by deriving a metric representation of the (dis)similarity data that are collected in any of a number of ways. A correlation matrix can be construed as a matrix of similarities, or (if subtracted from the maximum value) dissimilarities (Davison, 1992). If we wish to represent similarities or dissimilarities in Euclidean space, the data must satisfy four fundamental axioms given by Davison (1992) as

$$d(a,b.) \geq 0 \quad (1.1)$$

$$d(a,a.)=0 \quad (1.2)$$

$$d(a,b.) = d(b,a.) \quad (1.3)$$

$$d(a,b.) + d(b,c.) \geq d(a,c) \quad (1.4)$$

The first three axioms merely assert that a distance must be zero or positive, that the distance from a point to itself is zero, and that the distance from point A to point B is the same as the distance between point B and point A. If we are viewing dissimilarities as distances where greater dissimilarity implies greater distance, then correlation coefficients (suitably reversed) meet the first three axioms. Coombs (1964) shows that this interpretation is comparable to factor-analytic strategies wherein a geometrical interpretation of a correlation coefficient is given as the scalar product of two vectors. For the special case of variables expressed in standard scores, it is possible to consider distance as $d=(1-r_{jk})^{1/2}$, which is merely a monotonic transformation of the correlations.

For high correlations, we have a small distance and vice-versa, and the MDS solution is “a nonmetric factor analysis of a correlation...matrix” (Coombs, 1964, p. 513).

A basic problem arises with the last axiom (known as the triangular inequality). As Davison (1992, p.3) points out, “*there is nothing about psychological dissimilarity to suggest that measures of dissimilarity would or would not satisfy the fourth axiom...In the social and behavioral sciences, however, three out of four is not bad, so the analogy caught on.*” However, as Coombs (1964) points out, the extent to which this axiom is satisfied is a necessary, but not sufficient condition for a least squares fit of a set of estimates to real data. The algorithm for fitting MDS solutions generally solves all triangles giving priority to fitting the largest triangles first. This helps to determine the rank order of projections between two points on a dimension and to permit the scaling of the objects to a greater or lesser degree of accuracy, with poorer fit assigned to the smaller distances.

The MDS model for dissimilarity is expressed as

$$\delta_{ij} = \left[\sum_{k=1}^k (x_{ik} - x_{jk})^p \right]^{1/p}, \quad (1.5)$$

where δ_{ij} is an observation on pair (i,j) and d_{ij} is an estimate of δ_{ij} derived by procedures discussed below. The x values are estimated coordinates on dimensions, the distances between which (raised to a power, summed, and a root taken) are the d_{ij} . Typically p is taken to be 2, which gives rise to another issue: the nature of the space. Distances can be estimated in Euclidean space (i.e., where $p=2$, and the d_{ij} are the square roots of the sums of squared distances), or a generalized Minkowski space (where $p \neq 2$). Following the recommendation of Davison (1992, p. 85) the absence of a strong theoretical reason for preferring some Minkowski space leads us (on the grounds of computational efficiency) to consider a Euclidean space in the present dissertation.

The INDSCAL model is similar to the MDS model, except that an additional parameter is estimated for each matrix included in the analysis (i.e., a subject weight, or weirdness coefficient. Known as the weighted Euclidean model, $p=2$, and the expression for the INDSCAL model is given by Davison (1992, p. 123) as

$$\delta_{ij} = d_{ij} = \left[\sum_k w_k^2 (x_{ik} - x_{jk})^2 \right]^{1/2}, \quad (1.6)$$

where the w are the weights estimated for each subject matrix on each dimension, and which are sometimes known as “importance” or “salience” weights. The existence of negative weights indicates a violation of the assumptions of the Euclidean model that underlies the technique.

An index of badness-of-fit is also required to establish the extent to which the model conforms to the data. Young’s S-Stress⁴ formula 1 is recommended when the data are (dis)similarities (Davison, 1992). This is essentially the square root of the ratio of the sum of the squared deviations of the data from the model to the sum of the squared structure coefficients. Computational details of this and other formulae are given in Davison (1992, pp. 88-89).

Establishing Structural Similarity

As part of this dissertation, the relationship between two indices of structural similarity will be studied. As noted above, the Quadratic Assignment Procedure (QAP; Hubert, 1987) is based on element-wise comparisons of the entries of two matrices using Pearson’s r . Canonical correlation, on the other hand, provides one or more generalized coefficients that can be construed as indices of several orthogonal components of two sets of vectors.

THE QUADRATIC ASSIGNMENT PROCEDURE

The quadratic assignment procedure (QAP) has been recommended as a technique for the comparison of two matrices (Hubert, 1987). It is a general combinatorial optimization task based on exact tests or approximately-exact randomization tests which rely on the fact that matrices can be viewed as sequences of values which (when a correlation exists) cannot easily be permuted to produce a structure that is larger than the one observed in the original data. The observed sequences in the two matrices are correlated as with an ordinary Pearson r , using pairs drawn from the same position in the matrix (X_{ij} from matrix 1 and Y_{ij} from matrix 2). The order of the rows and columns in one of the matrices is then randomly permuted to determine the probability that another permutation will provide a larger value of r .

For small matrices, exact distributions can be computed readily. However, for large matrices, resampling methods can be used such that 1000 or 2000 permutations from the larger completely-enumerated distribution provide an approximation to the exact p-value. For example, to compare two 17x17 correlation matrices, we consider a sequence of $17 \times (17-1)/2 = 136$ values, of which there are $136! = 3.659 \times 10^{232}$ possible permutations. Complete enumeration even on the best computers available today would be excessively time-consuming. However, randomly sampling 1000 of the possible permutations can provide an accurate picture of the relative improbability of the given pair of matrices.

Not all writers have been favorable to the use of QAP as a method for testing goodness of fit of correlation matrices in particular. While accepting QAP as a viable model for social network analysis Krackhardt (1993; personal communication, April 11, 1997) has been critical of this application of the method, at least as it has been presented by Hubert & Golledge (1983), who suggested that taking a residual matrix of differences between a normalized model and the original normalized data, a non-significant correlation could provide evidence of goodness of fit. Krackhardt (1993) provides a mathematical proof that this is unreasonable. However, his critique of Hubert's method does not address the direct comparison approach that is proposed in the present research. The direct application of QAP to lower-half correlation matrices has been shown to give good results for correlation matrices with known structure even where subsampling of 10 subjects at a time is used (Gee, 1997b).

Where goodness-of-fit between the data and a theoretical model is required, a QAP analysis of matrix-to-matrix similarity may be obtained by coding a matrix that contains the theoretical structure and comparing it directly to the raw data matrix. In this event, a sort of "poor man's structural equation modeling" may be achieved which provides insight into the extent of the fit (Gee, 1997b).

CANONICAL CORRELATION

While QAP is actually a fairly straightforward generalization of the correlation coefficient which takes advantage of element-wise matching and perturbations of that

matching, canonical correlation is somewhat more refined, and has been known for some time. Cooley & Lohnes (1971, p. 169) cite papers by Hotelling in the mid-1930s as marking the original development of the technique. They describe it as “*an exploration of the extent to which individuals occupy the same relative positions in one measurement space as they do in another. We want to know to what extent the vector variable $\mathbf{z}_1$ maps subjects the same as does the vector variable $\mathbf{z}_2$* ” (Cooley & Lohnes, 1971, p. 169) If instead of “subjects” we substitute “project features” then we have a tool that can establish the degree of similarity between two sets of derived structure coefficients such as those obtained via INDSCAL and MDS. Identical structures will yield k canonical correlations equal to 1.0, where k is the number of vectors in the smaller of the two sets of variables. However, it will be shown below that for small samples, even where there is substantial variation between the vectors on the two sides large values can be obtained by chance, and so part of the present investigation has involved determining what magnitude of canonical goodness-of-fit indices we can call “good” under the sort of conditions that obtain in the MDS and INDSCAL analysis of Project Spaces.

Specifically, both simulation and permutation comparisons are made. Simulation involves the generation of random coordinates from a sphere or hypersphere with no preset structure, and the comparison of the canonical correlation between a specific model and the randomly-generated model. Permutation involves a generalization from the exact tests based on the univariate techniques such as those implemented in the NPStat suite of programs (May, Hunter & Masson, 1996). The permutation method involves randomly permuting the rows and columns within each row of one of the two sets of variables a large number of times. For multivariate data, it is necessary to permute the columns within rows because solution to the canonical equation will not be affected by permutation of only the rows. This is due to the way the correlation matrix is partitioned. Consider a matrix $\mathbf{R}$ where $\mathbf{R}_{11}$ is the submatrix representing intercorrelations among one set of variables, and $\mathbf{R}_{22}$ is the intercorrelation submatrix for the opposite set. $\mathbf{R}_{12}$ is the set of intercorrelations among the variables of both sets and

$\mathbf{R}_{21}$ is the transpose of $\mathbf{R}_{12}$. Cooley & Lohnes (1971, p. 176) give the canonical equation as

$$\mathbf{M} = [\mathbf{R}_{22}^{-1} \mathbf{R}_{21} \mathbf{R}_{11}^{-1} \mathbf{R}_{12}] \quad (1.7)$$

The roots $\lambda_1, \lambda_2, \dots, \lambda_k$ of $\mathbf{M}$ are then found, and the square roots of these values are the canonical correlations. The effect of permuting only the rows of one set of variables is on $\mathbf{R}_{21}$ and $\mathbf{R}_{12}$, but $\mathbf{R}_{11}$ and $\mathbf{R}_{22}$ are unaffected. For a given structure where we hold one side (say, $\mathbf{R}_{11}$) constant, holding $\mathbf{R}_{22}$ constant results in variation due solely to the random pairing, but not due to the *structure* of the model being permuted. Because the null hypothesis is that of no appreciable relationship between the structures, not only do we need to vary $\mathbf{R}_{12}$ and $\mathbf{R}_{21}$, but we also must vary the remaining portion of the matrix in $\mathbf{R}_{22}$ to maximize the variation available in an effort to find a better covariance structure within that block. It is unwise to presume that the covariance structure is constant when in fact our sample is one of many possible ones that will be subject to sampling variation, and which may result in smaller correlations than another randomly selected covariance structure.

For present purposes, the use of standardization by the MDS routine renders the several dimensions comparable with respect to the scores, and renders the scores interchangeable across rows. The same *generalized* variance in each matrix is preserved, while the overall structure is molded to many different shapes to attempt to find a better mapping than the observed one, without actually double-centering the matrix (i.e., ipsatizing at the feature level). Rather, simple re-assignment of the dimensions is involved with no further transformation.

Poisson Regression and the Presumed Link Function

The basic mathematics of generalized linear models have been presented elsewhere (e.g., McCullagh & Nelder, 1983). However, a discussion of the basic concepts is in order at this point, because the Poisson regression technique used below is a member of this family.

Classical linear models are familiar to psychologists, and assume a particular distribution (i.e., a Gaussian normal one) for the variables in question, including the

dependent. However, not all outcome measures are so distributed. Counts, for instance, often follow a Poisson distribution which approximates to a binomial distribution (and so to a normal one) when zero becomes a relatively rare (as opposed to modal) value. The number of projects in a given category in a given project system appears to follow this distribution, for instance.

A good model, according to McCullagh & Nelder (1983, p. 5) is one that produces a set of values $\hat{y}$ which minimize some discrepancy measure such as $\sum (y - \hat{y})^2$ without going so far as to simply “repeat” the dataset by fitting as many parameters as there are observations resulting in nothing but a linear transformation of the data. This is the principle of parsimony at work, and some tradeoff between goodness-of-fit and parsimony is required.

To summarize the key points presented in detail by McCullagh & Nelder (1983), in classical linear models, a vector of predicted scores is obtained by finding some vector of parameters β such that the product of the predictor matrix X (i.e., the covariates) multiplied by β produces a vector of predicted values, or means, and so $\mu = \sum \beta_j x_j$. In matrix notation, $\mu = X\beta$, and the expected normal, independent Y have $E(Y) = \mu$. In generalized linear models, it is further assumed that there is some link function which relates the vector of predicted values to the actual distribution. This gives a linear predictor $\eta = \sum \beta_j x_j$, plus a link that specifies some kind of identity between μ and η where $\eta_i = g(\mu_i)$. The link function is $g(\cdot)$. This permits the distribution of $E(Y)$ to be from families such as the exponential (e.g., Poisson) and the link function “to become any differentiable monotonic function” (McCullagh & Nelder, 1983, p. 20). In fact, we may consider classical linear models to be a special case of generalized linear models where the link function $g(\cdot)$ is the identity function, i.e., $\eta_i = 1 \cdot \mu_i + 0$.

This latter point resembles the assumed existence of a monotonic function that is used in nonmetric multidimensional scaling as conceived by Shepard (1962). Davison (1992) refers to δ_{ij} as an empirical observation on an object pair (i, j) , and distinguishes δ_{ij} from d_{ij} in that the latter is a theoretical entity that must be inferred from the data.

Nonmetric scaling assumes the following form:

$$\delta_{ij} = f(d_{ij}) = f(\sum (x_{ik} - x_{jk})^2)^{1/2} \quad (1.8)$$

where f is a monotonic function subject to

$$d_{ij} < d_{i'j'} \Rightarrow f(d_{ij}) < f(d_{i'j'}) \quad (1.9)$$

for all i, i', j and j' (Davison, 1992, p. 82). The existence of some kind of *monotonic* function that maps the d_{ij} to the δ_{ij} is assumed, which is not as restrictive as the assumption of earlier forms of MDS (e.g., Torgerson, 1952) in which data must be proportional to distances. The Torgerson model assumes some kind of direct functional link, just as in the case of generalized linear models, which as a result of the proportionality requirement must be some differentiable monotonic function (just as in generalized linear models). However, in the nonmetric model, the existence of some *unknown* function that links the observed data to the estimates under the sole condition of monotonicity is assumed, however, differentiability is not explicitly assumed.⁵

With these technical details in mind, we may now proceed to the following chapter, which provides the results of some preliminary investigations. These studies will serve to illustrate some of the procedures that are used extensively in the subsequent research.

Chapter 4: Preliminary Results

In this chapter the results of some preliminary analyses are presented based on a single case (my own) presented in Appendix A. These results were obtained not only to provide some examples of the analytical approaches to be taken in the main study, but also to establish some of the parameters to which the main results must conform. First, some preliminary results on the stability of MDS solutions is presented which discusses some results summarized more fully in the Technical Appendix. Secondly, an example of solving a Project Space using MDS is provided, followed by an example of QAP in establishing matrix-to-matrix similarity.

Preliminary Results: the Stability of MDS Solutions

Non-metric MDS techniques do not provide estimates of the error associated with the various coefficients that are estimated. Because of the small number of projects on which an exploration of the presumed Project Spaces will be based, we will need to have some sense of the degree of error involved in our solutions. Thus, a Monte Carlo simulation of MDS S-stress levels for PPA-like data is summarized here.

THE NATURAL ABILITY OF MDS TO REDUCE S-STRESS

If Project Spaces are 3- or 4-dimensional, then it is possible that MDS methods will find a low-S-stress structure where none exists. Since decisions about dimensionality will rest upon the S-stress levels for the solutions of varying dimensionality, some estimate of the lower bounds of S-stress for random data will be necessary in order to assert that individual matrices are differentiable from random data. Thus, Monte Carlo simulations have already been conducted which provide empirical estimates on the behaviour of the MDS algorithm with respect to PPA-like correlation matrices (see Technical Appendix B). We find that for random PPA-like data, a 4-dimensional solution to 17 random, uncorrelated variables can produce S-stress values of less than .086 5% of the time, while the lower 5% bound of the confidence interval for 3-dimensional solutions is 0.152057 . However, while these random data provide a caution

about directly interpreting a low S-stress value as directly implying the existence of a structure, random data are uncorrelated to theoretical models. Where a solution for a single case has a strong relationship to a theoretical PPA structure based on canonical analysis, there are solid grounds for arguing that the Project Space for that case has structure. Unfortunately, where there is no such relationship, the difference between entropy and idiosyncrasy is less clear.

Modern jackknifing and bootstrap methods are now computationally possible (Efron & Tibshirani, 1993), and can be applied directly to the individual data in two ways. Jackknifing (sometimes known as Leave-One-Out, or LOO analysis) involves re-running the analysis in question N times for N subjects, with each subject removed iteratively, and then replaced. The stability of jackknifed INDSCAL solutions has been explored already, and their stability shown to be quite good (Weinberg, Carroll & Cohen, 1984). Bootstrapping involves repeated resampling with replacement, and is known to provide stable estimates of error variance, although it has not been applied to MDS solutions (Efron & Tibshirani, 1993).

In the present research, variations on these methods are proposed as a means of examining inherent variability in the project space. At one level, repeated resampling from the available projects can provide a large number of different correlation matrices. An INDSCAL solution will find a common space in which the “average” project space is represented for that individual case. Weirdness coefficients for the various solutions for a random sample of subjects can provide insight into the solutions which deviate markedly from the overall solution, revealing influential sets of projects. Clinically, this could prove to be extremely useful data. Examination of ten randomly sampled cases from SEAbank will provide a good feel for the stability of the solutions.

The fact that (as shown above) normatively-defined coefficients in fact depend on the average intra-subject variability for which these methods are not defined suggests that an individual-up, rather than group-down perspective on reliability represents something of a turnaround in reliability theory. At one level, the use of these methods affords us an opportunity to compare two analytical tools to one another, and confirm or

disconfirm the validity of the proposed application of QAP to PPA data with reference to the more well-established results of MDS. From a substantive rather than technical point of view, the availability of techniques that permit inferences about within- and between-subject variation affords us the opportunity to make statements about the extent of social-ecological and personality differences among people in terms of the Project Space.

An Example of MDS and Canonical Goodness-of-Fit for a Single Case

The PPA matrix provided in Appendix A is accompanied by simple descriptive statistics and a correlation matrix which presumably captures the Project Space from which the data arose. Table 1 presents the MDS results for that Project Space (using the SAS module PROC MDS; SAS Institute, 1995), and shows that an S-stress value slightly below .10 was found for a three-dimensional solution. Figures 7 through 9 plot the 17 standard features in the three dimensions obtained. As an example of the use of canonical correlation to establish goodness-of-fit, a separate solution was obtained using PROXSCAL, a new MDS computer program (Busing, Commandeur & Heiser, 1996). The main difference between these two programs lies in the fact that PROXSCAL works directly on untransformed data, while SAS works on transformed data. The solution obtained by PROXSCAL achieved an S-stress value of .0085 when three dimensions were requested. The SAS MDS coordinates (see Table 1) were compared to the PROXSCAL coordinates (see Table 2) via canonical correlation using the SAS module PROC CANCORR (SAS Institute, 1996).

The first two canonical correlations were very substantial (.997 and .961, respectively) while the third was comparatively weak (.54). In terms of the significance levels reported, the first two variates were at a comfortable $p < .0001$, while the third, with $p < .03$, did not meet the recommended strict criterion (Schiffman, Reynolds & Young, 1981). The correlations between the coordinates and their canonical variables followed a clear pattern. On the first variate, PROXSCAL and SAS agreed almost entirely, with the first dimension of each solution having a correlation above .99 with the respective

variate, while the other two dimensions were essentially unrelated to it ($|r| < .12$ in all cases).

On the second variate, the PROC MDS coordinates were less clear. Dimension 2 correlated .86 with its variate while dimension 3 correlated .51. The PROXSCAL dimensions were more distinct, as dimension 2 correlated .95 with the variate, compared to a correlation of .14 for dimension 3. On the third and more trivial variate, the PROC MDS dimension 3 correlated .86, with dimension 2 loading at a more moderate -.50. For the PROXSCAL solution, Dimension 3 correlated .54, with both of the other dimensions having $|r| < .08$. Thus, from the pattern of loadings, there is very good agreement between the programs about the first dimension. However, the fact that the PROXSCAL Dimension 2 is partly composed of the SAS dimension 2 and 3, then vice-versa on the third variate indicates that the two programs gave different weight to those dimensions. Nevertheless, it appears that at least a gross structure is clearly identifiable in the data, although the nonmetric scaling used by SAS changes the positions on dimensions 2 and 3 to some degree.

Redundancy analysis revealed a fairly balanced picture, with the canonical redundancies for the three variates being identical to several decimal places for the two sets of variables in the case of the standardized estimates ($r_{d1}=.33$, $r_{d2=.31}$ and $r_{d3}=.10$). Standardization balanced the first two variates, which were composed largely of the first two dimensions. The total redundancy was thus .74 for both sets. The proportion of raw variance accounted for was substantial, and largely attributable to the first variate ($r_{d1}=.70$ for the PROXSCAL variables and .67 for the PROC MDS set, $r_{d2}=.16$ for both sets and $r_{d3}=.04$ for both sets). This gives a total redundancy of .90 to the PROXSCAL set and .88 to the PROC MDS solution, suggesting that the spaces are in fact very similar. The good yet imperfect agreement between two MDS programs about the *same* Project Space noted in this case also indicates what the upper bound may be when comparing *different* project spaces.

Figure 7: Plot of MDS configuration for sample project space.

Figure 8: Plot of MDS configuration for sample Project Space

Figure 9: Plot of MDS configuration for sample Project Space.

A Simulation

The underlying multivariate distribution for this sort of test is not only obscure, but it requires the satisfaction assumptions that are probably violated to some degree (as noted above). Thus, in order to explore the ability of this procedure to extract apparent signal from random noise, the PROXSCAL solution was compared to three uncorrelated vectors of random normal deviates 5000 times using the SAS program `cancorr.sim.sas` (Technical Appendix C: Key Programs). The first canonical correlation averaged .62, with 98% falling between .34 and .87. The second averaged .36, with 98% falling between .11 and .64. The third averaged .12, with 98% falling between .002 and 0.38. The distributions are presented in Figures 10 through 12, and show a decreasingly non-central r distribution across the three successive canonical correlations. While the first canonical correlation can be substantial (confirming Schiffman, Reynolds & Young's (1981) assertion that caution is necessary), it is unlikely to exceed a value of .8 in more than 5% of cases when no association exists (at least, for 3 variables and 3 attributes for 17 elements). Thus, the bar is set rather high for goodness-of-fit indices derived using this approach.

Distribution of Canonical Correlations

based on 5000 simulations

Figure 10: Distribution of 1st Canonical Correlation from Simulation

Figure 11: Distribution of 2nd Canonical Correlation from Simulation

Distribution of Canonical Correlations

based on 5000 simulations

Figure 12: Distribution of 3rd Canonical Correlation from Simulation

Multidimensional Scaling
 Shape=TRIANGLE Condition=MATRIX Level=ORDINAL
 Coef=IDENTITY Dimension=3 Formula=1 Fit=2
 Mconverge=0.01 Gconverge=0.01 Maxiter=100 Over=2 Ridge=0.0001

Iteration	Type	Badness- of-Fit Criterion	Change in Criterion	Convergence Measures	
				Monotone	Gradient
0	Initial	0.18442	.	.	.
1	Monotone	0.13155	0.05287	0.07874	0.49032
2	Gau-New	0.11476	0.01679	.	.
3	Monotone	0.10894	0.00582	0.03401	0.25289
4	Gau-New	0.10798	0.0009595	.	.
5	Monotone	0.10173	0.00625	0.03321	0.15015
6	Gau-New	0.10144	0.0002939	.	.
7	Monotone	0.10033	0.00111	0.01474	0.12563
8	Gau-New	0.10021	0.0001242	.	.
9	Monotone	0.09979	0.0004129	0.00894	0.11353
10	Gau-New	0.09929	0.0005010	.	0.03431
11	Gau-New	0.09925	0.0000441	.	0.01142
12	Gau-New	0.09924	5.29099E-6	.	0.00461

Convergence criteria are satisfied.

	CONFIGURATION		
	DIM1	DIM2	DIM3
IMPORTANCE	-1.34	0.24	0.36
ENJOYMENT	2.34	-0.11	-0.22
DIFFICULTY	-1.25	0.62	-0.55
VISIBILITY	-1.53	-0.07	-0.13
CONTROL	2.00	1.23	0.60
INITIATION	2.10	0.53	0.98
STRESS	-1.72	0.63	0.23
TIME ADEQUACY	-0.20	-0.53	-0.34
OUTCOME	-0.68	-1.30	-0.30
SELF-IDENTITY	1.81	-0.17	-0.72
OTHER'S VIEW	-1.35	0.73	0.83
VALUE CONGRUENCY	1.70	-0.28	-0.18
NEG. IMPACT	-0.25	0.87	-1.32
POS. IMPACT	-1.20	-0.67	0.80
PROGRESS	-0.78	0.22	-0.84
CHALLENGE	-0.92	-0.72	0.60
ABSORPTION	1.27	-1.22	0.19

Table 1: Multidimensional Scaling Solution to Sample PPA Matrix

Example: The Quadratic Assignment Procedure

As an example of the QAP approach, several preliminary analyses have been run, comparing a Project Space to other structures. The first involves a matrix abstracted from the Project Space defined on the PPA matrix presented in the Appendix. A second matrix was derived from a theoretical

model, and a third matrix was the Project Space of a single case randomly sampled from SEAbank. analyses have been run. A third matrix was derived from a variant of the preceding theoretical mode. Thirdly, a QAP analysis of self-similarity amongst 50 pairs of bootstrapped correlation matrices was performed. Lastly, a comparison was made between the present example of a Project Space and a randomly-sampled case from SEAbank.

	D1	D2	D3
	-0.553	-0.025	-0.090
	0.925	-0.021	0.114
	-0.481	0.385	0.108
	-0.612	-0.052	0.118
	0.833	0.414	-0.288
	0.867	0.078	-0.386
	-0.683	0.236	-0.129
	-0.035	-0.121	0.079
	-0.278	-0.482	0.228
	0.695	-0.023	0.269
	-0.543	0.188	-0.361
	0.642	-0.104	0.054
	-0.082	0.474	0.381
	-0.507	-0.306	-0.334
	-0.323	0.139	0.316
	-0.346	-0.311	-0.130
	0.48	-0.469	0.005

Table 2: PROXSCAL coordinates for Single PPA Matrix.

MATRIX 1

A matrix of [-1,0,1] values was generated based on the actual correlational structure of the PPA matrix presented in the Appendix. Where a correlation attained .5 or more, a 1 was coded (or a -1 if the correlation was at or below -.5). Zeroes were coded elsewhere. A QAP analysis was conducted using ANTHROPAC3.0 (Borgatti, 1990) and a correlation of .82 was observed between the abstracted structure matrix and the original data. Nevertheless, none of 1,000 permutations produced a higher value (so we estimate that $p < .001$). Thus, while this approach appears to underestimate the similarity coefficients, the power to detect similarities would appear to remain high.

MATRIX 2

The second matrix was a structure matrix of zeros and ones that was coded based upon the theoretical 5-factor structure of PPA (Little, 1987, 1988). A correlation of .148 was observed, and 65 of 1,000 permutations exceeded this result. This suggests that the 5-factor theoretical model derived from the analysis of system-level data does not fit very well with ipsatively-analyzed PPA data, although the structural similarities are not entirely random.

MATRIX 3

The third matrix was a structure matrix of zeros and ones that was coded based upon a theoretical 3-factor structure (Little, 1993), which posited a “Social Identity/Communion” factor, a “Negative Affect/Stress” factor and a “Personal Identity/Agency” factor. Since Challenge and Absorption were not included in this model, two assumptions were made in coding it. One: Challenge would load on both the Personal Identity/Agency dimension and the Negative Affect/Stress dimension. Two: Absorption would load on the Personal Identity/Agency dimension. A correlation of .215 was observed, and 26 of 1,000 permutations exceeded this result. This result, being somewhat larger than the preceding one, suggests that the 3-factor theoretical model has a somewhat better, although far-from-perfect fit with this particular case. However, this is a suggestion that is not without some difficulty, as it is possibly due to limitations of the QAP approach rather than the objective reality which we attempting to access.

BOOTSTRAP SELF-SIMILARITY

The stability of the individual Project Space is also subject to variation attributable to sampling of projects. Perturbations attributable to this source may affect part of the Project Space or all of it, depending on the properties of the space itself. For this reason, the BOOTSAM macro (Davis, undated) was used in conjunction with the SAS system to generate 100 bootstrapped copies of the original raw data for the Project Space in the Appendix. From this, 100 correlation matrices were derived, and even ones were compared to neighbouring odd ones using QAP to establish the extent to which variation amongst the projects within a single case may affect the apparent stability of

the Project Space. Thus, 50 pairs of lower-half correlation matrices were analyzed, resulting in an average between-matrix correlation of .71 (std. Dev.=.16). The 98% C.I. on the raw values ranged from .337 to .943, and the 2000-iteration bootstrapped confidence interval on the mean was from .644 to .769. This analysis suggests that the loss of information due to random resampling of the same projects (with replacement) is somewhat smaller than the loss incurred in the preceding section due to abstraction by recoding as 0's and 1's. The high degree of bootstrapped self-similarity of a Project Space to itself thus provides one more numerical benchmark for analysis of both intra-subject temporal stability and between-subject differences.

GENERALIZABILITY TO A SECOND CASE

To avoid the possibility that this was a fluke peculiar to one matrix, especially one belonging to the authour, a single case was randomly selected from available data in SEAbank. Case #32 was a high school student from a study by Lecci (1990) who scored within 1 standard deviation of the mean on all of the NEO-PI major factors except Openness, where he or she scored at the 94th percentile. This correlation matrix was compared directly to the one presented in the Appendix, and a correlation of .276 was observed. One thousand random permutations of the matrix produced only eight values greater than this, indicating that a common underlying structure was shared by the two matrices. When this randomly-selected matrix was compared to the theoretical model matrices described above neither the 5-factor structure nor the 3-factor theoretical model fit this case particularly well ($r = .049$ and $.037$, respectively, both $p > .28$).

A CANONICAL FOLLOW-UP

The similarity of this case to the one in the Appendix was further established through a canonical analysis of the coordinates produced by the MINISSA-based algorithm of ANTHROPAC (Borgatti, 1990). The three canonical correlations were .84, .49 and .13, respectively. Redundancy analysis revealed that thirty-one percent of the variance in Case #32 was accounted for by the structure of the present example, and 41% of the variance in the present example was accounted for by the structure of the random

case. These effects are in very large part due to the first pair of variates, which were the only ones that appear to be outside the range of the simulated distributions described above. A plot of the locations of the configuration on the first dimensions of each solution is provided in Figure 13. The overall canonical correlation appears to have been driven by this relationship ($r=.66$), in which the Stress and Community variables seem to differentiate themselves from the Meaning variables, clustering around Positive impact at the former group's end of the continuum and Negative Impact at the latter. Substantively, this common structure suggests that in both of these cases, visible and

Figure 13 : Plot of the First Dimensions for the Present Example and Case 32.

stressful projects are seen as having the greatest beneficial impact on other projects, while personally meaningful projects tend to hinder other projects.

Discussion

Although the preliminary analyses conducted as part of this project provided some interesting and illustrative results, they did not provide a clear indication as to the relative merits of QAP and canonical correlation as methods for the comparison of Project Spaces. The degradation of a matrix by direct coding of observed data into binary or trinary codes is apparent from the results of Matrix 1, and so it is not so surprising that a theoretical model *not* based directly on the observed data would exhibit a much lower absolute value of the correlation coefficient, as with Matrix 2. However, the marked statistical significance of the result for Matrix 2 suggests that in spite of the apparent low correlation, a sufficiently robust structure may underlie Project Spaces that more finely-differentiated methods can detect it. The same may be said of the somewhat better 3-dimensional model of Matrix 3, which suggests (but is far from confirming) that a five-factor model may be somewhat unparsimonious, and that a lower dimensionality is more appropriate to the single case.

The argument for an underlying 3- or 4-dimensional model for individual spaces is bolstered by the similarity of the authour's case to a randomly-selected second case. This similarity, originally indicated by QAP, was more clear when canonical correlation was used with a full redundancy analysis. While the p-values were not reported above due to caution about interpreting such coefficients arising from concerns about violated assumptions (Schiffman, Reynolds & Young, 1981), it will be clear from work reported below that these are actually quite good values.

The next chapter provides an overview of the database to be used for the main part of this study, as well as a description of the analytic strategy that was adopted to resolve the issues raised thus far.

Chapter 5: Methodological Overview

In this chapter we begin with a description of the data available in SEABank that conform to the basic requirements of this study, namely that the 17 standard project features discussed above were obtained. Secondly, an overview of the analytical strategy used in the main part of the dissertation is presented.

Subject Pool

A large number of cases are stored in SEABank, however only a subset (739) complete data forms on which appear the 17 standard PPA features noted above. These cases come from seven studies which are described briefly in this section.

Benton (1987) studied 88 undergraduate students (53 females and 35 males), who were on average 22 years of age with a range from 17 to 63. The majority of the sample were full-time students in their first or second year of university. Dillon (1991) studied burnout in 91 undergraduate students.

Data are available from 73 of Lecci's (1988) 76 cases examined in his study of personal projects, personality and social competency. This group had a mean age of 20.3 (std. dev.=3.5). Lecci (1990) also provides data on a different sample 180 undergraduate students in their first year of university, who were on average 18.8 years of age (std. dev. = .71). An undergraduate sample of 78 cases that were taken from a larger dataset by Pychyl (1986) was also available. While further demographics on this group are unavailable, this larger sample from which this group was drawn consisted of 271 undergraduates who received course credit for participation. Twenty four subjects were discarded to homogenize the age range, resulting in an average age of 20 years (std. dev.=1.4), and a gender mix of 59% male and 41% female.

Szawlowski (1987) followed up 110 female and 61 male undergraduates (mean age=22.2), of whom 165 returned for a re-test at a second point in time. Xiao (1986) studied 29 Chinese and 29 Canadian undergraduate students. The Chinese sample

comprised 12 males and 17 females who were 21.3 years of age on average, who were all unmarried and who represented a variety of academic disciplines. The Canadian sample was also diverse in terms of academic major, but was similar in composition (13 males and 16 females, who were closely matched to the Chinese sample on age). While this study reports an additional cross-validation sample, it appears that they were drawn from Lecci's (1988) data and so are already included in the present study.

These studies do not reflect the full range of applications of PPA that have been studied. Rather, they represent work done on the 17 standard project features which have been collected in the great majority of studies. However, in various pieces of research, some features have been dropped or modified in other studies. For example, Time Adequacy may appear as Time Pressure in some studies, which would have an opposite interpretation. Given that adequate data exist for the present purposes, we will not assume that simple reversal of scale will rectify such discrepancies.

The Analytic Strategy

The analyses proceeded in five main phases. First, an examination of general properties of individual MDS solutions was conducted, which resulted in some useful exclusion rules and some indication of predictors of these properties. Secondly, the reliability of ipsative properties and predictors of reliability were explored. The third phase involved the examination of the joint Project Space by INDSCAL analysis, and the fourth examined the goodness-of-fit of various structural models. In the last phase, we return to a consideration of several individual cases drawn from the available data.

PHASE 1: PROPERTIES AND PREDICTORS OF MDS SOLUTIONS

In this phase, MDS solutions were computed for a large number of cases. The properties of the individual space with respect to MDS are several. The badness-of-fit for solutions of varying dimensionality was obtained, and a rule of thumb was applied to establish an optimal dimensionality that balances fit against parsimony. Useful exclusion rules-of-thumb regarding number of projects in a system and amount of missing data were established. An investigation was conducted to explore possible predictors of the optimal dimensionality of a given solution, and whether the badness-of-fit of solutions of

varying dimensionality was related to personality factors and category of project content. These results comprise Chapter 6 of the present work.

PHASE 2: RELIABILITY OF INDIVIDUAL PROJECT SPACES

In the second phase, the reliability of features of individual Project Spaces was examined. A preliminary QAP approach to estimation of between- and within-subject similarity of project spaces (as an analogue to classical reliability) was undertaken using Thorngate's (1992) Ordinal Pattern Analysis (OPA). QAP and canonical correlation were both used to derive indices of stability, which were compared to one another directly. Furthermore, possible links between these indices and personality variables were explored. These results are reported in Chapter 7.

PHASE 3: THE JOINT PROJECT SPACE

A joint Project Space was obtained via INDSCAL, and predictors of deviation from that common space were explored. One factor was stable personality traits (where data were available), and a second factor was between-study differences which may reflect broader social ecological differences. A separate analysis was run within the data from one study (Xiao, 1986) to examine cross-cultural differences among Chinese and Canadian undergraduates while controlling for other systematic factors arising from between-study and across-time differences. As a check on the clustering effect of the presumed projects-within-subjects nesting that has formed the basis for much research to date, I also compared results obtained from the analysis of intact project system data and "synthetic" project systems, to determine the significance of within-individual clustering of projects. These results are related to the problem of Simpson's Paradox as well as the results obtained through MDS and INDSCAL analyses, and will be reported in Chapter 8.

PHASE 4: THEORETICAL MODELS

In this phase of the study, the results of the joint space analyses are compared to what has previously been stated about the structure of PPA dimensions. Factor analysis was used to derive a solution that ignored within-subject clustering (following on the failure of INDSCAL to clearly differentiate between real and synthetic spaces). The

apparent reliability is reconsidered in light of the general structure obtained in Phase 3, and an improved model is shown to have better fit to the results. Simulation and permutation tests were applied to the fit indices to explore the extent to which asymptotic estimates based on data that probably violate assumptions can reveal significant effects, where the latter cannot. Chapter 9 reports these findings.

PHASE 5: THE SINGLE CASE REVISITED

In the last phase, reported in Chapter 10, cases were selected deliberately on the basis of extreme NEO-PI dimension scores (Costa & McCrae, 1985; McCrae & Costa, 1996) in order to evolve a method for looking at variation within the single case. Bootstrapping a single matrix provides a large number of variations of the Project Space, and MDS solutions can be found for each. Since the basic model for dissimilarity is

$$\delta_{ij} = d_{ij} = \left[\sum_{k=1}^k (x_{ik} - x_{jk})^p \right]^{1/p}, \quad (1.5)$$

any instability in the δ_{ij} will result in variability of these empirical data. Estimation of the d_{ij} will be based on attempts by the algorithm to fit based on triangles that “wobble” at each vertex. We will therefore get a distribution of δ_{ij} for which there will exist an expected value $E(\delta_{ij})$ and a variance $E(\delta_{ij} - E(\delta_{ij})) = \Sigma(\delta_{ij} - E(\delta_{ij})) = \Sigma \delta_{ij}^2 - (\Sigma \delta_{ij})^2 / N$. Due to the arbitrary assignment of signs to the dimensions, however, the actual values of $E(\delta_{ij})$ will be biased by the occasional negative value that arises from a reversal of the scale. Nevertheless, if the features are plotted on a line that represents the dimension, a large cluster will appear where the feature is most likely to be situated, with a “smudge” around that point and a few points “reflected” on the opposite end of the dimension equidistant from the origin at zero. The “smudgeplot” detailed in Chapter 10 reveals exactly these features, taking full advantage of the bootstrap and advanced graphical capabilities that are now available to the average researchers. This technique is proposed as a tool for interpreting project spaces. As Tukey (1977, p. 1) observes, “*If he [i.e., a detective] has no fingerprint powder, he will fail to find fingerprints on most surfaces.*”

With this in mind, we may begin to establish a basis for our detective work by examining the properties of individual Project Spaces.

Chapter 6: The Project Space: General Properties of Individual Spaces

As part of the investigation of general properties of Project Spaces, a comparison of a large number of cases was done in order to provide points of reference for the more detailed exploration of selected cases in the following chapter. This first major component of the present research thus comprised a set of analyses of Project Spaces both at the individual level, using multidimensional scaling. For the initial set of analyses, the Pearson correlation coefficient was selected as a computationally efficient statistic that provides essentially the same information about the Project Space as other nonparametric measures. This assumption is tested in the examination of the joint space in Chapter 8, where the sensitivity of the solution to changes in the similarity measure can be tested for both structural coefficients and “weirdness” coefficients.

Armed with an understanding of the properties of Project Spaces, an exploration of the relationship of social-ecological differences and personality factors with various Project Space indicators is conducted which aids later on in the isolation of “typical” and “unusual” cases for comparison in the next chapter.

Characteristics of the Individual Project Space

Individual Project Spaces may differ in terms of the S-Stress (i.e., badness-of-fit) associated with a solution of a given dimensionality. It is therefore important to examine the distribution of S-Stress across a range of dimensionalities, and to determine the optimal dimensionality of the solutions for Project Spaces. A common rule of thumb for determining “good fit” is when S-Stress is under .10 (Kruskal & Wish, 1978, p. 56). It is expected that once an optimal dimensionality has been obtained, higher-dimensional solutions are unlikely to increase S-Stress above .10, and should, in fact, provide monotonically decreasing levels of S-Stress. Nevertheless, it is also possible to obtain degenerate solutions in low dimensionality for which a solution of higher dimensionality is more appropriate.

In such cases, an apparent low-dimensional solution may be followed by a higher S-Stress level at a higher dimensionality. For example, a 1-D solution might provide an S-Stress of .08, but the 2-D solution has an S-Stress of .12, and the 3-D solution an S-Stress of .05. Where this occurs, the optimal dimensionality is in question. For lack of a better rule of thumb, when such a pattern occurred, the optimal dimensionality was viewed as the next higher dimensionality that provides a solution with S-Stress less than .10. In the example, that would be the three-dimensional solution. The distributions of S-Stress, dimensionality, and degenerate solutions in Project Spaces is unknown, and so all cases in SEABANK which had complete data on the 17 standard PPA dimensions were analyzed separately to examine the properties of these measures.

Personality, Project Categories and S-Stress

To the extent that different personality factors (as defined by the available NEO-PI data; Costa & McCrae, 1985) result in differential reporting of projects, and the characteristics of project category affect the ability of an MDS routine to find a low-S-stress solution, either a direct or an indirect relationship between NEO-PI scores and the badness-of-fit of solutions may exist. Precisely stated, it is expected that both badness-of-fit measures and NEO-PI variables will predict the number of types of projects reported, as well as the number of each type of project in seven standard PPA categories (Occupational/Academic, Health, Interpersonal, Intrapersonal, Leisure, Administrative, and Other). The relationship between badness-of-fit and personality factors was tested using canonical correlation.

The nature of the distributions of these variables have several key features that must be considered in selecting an analytical tool. First, we must take into account the number of projects reported, because this will affect the count in each category. Secondly, we must recognize that these measures are counts that generally fall below 7 or 8, and so are likely to follow (at least approximately) a Poisson distribution. Lastly, both the limited time available to engage in different kinds of projects as well as the limited number of projects typically collected in the PPA methodology will induce negative correlations among these variables (except for the number of types, which is a

derivative of the other measures). For example, if one is swamped in administrative projects, there is likely to be little time for leisure pursuits, and vice-versa. If, however, one has equal numbers of several kinds of projects, but one wishes to emphasize one category within the space of ten blanks on a PPA form, it must be done at the expense of other categories.

The first two factors described in the preceding paragraph imply that Poisson regression should be used. While in theory, Poisson variables should be able to take on any real integer value from zero to infinity, PPA data are truncated by the number of available spaces in the questionnaire sheet. However, in the 401 cases in SEABANK for which we have project category information, one case listed 8 Administrative projects and another list 9 Leisure projects, suggesting that the probability of truncation due to methodology is less than half a percent. As well, it made *a priori* sense to retain the number of projects as an offset variable (i.e., a variable whose coefficient is known to be 1; McCullagh & Nelder, 1983). However, this approach was not viable for reasons discussed below.

The third factor noted above must also be weighed when interpreting the results of separate analyses. A multivariate analog to canonical correlation does not appear to exist for the case of Poisson-distributed variables, and so requires separate regressions to be run on intercorrelated outcome measures. A Bonferroni-corrected alpha of 0.0071 is therefore adopted for determining significance of parameters, and trends will be noted where this criterion is not met, but more conventional significance levels are exceeded or approached.

A final consideration is the problem of overdispersion of Poisson variables, where the variance is greater than the mean. Methods for dealing with this exist (see Glynn, 1993; <http://www.albany.edu/csda/genmod.html>). One of which (the DSCALE option) is provided in the SAS GENMOD module (SAS Institute, 1995). This option sets the scale parameter to the square root of (the deviance of the uncorrected model) divided by the degrees of freedom, resulting in a larger error term against which the parameters are compared.

A further question arises as to the relationship between another type of missing data in the Project Space. Some individuals may provide complete data for a project feature which nevertheless results in a row and column of missing data in the matrix of associations due to zero variance (e.g., a column of all 10's on Stress). The extent to which the number of features that have zero variance in a Project Space is related to badness-of-fit measures for solutions of varying dimensionality may also be examined with a further use of Poisson regression, where a simple count of the number of features exhibiting zero variance may be predictable from badness-of-fit, particularly in higher-dimensional solutions where the estimation of missing data points may capitalize on the smaller distances to which the algorithm gives lower priority than the non-missing larger distances (Davison, 1992).

Results: General Features

The Available Data

One thousand three hundred and ninety-three cases (from 13 different studies) for which PPA data exists at the project level have been archived in the SEABank dataset. However not all of these studies have used the 17 standard project features discussed above, nor are all cases complete and without missing data, so only part of the data were usable for the present purposes.

Within SEABank, there were 739 cases available that had at least partially -completed PPA matrices that contained the 17 standard features of interest in the present research. These cases were drawn from 7 different studies (Benton, 1987; Dillon, 1991; Lecci, 1988; Lecci, 1990; Pychyl, 1986; Szawlowski, 1987; Xiao, 1986). The frequency

STUDY	Frequency	Percent
Xiao	58	7.8
HSTS	180	24.4
Lecci	73	9.9
Szawlowski	171	23.1
Pychyl	78	10.6
Benton	88	11.9
Dillon	91	12.3

	739	

Table 3: Number of Cases Available in Studies that used the 17 standard PPA features.

distribution is presented in Table 3. In some cases, where a project was left blank the data entry operator often keyed in a record with all values missing. To avoid counting these null records, they were deleted before any analyses were performed. In addition, a single case was eliminated because only partial data were obtained on two projects, with one or two ratings on various features across seven others

In order to achieve a minimal degree of stability and generality in the derived Project Spaces, a rule of thumb was invoked which excluded cases who listed fewer than 7 projects in the matrix, and cases which had missing data on 10% or more of the possible ratings, resulting in the reduced frequency distribution based on 715

cases that is presented in Table 4. Mean number of projects per study, and the average proportion of missing data per subject are presented in Table 5 (these figures include those cases that were later excluded by the criteria described above).

STUDY	Frequency	Percent
Xiao	58	8.1
HSTS	167	23.4
Lecci	73	10.2
Szawlowski	167	23.4
Pychyl	77	10.8
Benton	83	11.6
Dillon	90	12.6

		715

Table 4: Number of Cases with 7 or more projects having < 10% missing data.

Average number of projects and proportion missing values per case, by study.

	Avg. # of Projects (Std.dev.)	Avg. Proportion missing values (Std. Dev)
Xiao	10.0 (0.00)	0.0 (0)
HSTS	9.8 (.86)	0.02 (.085)
Lecci	9.9 (1.04)	<10E-4 (<10E-3)
Szawlowski	9.8 (.80)	0.002 (0.0152)
Pychyl	9.7 (.88)	0.003 (.0890)
Benton	10.0 (0.00)	0.022 (.0890)
Dillon	9.8 (.70)	0.002 (.0088)
Total	9.8 (.01)	0.009 (.054)

Table 5: Number of projects and missing data patterns in SEABank.

Characteristics of Project Spaces

The intercorrelations among the 17 standard PPA features were computed on a casewise basis to provide 739 Project Spaces for MDS analysis. In four cases, the procedure stopped after 500 iterations because of a failure to reduce S-Stress on one of the dimensions. However, each of these cases received only a single warning, and a different dimensionality successfully reduced S-Stress to an acceptable level within the maximum number of iterations permitted. In seven other cases, missing values were estimated by the program. None of these cases had more than one value in the lower half of the matrix that was missing due to zero variance on one or more variables.

EXCLUSIONS

Although 739 cases were available, not all had complete or adequate data. One case was eliminated from further consideration because only two projects had full ratings, while only one or two features were rated on each of the remaining projects. An additional 23 cases were excluded using a criterion of having either less than 7 projects rated or more than 10% missing data. Missing data are summarized in Table 5. The following analyses were limited to 715 cases on which seven or more projects were rated with less than 10% missing data. For the time 2 data, 219 cases met this criterion, while for the time 3 data, 113 cases (from the High School dataset only) did so.

S-STRESS

Simple univariate statistics for S-Stress on each of the six requested dimensionalities (variables BADFIT1-BADFIT6) are presented in Table 6; each distribution was approximately normally distributed (see Figures 14 through 19).

Badness-of-fit in 1 dimension

Figure 14: Distribution of Stress in 1 Dimension

Badness-of-fit in 2 dimensions

Figure 15: Distribution of Stress in 2 Dimensions

Badness-of-fit in 3 dimensions

Figure 16: Distribution of Stress in 3 Dimensions

Badness-of-fit in 4 dimensions

Figure 17 Distribution of Stress in 4 Dimensions

Badness-of-fit in 5 dimensions

Figure 18 Distribution of Stress in 5 Dimensions

Figure 19 Distribution of Stress in 6 Dimensions

A progression from slight negative to slight positive skewness was apparent across increasing dimensionalities, as well as a movement from slight platykurtosis to marked leptokurtosis.

Figures 20 through 24

plot the raw squared
distances (FITDATA)
against the distances
obtained for each of the
first five dimension-

alities. The sixth is
excluded as there was
only one case that contributed to it.

Variable	Mean	Std Dev	Minimum	Maximum
BADFIT1	0.3466	0.1039	0.006210	0.5747
BADFIT2	0.1834	0.0618	0.003127	0.3585
BADFIT3	0.1023	0.0375	0.009376	0.2471
BADFIT4	0.0576	0.0224	0.000831	0.1567
BADFIT5	0.0348	0.0145	0.000831	0.1324
BADFIT6	0.0235	0.0075	0.002117	0.0736

Table 6: Simple Descriptive Statistics for Badness-of-Fit (Stress) across 6 Requested Dimensionalities

Table 7 presents the results of a multiple regression that was run to predict S-Stress of the 1-D solution based on the S-Stress from 2- through 6-D solutions. Approximately 71% of the variance in BADFIT1 can be accounted for by the remaining

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	5	5.48038	1.09608	349.069	0.0001
Error	709	2.22626	0.00314		
C Total	714	7.70664			
Root MSE	0.05604	R-square	0.7111		
Dep Mean	0.34659	Adj R-sq	0.7091		
C.V.	16.16761				
Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	0.122130	0.00852190	14.331	0.0001
BADFIT2	1	1.606551	0.07180630	22.373	0.0001
BADFIT3	1	-0.358994	0.15633227	-2.296	0.0219
BADFIT4	1	0.077072	0.21831271	0.353	0.7242
BADFIT5	1	0.175559	0.22864509	0.768	0.4428
BADFIT6	1	-1.871945	0.38110537	-4.912	0.0001

Table 7: Multiple regression showing BADFIT1 strongly related to other S-Stress measures.

S-Stress values (especially for 2,3 and 6), which suggests that the solutions to the largest distances between features in the MDS space account for that much of the badness-of-fit, while approximately 29% are accounted for by adding further dimensions to the solutions. In particular, the relationships among the first three dimensions suggest that at least three should be required for most cases, which is consistent with the observed results for optimal dimensionality that are discussed in the following section.

OPTIMAL DIMENSIONALITY

It was assumed that for each matrix, some optimal dimensionality exists which minimizes S-Stress while providing a parsimonious number of dimensions. This optimal dimensionality was determined for each case as the first dimensionality which produced a Kruskal S-Stress value below 0.10. In cases where a low dimensionality provided a low-S-Stress solution, but a solution of higher dimensionality failed to meet the .10 criterion, the next higher dimensionality providing an S-Stress below .10 was assigned to the case. This was exceedingly rare, however, occurring in only one of the 738 cases from whom three more projects were available. (This case was not one that was excluded from subsequent analyses due to having too few projects or too much missing data: see below).

For the time 1 and time 2 data, it was possible to compare optimal dimensionality across the two studies that collected longitudinal data (Lecci, 1990; Szawłowski, 1987). A split-plot factorial ANOVA indicated a significant interaction between study and the repeated factor (Wilks' Lambda = .733, $F_{1,102.9}=102.91$, $p < .0001$). The means are plotted in Figure 25, and reveal a marked drop for the HSTS data (which was collected on different projects much later) relative to the drop for the Szawłowski data (the same projects shortly after the first administration).

Figure 20: Actual vs. Transformed Squared Distances in 1-D Solutions

Figure 21: Actual vs. Transformed Squared Distances in 2-D Solutions

Figure 22: Actual vs. Transformed Squared Distances in 3-D Solutions

Figure 23: Actual vs. Transformed Squared Distances in 4-D Solutions

Figure 24: Actual vs. Transformed Squared Distances in 5-D Solutions

MONOTONICITY OF IMPROVEMENTS IN S-STRESS:

A GROSS BUT WORKABLE CUTOFF

If, as expected, MDS should produce S-Stress coefficients that decrease monotonically as dimensionality of solution increases except in cases of degenerate solutions, then a rule may be invoked to automatically assign the optimal dimensionality that describes the case. If each successive dimension is coded as 0 if it fails to produce a suitably low S-Stress value, and 1 if it succeeds, then a near-perfect Guttman scale should emerge from the solutions except for problematic cases.

Assigned Dimensionality	GUTTMAN	Frequency	Cumulative Percent	Cumulative Frequency	Cumulative Percent
6	000001	1	0.1	1	0.1
5	000011	29	4.1	30	4.2
4	000111	338	47.3	368	51.5
(5)	001011	1	0.1	369	51.6
3	001111	279	39.0	648	90.6
2	011111	56	7.8	704	98.5
1	111111	11	1.5	715	100.0

Reproducibility: 1.000

Scalability: .988

Note: a 1 was assigned where the stress was below .10, and a zero elsewhere. The dimensionality (5) was the only one that required manual examination and re-assignment, as a result of its deviation from the perfect Guttman scale.

Table 8: Guttman scaling for optimal dimensionality based on stress < .10 over 6 dimensions.

Figure 25: Plot of Means for Optimal Dimensionality Over Time

GUTTMAN3	Frequency	Percent	Cumulative Frequency	Cumulative Percent
000011	2	1.8	2	1.8
000111	40	35.4	42	37.2
001111	65	57.5	107	94.7
011111	3	2.7	110	97.3
111111	3	2.7	113	100.0

Reproducibility = 1.00 Scalability=1.00

Table 9: Guttman patterns for Time 2 data, High School data only.

GUTTMAN2	Frequency	Percent	Cumulative Frequency	Cumulative Percent
000011	2	0.9	2	0.9
000101	1	0.5	3	1.4
000111	53	24.2	56	25.6
001101	1	0.5	57	26.0
001111	98	44.7	155	70.8
011111	50	22.8	205	93.6
111111	14	6.4	219	100.0

Note: The case exhibiting pattern 000101 was CBNKID=70.
 The case exhibiting pattern 001101 was CBNKID=160.
 Both were set to dimens2=6.

Reproducibility = 0.997 Scalability=0.971

Table 10 : Guttman patterns for Time 2 data, High School and Szawlowski's studies.

Using the .10 cutoff noted in the preceding section, these values were assigned to the cases. A reproducibility of 1.000 was obtained with a scalability of .988 (ANTHROPAC; Borgatti, 1990). Only one case deviated from the perfect Guttman scale (CBNKID=254; see Table 8). This case was solved in 5 dimensions at an S-Stress value of 0.031588, and the sixth dimension failed to improve this, giving a value of 0.031951. A single case required a six-dimensional solution to obtain S-Stress below .10. Given the near-perfect fit of the model, and the fact that an absolute maximum of six dimensions were required, optimal dimensionality was computed automatically as 7 minus the number of dimensions that provided solutions with S-Stress below 0.10. For the single case with an aberrant pattern, an optimal dimensionality of 5 was assigned. Comparable results were obtained for the time 2 and time 3 data from Szawłowski's data and the HSTS data (see Tables 9 and 10).

DIFGUTT	Frequency	Percent	Cumulative Frequency	Cumulative Percent
00101	1	0.1	1	0.1
00111	1	0.1	2	0.3
01111	1	0.1	3	0.4
10011	1	0.1	4	0.6
10110	1	0.1	5	0.7
10111	2	0.3	7	1.0
11001	2	0.3	9	1.3
11010	2	0.3	11	1.5
11011	4	0.6	15	2.1
11100	7	1.0	22	3.1
11101	23	3.2	45	6.3
11110	66	9.2	111	15.5
11111	604	84.5	715	100.0

Table 11: Frequency of patterns of monotonicity of change in stress.

MONOTONICITY OF IMPROVEMENTS IN S-STRESS: A FINER DIFFERENTIATION

The preceding approach made gross cuts based on a single cutoff. However, in the case of S-Stress values below .10, a range of changes could still occur that are *not* monotonically decreasing. In fact, five variables were computed (CHANGE1-CHANGE5) which contain the difference between the S-Stress levels of solutions of successive dimensionality. Initially, these changes were coded as 1 if negative (i.e., monotonically decreasing), or 0 if positive. The frequency of these patterns is summarized in Table 11, where the patterns are coded into the variable "DIFGUTT." Eighty-four and a half percent of the sample exhibited perfect monotonically decreasing S-Stress of solutions over the six dimensions requested (i.e., a "DIFGUTT" pattern of 11111). Just over nine percent showed an increase on the sixth dimension. Another 3.2% showed an increase on the five-dimensional solution, but a decrease on the six-dimensional solution. One percent showed increases on both the five- and six- dimensional solutions. The remaining 2.1% exhibited some instability in the first three dimensionalities. A detailed presentation of the average change from one dimensionality to the next is given in Table 12. From this it can be seen that where the changes are positive, they are typically very small on average, with none of them showing a mean change in S-Stress of more than +0.02.

PREDICTORS OF OPTIMAL DIMENSIONALITY

When the time 1 data for all available studies were analyzed, between-study differences on optimal dimensionality were not found ($F_{7,707}=1.67, p>0.1258$), with mean optimal dimensionality ranging from 3.36 to 3.59 across the seven studies. Number of projects rated (mean=9.78, std. Dev.=.76, min.=3, max=17) was tested for linear and quadratic components, and neither model was significant ($F_{1,712} < 1.5, p > .2$ for both components). Three hundred and forty-six cases had complete NEO-PI data. Scale scores for each of the five major personality factors of Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness were tested for linear, quadratic and crossproduct effects. The model was not significant ($F_{20,325} = 1.366, p = 0.1369$) and did not account for a great deal of variance ($R^2=.078$).

S-STRESS AND MISSING DATA

The effect of missing data on a Project Space is indirect. While the correlation matrix may be (with a few trivial exceptions) complete, the standard error of each element in the matrix is a function of the number of observations used to compute it. This can vary slightly as a result of both random and methodological factors. Where the variations are marked as a result of large quantities of missing data, this may impact on the stressfulness of the solutions obtained through MDS, because correlations based on different numbers of projects will vary to different degrees. Examination of the scatterplots relating the proportion of missing data for each case (PROBMISS) to the six S-Stress variables (BADFIT1-BADFIT6) suggested that an inverse regression would provide a good model for relating missing data to S-Stress. Therefore inverse badness-of-fit measures were computed as 1/S-Stress (IBF1-IBF6) and tested in a backwards-elimination model with a significance-level-to-stay of .05. The results

DIFGUTT	CHANGE1	CHANGE2	CHANGE3	CHANGE4	CHANGE5
00101	0.00194*	0.004360*	-0.012812	0.006331*	-0.004460
00111	0.01474*	0.020132*	-0.017131	-0.005371	-0.001107
01110	0.00236*	-0.006723	-0.002443	-0.000383	0.002825*
01111	0.00244*	-0.014215	-0.001691	-0.001310	-0.000555
10011	-0.13016	0.003036*	0.013759*	-0.007989	-0.011433
10100	-0.03553	0.000050*	-0.000000	0.004466*	0.006822*
10110	-0.07075	0.005583*	-0.002476	-0.004132	0.005975*
10111	-0.16553	0.008565*	-0.000470	-0.004185	-0.002484
11001	-0.04801	-0.008411	0.000064*	0.012988*	-0.021405
11010	-0.25287	-0.056121	0.024814*	-0.041432	0.002466*
11011	-0.14418	-0.091075	0.012686*	-0.011909	-0.030473
11100	-0.16861	-0.053526	-0.027134	0.000243*	0.002814*
11101	-0.15628	-0.069638	-0.031075	0.019750*	-0.036974
11110	-0.14458	-0.065945	-0.041534	-0.017906	0.002162*
11111	-0.16730	-0.084565	-0.046905	-0.025571	-0.011736

Note: "DIFGUTT" was scored as 0 if the change from dimensionality X to dimensionality X+1 was monotonically decreasing, else it was coded 1. Thus the pattern 101111 is associated with cases that experienced an increase in stress from Dim=1 to Dim=2. Values of Change were computed directly as (Stress at next highest dimensionality) minus (Stress at Current Dimensionality). Increasing mean stress values are denoted with asterisks, and these correspond to the zeroes in the "DIFGUTT" pattern. Decreasing values correspond to improvements and are denoted with 1's.

Table 12: Detailed Analysis of Mean Change in Stress Across Dimensionality of Solution.

of this analysis are presented in Table 13.

While the inverse S-Stress levels for dimensionalities 1 and 2 were eliminated in two steps, all of those pertaining to higher-dimensional solutions were significant, with the final model accounting for 35.7% of the variance in missing data. As an argument in favour of the elimination of cases with fewer than six projects and/or over 10% missing data, the elimination of these 23 cases from the analysis led to completely non-significant results when the backwards inverse regression was re-run without them. Intriguingly, the parameter estimates for the even-number dimensionalities is negative, while for the odd-numbered dimensionalities it is positive.

Missing data at the project level can cause slight irregularities in the correlation matrix. However, even complete project data can result in missing data points in a Project Space when one or more variables has zero variance, which results in non-calculable values of a given element. Of the 738 non-problematic cases, a full 252 cases exhibited some degree of missing data as a result of this. However, when a dummy variable was coded to identify cases that had one or more missing elements in the Project Space, only the S-stress value for solving in four dimensions was a significant covariate in a logistic regression (parameter = 23.6, OR > 999, $p < .0047$), indicating that the estimation of missing data used by the SAS PROC MDS module is not markedly affected by the missing data except when solving in a higher dimensionality, where fine-tuning can be done which takes advantage of the flexibility afforded by estimating missing points.

S-STRESS AND NUMBER OF PROJECTS

While missing data do not appear to be a significant problem, methodological and random factors affecting the number of projects rated will influence the standard error of the correlation coefficients being used to establish the structure of the Project Space. Examination of the scatterplots suggested that (as with PROBMIS) inverse regression was appropriate to relate number of projects rated (NPROJ) to S-Stress. The IBF1-IBF6 variables described above were entered in a backwards elimination regression, and the inverse S-Stress values for all dimensionalities higher than 2 were significant (Table 14), accounting for 16.8% of the variance in NPROJ. However, when the 23 problematic cases were eliminated,

	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	4	0.62239527	0.15559882	100.49	0.0001
Error	733	1.13492573	0.00154833		
Total	737	1.75732100			
R-square = 0.35417278 C(p) = 6.33757685					
Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
Backwards elimination inverse regression predicting probmiss					
10:53 Wednesday, October 15, 1997					
INTERCEP	0.00358488	0.00411767	0.00117357	0.76	0.3843
IBF3	0.00105256	0.00008599	0.23197533	149.82	0.0001
IBF4	-0.00064262	0.00011015	0.05269822	34.04	0.0001
IBF5	0.00097840	0.00011783	0.10676055	68.95	0.0001
IBF6	-0.00063688	0.00010530	0.05664068	36.58	0.0001
Bounds on condition number:		19.60674,	164.1996		

All variables left in the model are significant at the 0.0500 level.

Summary of Backward Elimination Procedure for Dependent Variable PROBMIS3

Step	Variable Removed	Number In	Partial R**2	Model R**2	C(p)	F	Prob>F
1	IBF2	5	0.0004	0.3567	5.5081	0.5081	0.4762
2	IBF1	4	0.0025	0.3542	6.3376	2.6314	0.0929

Table 13: Backwards elimination inverse regression predicting probmiss for 715 non-problematic cases.

the inverse S-Stress value for dimensionalities five and six remained significant (Table 14) but accounted for only less than 3% of the variance in NPROJ.

A COMPARISON TO SIMULATED RANDOM DATA

It is also informative to consider the distribution of S-Stress in the most common optimal dimensionalities as compared with the randomly-generated data described above. As solutions in 1,2, 5 or 6 dimensions are relatively unusual, we may focus our attention on those requiring 3 or 4 dimensions to solve. With respect to the 3-dimensional (or 3-D) cases, the mean S-Stress for the 3-dimensional solution was 0.078, with a standard deviation of 0.0158. This compares very favourably to the distribution of random data provided in the Technical Appendix (mean=0.1949, std. dev.=0.02704 in Table TA2). Likewise, for the 4-D cases, the

mean S-Stress for the 4-dimensional solution was 0.069 (std. dev.=0.0144), as compared to the random distribution of Table TA1 which had a mean S-Stress of 0.120 (std. dev.= 0.0197).

We may consider these values across the entire sample of Project Spaces as well, ignoring the optimal dimensions. Across all cases, the 90th percentile for BADFIT3 was .15, which corresponds approximately to the fifth percentile of the 3-D solutions to random data. Likewise, the fifth percentile for 4-D solutions to random data was 0.087, which is approximately equal to the 90th percentile for real data (0.089). The separation between real and simulated data is therefore nearly complete.

PERSONALITY, S-STRESS AND PROJECT CATEGORY:

EVIDENCE FOR AN INDIRECT RELATIONSHIP

Three hundred and thirty-six non-problematic cases (as defined above) that listed 10 projects on the PPA form were drawn from three studies (the HSTS data from Lecci, 1988, those of Lecci, 1990, and Szawlowski's 1987 data). One category in the Szawlowski data was uncoded, and no record could be found to enable re-coding of the sixty-five projects that fell into it in the entire dataset. Including these values that were set to missing, there were missing project categories on a single project in 13.5% of the cases, and on two or three projects in 2.9% of the cases.

The Poisson regression model tested for each outcome measure included the five NEO-PI personality measures (transformed to Z-scores for ease of interpretation of regression coefficients), study (as a dummy-coded classification variable) and the badness-of-fit S-Stress values from the MDS analyses described above. Originally, the number of projects reported was entered as the offset variable. However, the distribution of number of projects was not at all normal, and the inclusion of outliers produced dubious solutions. It is for that reason that analyses were restricted to cases where ten projects were provided by the respondent. The deviance of all models was greatly improved by this. As a result of overdispersion on all measures except number of types of project reported (NTYPES), number of interpersonal projects (INTERPER) and number of Health projects (HEALTH), the scale parameter was

adjusted according to the DSCALE method for all outcome variables. The SAS module PROC GENMOD (SAS Institute, 1996) for generalized linear models was used, with the error distribution specified as Poisson and the link function set to logit.

Number of different types of projects was computed by counting the number of non-zero values on each of the other 7 count variables (number of occupational/academic projects, number of interpersonal projects, etc.). This measure had no significant predictors, suggesting that project variety is unrelated to either NEO or MDS S-Stress measures. Details of the following results are presented in Tables 15 through 22.

Number of Occupational/Academic projects was predicted by NEO-PI Openness, which had a significant negative relationship ($p < .0001$). A negative trend was noted for the 2-D S-stress measure ($p < .0401$) and a positive trend for the 3-D S-Stress measure ($p < .0602$ for unique variance, $p < .0138$ for the Type 1 analysis). The HSTS data produced significantly fewer of these kinds of projects than in the Szawlowski data (the reference category), while the Lecci data produced significantly more (both $p < .003$).

Backward Elimination Procedure for Dependent Variable NPROJ					
Step 0	All Variables Entered		R-square = 0.16765898		
	DF	Sum of Squares	Mean Square	F	Prob>F
Regression	6	71.94796807	11.99132801	24.54	0.0001
Error	731	357.18482325	0.48862493		
Total	737	429.13279133			
Variable	Parameter Estimate	Standard Error	Type II Sum of Squares	F	Prob>F
INTERCEP	10.10515803	0.07433732	9029.17336139	18478.7	0.0001
IBF1	-0.00577023	0.00282957	2.03199286	4.16	0.0418
IBF2	0.00457977	0.00260451	1.51081863	3.09	0.0791
IBF3	-0.01593451	0.00291195	14.63137473	29.94	0.0001
IBF4	-0.01151626	0.00210544	14.61890118	29.92	0.0001
IBF5	0.01432903	0.00232333	18.58606977	38.04	0.0001
IBF6	-0.00663707	0.00193487	5.74941119	11.77	0.0006
Final Model:	R-square = 0.16080563		C(p) = 9.01893244		

Table 14: Inverse Regression with Backwards Elimination for Predicting Number of Projects Rated: All 738 cases with > 2 Projects

For number of Health projects, only a negative trend was noted for Conscientiousness ($p < .0495$). None of the other NEO-PI measures, S-Stress measures or Study dummies were significant. The frequency with which Interpersonal projects were reported was unrelated to NEO-PI measures, and only a trend was noted for Study (with the Lecci data tending to be low, $p < .0695$). A negative trend was noted for the 4-D S-Stress measure ($p < .0524$) and a positive one for the 5-D S-Stress measure ($p < .0362$). Number of Intrapersonal projects was significantly related to Study, with a positive effect for the Lecci data ($p < .0001$) and a positive trend for the HSTS data ($p < .0171$). A strong positive effect was observed for Neuroticism ($p < .0001$), a negative trend for Extraversion ($p < .0343$), and positive trends for Openness ($p < .0105$) and Conscientiousness ($p < .0543$). A negative trend was observed for the 1-D S-Stress vector BADFIT1 ($p < .0253$). Number of Leisure projects differed among the studies, with the HSTS and Lecci data being significantly higher in the former ($p < .0001$) and tending to be higher in the latter ($p < .0249$). A non-significant positive trend emerged for Openness ($p < .0558$) and the 2-D S-Stress vector ($p < .0647$), while a negative trend emerged for the 3-D S-Stress vector. Canonical correlation was used to explore the relationship between the S-Stress in 1 to 5 dimensions and the five main NEO-PI factors. Although the 381 available cases provided ample statistical power, no significant effects were noted. The first canonical correlation had a value of 0.19, $p > .29$, and the remaining four decreased from there.

Dependent Variable	NTYPES	number of different categories reported
Observations Used	336	
Missing Values	43	

Class Level Information

Class	Levels	Values
STUDY	3	HSPASYT1-3 LLSERIES SZSPFA

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	323	58.4285	0.1809
Scaled Deviance	323	58.4285	0.1809
Pearson Chi-Square	323	56.3930	0.1746
Scaled Pearson X2	323	56.3930	0.1746
Log Likelihood	.	-843.5451	.

Analysis Of Parameter Estimates

Parameter		DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT		1	1.5653	0.0395	1567.9797	0.0001
STUDY	HSPASYT1-3	1	-0.0571	0.0583	0.9584	0.3276
STUDY	LLSERIES	1	-0.0144	0.0740	0.0376	0.8462
STUDY	SZSPFA	0	0.0000	0.0000	.	.
NEUR		1	0.0159	0.0275	0.3328	0.5640
EXT		1	-0.0035	0.0274	0.0166	0.8974
OPEN		1	-0.0039	0.0268	0.0215	0.8833
AGREE		1	-0.0018	0.0263	0.0044	0.9472
CONS		1	0.0059	0.0270	0.0485	0.8258
BADFIT1		1	0.0137	0.0443	0.0942	0.7588
BADFIT2		1	0.0306	0.0711	0.1855	0.6667
BADFIT3		1	-0.0552	0.0731	0.5707	0.4500
BADFIT4		1	0.0159	0.0610	0.0683	0.7939
BADFIT5		1	0.0029	0.0374	0.0061	0.9376
SCALE		0	1.0000	0.0000	.	.

NOTE: The scale parameter was held fixed.

Table 15: Poisson regression predicting Number of Types of Project

Dependent Variable OCCACAD number of occ/acad projects
 Observations Used 336
 Missing Values 43

Class Level Information

Class	Levels	Values
STUDY	3	HSPASYT1-3 LLSERIES SZSPFA

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	323	291.9053	0.9037
Scaled Deviance	323	323.0000	1.0000
Pearson Chi-Square	323	249.4067	0.7722
Scaled Pearson X2	323	275.9743	0.8544
Log Likelihood	.	-199.8630	.

Analysis Of Parameter Estimates

Parameter		DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT		1	0.7361	0.0571	166.4333	0.0001
STUDY	HSPASYT1-3	1	-0.5917	0.0967	37.4393	0.0001
STUDY	LLSERIES	1	0.2853	0.0960	8.8269	0.0030
STUDY	SZSPFA	0	0.0000	0.0000	.	.
NEUR		1	-0.0618	0.0419	2.1758	0.1402
EXT		1	0.0234	0.0432	0.2933	0.5881
OPEN		1	-0.1784	0.0401	19.8293	0.0001
AGREE		1	0.0121	0.0402	0.0906	0.7634
CONS		1	-0.0063	0.0418	0.0226	0.8806
BADFIT1		1	0.0355	0.0637	0.2674	0.6051
BADFIT2		1	-0.2268	0.1105	4.2147	0.0401
BADFIT3		1	0.2104	0.1120	3.5328	0.0602
BADFIT4		1	0.0428	0.0937	0.2088	0.6477
BADFIT5		1	-0.0745	0.0624	1.4238	0.2328
SCALE		0	0.9506	0.0000	.	.

NOTE: The scale parameter was estimated by the square root of DEVIANCE/DOF.

Table 16: Poisson regression predicting Number of Occupational/Academic Projects

Dependent Variable	HEALTH	number of health projects
Observations Used	336	
Missing Values	43	

Class Level Information

Class	Levels	Values
STUDY	3	HSPASYT1-3 LLSERIES SZSPFA

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	323	279.8658	0.8665
Scaled Deviance	323	279.8658	0.8665
Pearson Chi-Square	323	226.1435	0.7001
Scaled Pearson X2	323	226.1435	0.7001
Log Likelihood	.	-322.6574	.

Analysis Of Parameter Estimates

Parameter		DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT		1	0.1988	0.0784	6.4306	0.0111
STUDY	HSPASYT1-3	1	-0.1283	0.1170	1.2016	0.2730
STUDY	LLSERIES	1	0.0717	0.1428	0.2525	0.6153
STUDY	SZSPFA	0	0.0000	0.0000	.	.
NEUR		1	0.0896	0.0547	2.6815	0.1015
EXT		1	0.0669	0.0555	1.4523	0.2281
OPEN		1	-0.0330	0.0531	0.3860	0.5344
AGREE		1	0.0664	0.0537	1.5285	0.2162
CONS		1	-0.1055	0.0537	3.8591	0.0495
BADFIT1		1	0.0885	0.0871	1.0308	0.3101
BADFIT2		1	-0.1929	0.1400	1.8991	0.1681
BADFIT3		1	-0.0111	0.1433	0.0060	0.9325
BADFIT4		1	0.1454	0.1188	1.4992	0.2203
BADFIT5		1	-0.0198	0.0740	0.0718	0.7883
SCALE		0	1.0000	0.0000	.	.

NOTE: The scale parameter was held fixed.

Table 17: Poisson regression predicting Number of Health Projects

Dependent Variable INTERPER number of interper projects
 Observations Used 336
 Missing Values 43

Class Level Information

Class	Levels	Values
STUDY	3	HSPASYT1-3 LLSERIES SZSPFA

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	323	345.3311	1.0691
Scaled Deviance	323	345.3311	1.0691
Pearson Chi-Square	323	282.7304	0.8753
Scaled Pearson X2	323	282.7304	0.8753
Log Likelihood	.	-228.0258	.

Analysis Of Parameter Estimates

Parameter	DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT	1	0.6273	0.0629	99.3049	0.0001
STUDY HSPASYT1-3	1	0.0716	0.0899	0.6336	0.4260
STUDY LLSERIES	1	-0.2314	0.1275	3.2952	0.0695
STUDY SZSPFA	0	0.0000	0.0000	.	.
NEUR	1	0.0111	0.0430	0.0660	0.7972
EXT	1	0.0302	0.0437	0.4771	0.4897
OPEN	1	0.0218	0.0425	0.2629	0.6082
AGREE	1	0.0155	0.0424	0.1340	0.7143
CONS	1	0.0386	0.0425	0.8219	0.3646
BADFIT1	1	-0.0359	0.0706	0.2593	0.6106
BADFIT2	1	0.0356	0.1141	0.0976	0.7547
BADFIT3	1	0.0867	0.1185	0.5357	0.4642
BADFIT4	1	-0.1865	0.0961	3.7626	0.0524
BADFIT5	1	0.1159	0.0553	4.3692	0.0362
SCALE	0	1.0000	0.0000	.	.

NOTE: The scale parameter was held fixed.

Table 18: Poisson regression predicting Number Interpersonal Projects

Dependent Variable	INTRAPER	number of intraper	projects
Observations Used	336		
Missing Values	43		

Class Level Information

Class	Levels	Values
STUDY	3	HSPASYT1-3 LLSERIES SZSPFA

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	323	411.8929	1.2752
Scaled Deviance	323	323.0000	1.0000
Pearson Chi-Square	323	506.6672	1.5686
Scaled Pearson X2	323	397.3205	1.2301
Log Likelihood	.	-205.5340	.

Analysis Of Parameter Estimates

Parameter		DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT		1	-1.1495	0.1633	49.5762	0.0001
STUDY	HSPASYT1-3	1	0.4922	0.2064	5.6857	0.0171
STUDY	LLSERIES	1	1.0434	0.2321	20.2056	0.0001
STUDY	SZSPFA	0	0.0000	0.0000	.	.
NEUR		1	0.3582	0.0877	16.6907	0.0001
EXT		1	-0.1670	0.0789	4.4798	0.0343
OPEN		1	0.2239	0.0875	6.5437	0.0105
AGREE		1	0.0204	0.0855	0.0571	0.8112
CONS		1	0.1728	0.0898	3.7025	0.0543
BADFIT1		1	-0.3472	0.1552	5.0027	0.0253
BADFIT2		1	0.1480	0.2370	0.3901	0.5323
BADFIT3		1	0.0082	0.2322	0.0013	0.9717
BADFIT4		1	-0.1068	0.1916	0.3106	0.5773
BADFIT5		1	0.1554	0.1058	2.1561	0.1420
SCALE		0	1.1293	0.0000	.	.

NOTE: The scale parameter was estimated by the square root of DEVIANCE/DOF.

Table 19: Poisson regression predicting Number of Intrapersonal Projects

Dependent Variable	LEISURE number of leisure projects
Observations Used	336
Missing Values	43

Class Level Information

Class	Levels	Values
STUDY	3	HSPASYT1-3 LLSERIES SZSPFA

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	323	406.8062	1.2595
Scaled Deviance	323	323.0000	1.0000
Pearson Chi-Square	323	361.7040	1.1198
Scaled Pearson X2	323	287.1893	0.8891
Log Likelihood	.	-150.0143	.

Analysis Of Parameter Estimates

Parameter		DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT		1	0.3333	0.0813	16.8209	0.0001
STUDY	HSPASYT1-3	1	0.5763	0.1046	30.3507	0.0001
STUDY	LLSERIES	1	0.3032	0.1352	5.0275	0.0249
STUDY	SZSPFA	0	0.0000	0.0000	.	.
NEUR		1	-0.0639	0.0487	1.7250	0.1891
EXT		1	-0.0728	0.0461	2.4989	0.1139
OPEN		1	0.0864	0.0463	3.6567	0.0558
AGREE		1	-0.0375	0.0460	0.6660	0.4145
CONS		1	-0.0257	0.0460	0.3131	0.5758
BADFIT1		1	-0.1328	0.0786	2.8504	0.0914
BADFIT2		1	0.2275	0.1231	3.4137	0.0647
BADFIT3		1	-0.2285	0.1265	3.2649	0.0708
BADFIT4		1	0.1520	0.1066	2.0332	0.1539
BADFIT5		1	-0.1073	0.0687	2.4412	0.1182
SCALE		0	1.1223	0.0000	.	.

NOTE: The scale parameter was estimated by the square root of DEVIANCE/DOF.
Projects

Table 20: Poisson regression predicting Number of Leisure Projects

Dependent Variable	ADMIN	number of admin	projects
Observations Used	336		
Missing Values	43		

Class Level Information

Class	Levels	Values
STUDY	3	HSPASYT1-3 LLSERIES SZSPFA

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	323	342.4450	1.0602
Scaled Deviance	323	323.0000	1.0000
Pearson Chi-Square	323	305.0322	0.9444
Scaled Pearson X2	323	287.7116	0.8907
Log Likelihood	.	-147.0304	.

Analysis Of Parameter Estimates

Parameter		DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT		1	0.7414	0.0615	145.2277	0.0001
STUDY	HSPASYT1-3	1	0.1175	0.0866	1.8409	0.1748
STUDY	LLSERIES	1	-0.4183	0.1323	9.9999	0.0016
STUDY	SZSPFA	0	0.0000	0.0000	.	.
NEUR		1	-0.0423	0.0422	1.0029	0.3166
EXT		1	0.0797	0.0423	3.4639	0.0627
OPEN		1	-0.0047	0.0415	0.0127	0.9101
AGREE		1	-0.0242	0.0415	0.3402	0.5597
CONS		1	0.0025	0.0403	0.0037	0.9513
BADFIT1		1	0.1122	0.0633	2.6934	0.1008
BADFIT2		1	0.0772	0.1084	0.5061	0.4768
BADFIT3		1	-0.0529	0.1129	0.2191	0.6397
BADFIT4		1	0.0180	0.0933	0.0368	0.8478
BADFIT5		1	-0.0214	0.0580	0.1357	0.7126
SCALE		0	1.0297	0.0000	.	.

NOTE: The scale parameter was estimated by the square root of DEVIANCE/DOF.

Table 21: Poisson regression predicting Number of Administrative Projects

Dependent Variable	OTHER	number of miscellaneous projects
Observations Used	336	
Missing Values	43	

Class Level Information

Class	Levels	Values
STUDY	3	HSPASYT1-3 LLSERIES SZSPFA

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	323	209.8929	0.6498
Scaled Deviance	323	323.0000	1.0000
Pearson Chi-Square	323	388.2079	1.2019
Scaled Pearson X ²	323	597.4055	1.8496
Log Likelihood	.	-232.8783	.

Analysis Of Parameter Estimates

Parameter		DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT		1	-0.8615	0.1130	58.1461	0.0001
STUDY	HSPASYT1-3	1	-2.1227	0.3053	48.3483	0.0001
STUDY	LLSERIES	1	-2.0699	0.4223	24.0279	0.0001
STUDY	SZSPFA	0	0.0000	0.0000	.	.
NEUR		1	-0.1185	0.0981	1.4604	0.2269
EXT		1	-0.3137	0.0674	12.8895	0.0003
OPEN		1	0.1674	0.0936	4.0050	0.0454
AGREE		1	-0.1447	0.0994	2.1208	0.1453
CONS		1	-0.0740	0.0954	0.6021	0.4379
BADFIT1		1	0.4460	0.1451	9.4496	0.0021
BADFIT2		1	-0.3618	0.2603	1.9320	0.1645
BADFIT3		1	-0.1989	0.2814	0.4993	0.4798
BADFIT4		1	-0.1612	0.2428	0.4407	0.5068
BADFIT5		1	0.1618	0.1316	1.5115	0.2189
SCALE		0	0.8061	0.0000	.	.

NOTE: The scale parameter was estimated by the square root of DEVIANCE/DOF.

Table 22: Poisson regression predicting Number of Other Projects

Zero-Variance Features, Personality and S-Stress

The number of project features that exhibited zero variance (NZERO) for a given case was established using the SAS module PROC MEANS. Three quarters of the cases did not exhibit any such patterns, while ninety-six percent of cases had two or fewer zero-variance features (ZVF's). Both the five main NEO-PI dimensions as well as the S-Stress values for the six dimensionalities requested in the MDS analyses were used as predictors in a Poisson regression for non-problematic cases. As shown in Table 23, a positive parameter was obtained for Neuroticism, suggesting a tendency for high-Neuroticism individuals to rate the dimensions in an excessively homogeneous fashion. A large negative parameter was observed for the 4-D and 6-D S-Stress values, which indicates that as predicted, the higher dimensional

Criteria For Assessing Goodness Of Fit

Criterion	DF	Value	Value/DF
Deviance	356	434.5962	1.2208
Scaled Deviance	356	434.5962	1.2208
Pearson Chi-Square	356	613.5887	1.7236
Scaled Pearson X2	356	613.5887	1.7236
Log Likelihood	.	-249.7692	.

Analysis Of Parameter Estimates

Parameter	DF	Estimate	Std Err	ChiSquare	Pr>Chi
INTERCEPT	1	-0.0475	0.5294	0.0080	0.9286
STUDY BXSERIES/BX	1	-0.1509	0.4354	0.1202	0.7289
STUDY HSPASYT1-3	1	0.2451	0.3610	0.4609	0.4972
STUDY LLSERIES	1	0.4461	0.4067	1.2033	0.2727
STUDY SZSPFA	1	-0.0531	0.3999	0.0176	0.8943
STUDY TPPASYS	1	-0.2183	0.5279	0.1710	0.6792
STUDY nbenton	1	0.3588	0.4232	0.7187	0.3966
STUDY vdillon	0	0.0000	0.0000	.	.
NEUR	1	0.0129	0.0061	4.5065	0.0333
EXT	1	0.0011	0.0134	0.0072	0.9324
OPEN	1	-0.0106	0.0114	0.8735	0.3500
AGREE	1	0.0029	0.0244	0.0143	0.9049
CONS	1	-0.0079	0.0193	0.1650	0.6846
BADFIT1	1	1.2735	1.2201	1.0896	0.2966
BADFIT2	1	1.2254	3.8680	0.1004	0.7514
BADFIT3	1	-7.5744	6.4441	1.3816	0.2398
BADFIT4	1	-33.7280	9.3285	13.0725	0.0003
BADFIT5	1	-1.1086	9.0124	0.0151	0.9021
BADFIT6	1	36.4411	15.0481	5.8643	0.0155

Table 23: Poisson Regression predicting Zero-Variance Features

solutions are affected to some extent by the missing data. However, the first three S-Stress values were unrelated to the number of zero-variance features (ZVF's).

Discussion: General Characteristics of Project Spaces

On the whole, it is possible to solve a Project Space that involves the 17 standard PPA features in 3 or 4 dimensions. In less than 10% of cases, one or two dimensions provide an adequate description of the Project Space, while in less than 5% of cases, 5 or 6 dimensions are necessary to reduce S-Stress below the .10 criterion. The solutions progress with minimal irregularities in the expected pattern of monotonically decreasing values of S-Stress over increasing dimensionality. The vast majority of cases provide adequate information provided that enough projects are sampled without an excess of missing data.

The presence of missing data and the number of projects rated each have a complex relationship to S-Stress, and indicates caution in the interpretation of Project Space solutions when missing data become excessive. Ten (or more) percent missing data, or six or less projects is suggested as a useful exclusion rule. The structure of the average Project Space is clearly non-random, as the S-Stress values for the most common dimensionalities are well below those of random data, even when cases that do not have that dimensionality as an optimal dimensionality are included in the comparison.

It also appears that personality measures have no direct relationship to the general features of the MDS solutions. However, a substantial *indirect* relationship is implied by the relationships between Project Category and both of these sets of measures. Stressfulness of the various solutions is related to the content of the projects in the space, and content of the space is predicted by personality measures. Thus it would appear that personality manifests itself in the projects that are selected, which in turn has an impact upon the dimensionality required to solve the Project Space.

A secondary set of relationships that is worthy of further empirical examination is the positive association between Neuroticism and ZVF's, and ZVF's and S-Stress. This indirect manifestation of personality in the Project Space may also tie in with other measures that have not yet been used in PPA research, such as response bias instruments (e.g., the BIDR; Paulhus, 1991) which may correlate with unusual patterns such as the ZVF.

The absence of a relationship between number of types of project and the set of NEO-PI predictors is unremarkable, since it is a gross measure of variety. In addition with ten projects taken from seven categories, the possible permutations that would be consistent with the various personality profiles but opposite in direction make it an unlikely candidate for prediction from personality. On the other hand, for MDS, it is plausible that because most individuals provide a moderately heterogeneous set of projects (mean NTYPES= 4.7, std.dev.=.90), more or less homogeneous sets will deviate to a certain extent, producing higher- or lower-dimensional solutions at the single-case level than the majority which solve in 3 or 4 dimensions. This does not, however, appear to be the case.

The relationships between the 2-D and 3-D stresses and **Occupational/Academic** projects is intriguing, suggesting a link between this type of project and complexity of solutions. The negative relationship with Openness suggests that open individuals tend not to list many of this sort of project, preferring (based on the observed positive relationships and trends) to list Leisure and Intrapersonal projects.

The trend towards reporting more **Health** projects among those low on Conscientiousness and fewer such projects among those high on this measure suggests that there may be more health *problems* among the unconscientious that demand attention. However, the data are not sufficiently fine-grained to permit further exploration of this hypothesis.

The weak relationships of **Interpersonal** project frequency with the 4-D and 5-D S-Stress vectors that are suggested by the model, and the absence of relationships to NEO-PI measures are possibly due to the fact that these projects are a feature of most project systems. In fact, although Interpersonal projects had the third highest mean frequency (mean=1.89, std. Dev. =1.3), the variances of the other two more common project categories (Leisure, mean=1.91, std. dev. = 1.54; Administrative, mean=2.11, std. dev.=1.51) were each fully one-third higher, suggesting that Interpersonal projects are a consistent feature of project systems.

The supposed preoccupation of Neurotic individuals with intrapsychic matters is reflected in the higher proportion of **Intrapersonal** projects among those high on this NEO-PI scale. Similarly, the “outward looking” perspective of Extraverts is consistent with the

tendency of high-extraversion individuals to neglect this category. The higher proportion of “revealing” intrapersonal projects among Open individuals is also consistent with expectations. The tendency of the Conscientious individuals to include them at a higher rate may also reflect an underlying pattern wherein a demand characteristic is perceived in the study that requires a degree of self-revelation for these people. Further investigation of these possibilities could be quite revealing and may be attributable at least in part, to the unknown category that was noted in the Szawlowski dataset.

Among Extraverts, one would also expect a plethora of **Leisure** projects, but this prediction is not supported by the data. It cannot be explained in terms of extraverts reporting a greater variety of projects, either, since the parameter for Extraversion on that measure was non-significantly *negative*. It may simply be that the specific groups sampled in the three studies (all of whom were university students) were so engrossed in novel adventures that their ordinary leisure projects were set aside, and they found their recreation in other externally-oriented pursuits that were not classified as Leisure in the very general categorizations that were used. It is possible that this is reflected in the weak trend towards a positive relationship between **Administrative** projects (which generally involve organizing *external* matters) and Extraversion.

The substantial negative relationship between Extraversion and **Other** projects indicates that the categories that extraverts prefer are not atypical ones, which highly social people who wish to ‘fit in’ would be expected to avoid. The positive trend for Openness complements this, suggesting that it is indeed those who are open to new experiences are more likely to engage in unusual projects. Furthermore, the positive relationship between this category and S-Stress for the 1-dimensional solution suggests that the increase in heterogeneity attributable to atypical projects makes it difficult to solve Project Spaces that contain several “Other” projects in under two dimensions.

The relationships between S-Stress measures for solutions of varying dimensionality and project content measures is intriguing. The miscellaneous nature of “Other projects” would be expected to introduce some heterogeneity, which would increase the badness-of-fit, particularly for 1-dimensional solutions which tend not to fit very well to begin with (recall the

small number of cases that exhibited an OD of 1). However, the positive relationship of 1-D S-stress and the negative relationship of 2-D S-stress to number of types, number of occupational/academic projects and health projects suggests that while these projects are construed in a way that defies summarization in one dimension, they produce a relatively simple space in two dimensions.

The differences among the studies are somewhat harder to interpret because of the need to re-categorize Szawlowski's data, the problem of missing data and the problem of ZVF's and their apparent link with Neuroticism. However, it is nonetheless interesting to note that in the HSTS data, markedly fewer Occupational/Academic projects were noted than in Szawlowski's data, which were in turn lower than Lecci's data on this measure. This is not surprising, since the sample consisted of high school students at the end of a summer term. It is likely that their summer jobs would have ended, but the school term had not fully begun for many of them. This probably accounts for their having the highest rate of Leisure projects (although not significantly higher than in Lecci's data, $p < .08$).

It would appear that Project Spaces can generally be solved in 3 or 4 dimensions with monotonically decreasing stress across increasing dimensionality. Marked fluctuations arising from degenerate solutions appear to be virtually unknown in PPA data. While missing data may be somewhat related to higher dimensions where MDS algorithms can "fudge" a fit, the global fit indicators are largely unrelated to personality measures, except in what appears to be a rather indirect fashion. With the preceding exclusion rules and understanding of individual spaces, we may now proceed to explore the stability of these indicators over time under two rather different sampling conditions.

Chapter 7: The Reliability of Individual Project Spaces

This chapter will address the issues surrounding reliability of Project Spaces, with reference to classical notions of between-subject and within-subject variability that can be referred to the single case in a meaningful way, then aggregated to explore the extent to which generalizations can be made. A supplementary exercise in comparing QAP and MDS methods of comparing matrices will else establish the superiority of the latter approach for most purposes.

Reliability of Project Space Measures

While only two studies have obtained PPA data at two or more points in time (Lecci, 1990; Szawlowski, 1987), there are enough cases to permit solid inferences to be made about the stability of the structure of individual project spaces over time. To obtain estimates of the stability of project spaces, data from the High School Transition Study (HSTS; Lecci, 1990) and Szawlowski's (1987) study were analyzed separately at the first two points in time. The timing of these two studies differed in that the time 2 data from the HSTS were collected approximately four months after the time 1 data, whereas Szawlowski's time 2 data were collected within a week, and contained a small degree of overlap in terms of the projects listed. The structure coefficients obtained through MDS were then compared via canonical correlation, as were the S-Stress values for solutions in 1 through 6 dimensions. In addition, optimal dimensionality was determined for the time 1 and time 2 data (where available) to determine the stability of this characteristic of individual Project Spaces, and the extent to which optimal dimensionality is stable. It was expected that the change in projects and the longer time between sessions in the HSTS data would result in generally lower stability coefficients for all indices.

Reliability of MDS Estimates

The reliability of the structure of the Project Spaces was studied for that vast majority of cases whose optimal dimensionality at time 1 was either 3 or 4. Stability coefficients were derived using canonical correlation, and for analyses that required it, they were transformed to

approximate normality. Differences across studies for the different optimal dimensionalities were examined, as well as a number of available predictors of stability.

The stability coefficients were derived on the basis of the canonical analyses of individual cases. For those cases which had an optimal dimensionality of 3 at time 1, a 3-dimensional solution was requested at time 2 on the assumption that elements of the fourth dimension should be at least present, if not sufficiently pronounced to warrant an additional dimension based on the .10 criterion noted above. Likewise, a 4-D solution was requested for 4-D cases at time 1. For the 3-D cases, three canonical correlations were computed, and for 4-D cases, four such coefficients were obtained. To normalize the correlation coefficients, Fisher's transform was applied, thereby creating up to four new variables (ZCAN1-ZCAN4). These measures of stability are orthogonal in any given case, but are not necessarily orthogonal across cases. This is because highly stable Project Spaces will exhibit stability on all components, while unstable ones are likely to be low on all stability indices. Thus, the Z-transformed canonical correlations provide several approximately-normal measures of the stability of the solution over time.

Reliability of Global Project Spaces

The same set of Project Spaces were also subjected to QAP analysis, which provides a single reliability coefficient. As it is based on r , this coefficient was also normalized using Fisher's transform to create the variable ZQAP. The relationship between this coefficient and the several canonical coefficients was examined within each study and dimensionality for all non-problematic cases. In addition to this measure, an additional index was based on a standardized version of the QAP correlation index. This index, ZR, is derived from the empirical mean permutation correlation (MEANPERM) and the empirical standard deviation of the computed permutation statistics (i.e., the permutation-based standard error) STDPERM. Because the permutation test provides a p -value which is supposed to be an approximation to the actual theoretical value based on a normal distribution, the relationship of a theoretical value derived from ZR to the empirical P was also explored.

DATA

For the first set of analyses, the non-problematic data on which information was to be had for a first and second point in time were used.

HYPOTHESES

To the extent that a Project Space exhibits complete stability across all dimensions, all values of the transformed canonical indices should be large. As well, to the extent that individuals differ in terms of their stability, it is likely that the indices of stability will exhibit individual differences across the board, which will induce marked correlations between them. Furthermore, since there are two studies that provided data for these analyses, it is worth remembering at this point that there was a marked methodological difference in the timing of the data collection and the degree of overlap between the projects rated at time 1 and time 2.

Szawlowski's data involved a re-rating of the same projects, with the time 2 collection following within approximately 6 to 8 weeks of the initial data collection. In the High School data, however, overlap was nearly nil, and the second wave of data collection was several months after the first. Since the HSTS data involved different projects and a longer intervening period of time, while Szawlowski's involved the same projects at different stages of completion over a rather shorter period of time, substantially less stability should be observed in the former study than in the latter by all indicators.

On the relative magnitude of Between- and Within-Individual Differences

Aside from the establishment of a means of estimating reliability of Project Spaces, it is worth exploring the potential value of QAP in establishing a more elaborate model consistent with the social ecological model espoused earlier in this dissertation. The single value obtained from QAP permits direct testing of specific hypotheses regarding reliability which have substantive implications. Classical notions of reliability (wherein low within-individual variation and high between-individual variation produce a substantial reliability coefficient) imply that if an individual Project Space is stable in spite of novel projects being rated, then two matrices from the same person will be more similar than two matrices from different people. This further implies that the QAP correlation for the Time

1/Time 2 matrices for Case J will be higher than the QAP index for randomly-paired matrices (e.g., Case J and Case K), which is a testable prediction given the data at hand.

Equally serious concerns arise from the fact that the classical perspective is unwieldy for homogenous populations, and when all cases have the same "true score" it falters entirely (Zimmerman & Little, 1982). If there is a general joint space shared by most people, then we have a homogeneity problem. A limited answer to this difficulty can be found by examining a second set of QAP similarities: those drawn from a different study.

DATA

To this end, 15 randomly-selected cases from the Time 1 HSTS data were compared with two other matrices: the one from the same case at Time 2, one randomly-selected matrix from another subject in the same study at either of the two points in time, and a third randomly selected from the Szawlowski dataset (either Time 1 or Time 2 in that study).

ANALYSIS

QAP was used to establish matrix/matrix similarity among the pairs of matrices described above. Ordinal Pattern Analysis (OPA; Thorngate, 1992) was used to compare two different theoretical models of the resulting data. This method is in the general class of "evidential statistics" (Thorngate, 1992) which do not pretend to complex probabilistic interpretations with equally convoluted assumptions. These statistics merely permit the comparison of different theoretical models through the derivation of a numerical index which provides a gauge of the goodness-of-fit between a theory and the data. OPA is quite simple both to compute and to interpret. A theory is used to generate predictions, and correct predictions are coded as "hits," while incorrect predictions are counted as "misses." The Index of Ordinal Fit (IOF) is computed using H (number of hits) and M (number of misses) as $IOF = (H - M) / (H + M)$, and so distributes between -1 and 1, with values approaching 1 as providing evidence of increasingly better fit. An IOF may be computed for various competing models of the data, and the model which results in the largest IOF is the one most supported by the data.

MODELS

In the present case, we may compare several models of the data. In the first, Project Spaces exhibit classical reliability in the presence of substantial individual differences across both studies. This means that the comparison of an individual Project Space to the space derived at a later time (with projects varied) should consistently produce larger similarity coefficients than the comparison of that case to a randomly-selected different one. This should hold whether the comparison case comes from the same study or not, and may be termed the "basic reliability model." In this model, within-subject differences are consistently larger than all between-subject differences, but the group of between-subject differences based on cases from the same ecology are no different from those based on cases from the same social ecology. A second, more elaborate model states that not only is the basic reliability model true, but cases drawn from the same social ecology (as represented by "the same study" in the present dataset) may be more similar among themselves than they are to cases drawn from another social ecology (i.e., study). I shall refer to this as the "homogenous ecology" model, where homogeneity within each ecology produces differences such that within-ecology comparisons are greater than between-ecology comparisons.

A third "constrained reliability" model states that within a given setting, individuals will be homogeneous. Thus, reliability will be constrained by that lack of individual differences, as is the case for in the classical reliability model (Zimmerman & Little, 1982). Thus, within-study comparisons will not be distinguishable from within-subject comparisons, but between-study comparisons will consistently exhibit lower coefficients than within-study comparisons.

The last model that was tested was an "individual emergence" model, where individual uniquenesses come out of a background of common social ecological pressures. In this view, apparent temporal reliability is an artefact of an underlying Project Space that is common to many people, but which exhibits instability in some persons. Specifically, greater self-similarity is expected within subjects, followed by within-study similarity and lastly across-study similarity for most cases, but those which exhibit within-case unreliability should be at least as similar to others within their particular setting (i.e., study) than to cases drawn

from other studies due to common social ecological constraints on projects. A further test of this model is tested through an examination of the rank-order associations between the coefficients. In this model, temporal unreliability should result in an individual "emerging" from the common space into a unique pattern of his or her own. This will induce a similar rank-ordering between the same-study similarity coefficients and the different-study similarity coefficients which is independent of whatever differences in magnitude there are between these columns.

Results: Reliability of Solutions

Reliability of Optimal Dimensionality and Stressfulness of Solutions

Correlations between the optimal dimensionalities computed at each of the first two time points for each longitudinal study are presented in Table 24. The substantial correlation of .39 in the Szawłowski data and the small, non-significant value of .11 for the HSTS data confirm that this value is relatively stable for the same projects over a short time, but unstable for different projects over a longer time.

As an alternative approach, weighted kappas were computed for 269 non-problematic cases within each of the two studies that collected longitudinal data. One case was excluded because it required six dimensions to solve at time 1, but no 6-D cases were obtained at time 2, thus making kappa non-calculable. As expected, within the HSTS set, the obtained kappa was not significantly different from zero ($\kappa = .016$, 95% C.I. = $-.034$ to $.066$), while for the Szawłowski data, a significant (although not large) value was obtained ($\kappa = .259$, 95% C.I. = 0.142 to 0.377), substantiating the results of the simple correlation.

Similarly, canonical correlations were computed for the six S-Stress levels associated with the six requested dimensionalities at the first and second point in time across the two different longitudinal studies. For the 214 non-problematic cases with data on these indices, the canonical correlation of .29 was non-significant, suggesting that both optimal dimensionality and patterns of S-Stress across possible solutions exhibit no discernible

pattern. Breaking the analyses down by study, non-significant canonical correlations of .35 and .37 were observed for the HSTS and Szawlowski data (respectively). A similar comparison was done for the subset of 84 cases which had non-problematic data at time 2 and time 3 in the HSTS data. The canonical correlation of .40 was again non-significant, suggesting that selection bias (through attrition) in favour of stable spaces is not at work. Although repeating this procedure for the time 1 and time 3 data in the HSTS set is not orthogonal to the other analyses, comparable results were obtained ($r_{cc}=.42$, n.s.).

HSTS data						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
DIMENS	122	3.5984	0.7002	439.0000	1.0000	6.0000
DIMENS2	122	2.5410	0.6699	310.0000	1.0000	5.0000
Pearson Correlation Coefficients / Prob > R under Ho: Rho=0 / N = 122						
		DIMENS	DIMENS2			
DIMENS		1.00000 0.0	0.11468 0.2085			
DIMENS2		0.11468 0.2085	1.00000 0.0			
Szawlowski's data						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
DIMENS	147	3.3946	0.7986	499.0000	1.0000	5.0000
DIMENS2	147	3.3265	0.7689	489.0000	1.0000	5.0000
Pearson Correlation Coefficients / Prob > R under Ho: Rho=0 / N = 147						
		DIMENS	DIMENS2			
DIMENS		1.00000 0.0	0.39106 0.0001			
DIMENS2		0.39106 0.0001	1.00000 0.0			

Table 24: Stability of Optimal Dimensionality

Reliability of Structure Coefficients

Excluding the problematic cases which met the criteria discussed above at either time 1 or time 2, there were one hundred and seven cases available from the High School Transition Study. Forty-six of these had an optimal dimensionality (OD) of 3, and the remaining 61 had an OD of 3. Eighty-six other cases were drawn from Szawlowski's (1987) data, of which 40 had an OD of 3 and 46 had an OD of 4. For each case, the structure coefficients generated by MDS at time 1 were related to the structure coefficients generated by MDS at time 2 for each subject using canonical correlation analysis, and the next three sections provide the results of these analyses.

Moments			
N	106	Sum Wgts	106
Mean	0.827808	Sum	87.74769
Std Dev	0.107871	Variance	0.011636
Skewness	-1.11364	Kurtosis	1.278491
USS	73.86007	CSS	1.221804
CV	13.03096	Std Mean	0.010477
Quantiles (Def=5)			
100% Max	0.973014	99%	0.971534
75% Q3	0.907283	95%	0.955951
50% Med	0.853203	90%	0.946557
25% Q1	0.770825	10%	0.672011
0% Min	0.426621	5%	0.627537
		1%	0.519529
Range	0.546393		
Q3-Q1	0.136457		
Mode	0.426621		

Table 25: Distribution of the First Canonical Correlation between Structure Coefficients, 3-D data.

Reliability of Three-Dimensional Solutions

A total of 106 cases were available for this analysis. The distribution of the first, second and third canonical correlations are presented in Tables 25 through 27, and illustrated in Figures 26 through 28. The median canonical correlation for these cases was .85, and the first quartile was .77. Compared to the random data described in Technical Appendix C, this is quite good, as the 99th percentile for the first canonical correlation in random data was .87. The third quartile of canonical r 's based on actual Project Spaces was .91, indicating substantial stability in a good portion of the data. No correlation fell below .51. For the second canonical correlation, the median was .58, with a first and third quartile of .47 and .72,

Moments			
N	106	Sum Wgts	106
Mean	0.581619	Sum	61.65158
Std Dev	0.183282	Variance	0.033592
Skewness	-0.32108	Kurtosis	-0.34744
Quantiles (Def=5)			
100% Max	0.910898	99%	0.907137
75% Q3	0.721467	95%	0.868331
50% Med	0.584443	90%	0.804624
25% Q1	0.468853	10%	0.333967
0% Min	0.070221	5%	0.289692
		1%	0.124457
Range	0.840677		
Q3-Q1	0.252614		
Mode	0.070221		

Table 26: Distribution of the Second Canonical Correlation, 3-D data.

Moments			
N	106	Sum Wgts	106
Mean	0.199991	Sum	21.19899
Std Dev	0.154672	Variance	0.023923
Skewness	1.159822	Kurtosis	1.775301
Quantiles (Def=5)			
100% Max	0.795035	99%	0.719588
75% Q3	0.28795	95%	0.442009
50% Med	0.162069	90%	0.407606
25% Q1	0.083868	10%	0.031644
0% Min	0.001744	5%	0.022443
		1%	0.002941
Range	0.793291		
Q3-Q1	0.204082		
Mode	0.001744		

Table 27: Distribution of the Third Canonical Correlation, 3-D Data

respectively. Once again this compares well with the random data, where an average of .36 was observed with a 99th percentile at .64. The third canonical correlation did not compare so favourably, as it had a median r of .16, with first and third quartiles at .08 and .29, respectively. Random data averaged .12, with a 99th percentile above .40, which was the 90th percentile for the real data, indicating that the deviation from normality, even where statistically significant, was not large. The absence of extreme values resulted in a near-linear relationship between the raw index (CORR) and the Z-transformed index (ZQAP). *Reliability of Four-Dimensional Solutions*

A total of 149 cases were available for this analysis. The distribution of the first through the fourth canonical correlations are presented in Tables 28 through 31, and illustrated in Figures 29 through 32. The median canonical correlation for these cases was .87, and the first quartile was .82. Compared to the random data described in Technical Appendix C, this is quite good, as the 90th percentile for the first canonical correlation in random data was .87. The third quartile of canonical r 's based on actual Project Spaces was .92, indicating substantial stability in a good portion of the data. No correlation fell below .57

For the second canonical correlation, the median was .68, with a first and third quartile of .58 and .79, respectively. Once again this compares well with the random data, where an average of .54 was observed with a 90th percentile at .68. The third canonical correlation compared favourably, as it had a median r of .43, with first and third quartiles at .34 and .54,

respectively. Random data averaged .32, with a 99th percentile at .57, which was just above the the 75th percentile for the real data. The fourth canonical correlation exhibited a median of .14, $Q1=.06$, $Q3=.21$, compared to random data where the median was .09, mean .08, and the 90th percentile stood at .20.

Figure 26: 1st Canonical Correlation, 3-D Data as of Time 1

2nd Canonical Correlation

3-D solution at t1
Figure 27: 2nd Canonical Correlation, 3-D Data as of Time 1

3rd Canonical Correlation

3-D solution at t1
Figure 28: 3rd Canonical Correlation, 3-D Data as of Time 1

Moments			
N	149	Sum Wgts	149
Mean	0.866373	Sum	129.0896
Std Dev	0.077148	Variance	0.005952
Skewness	-1.18029	Kurtosis	2.059535

Quantiles (Def=5)			
100% Max	0.981464	99%	0.979295
75% Q3	0.92343	95%	0.965155
50% Med	0.873756	90%	0.951311
25% Q1	0.824711	10%	0.75789
0% Min	0.568367	5%	0.730203
		1%	0.57321
Range	0.413097		
Q3-Q1	0.098719		
Mode	0.718105		

Table 28: Distribution of the First Canonical Correlation, 4-D Data.

Moments			
N	149	Sum Wgts	149
Mean	0.681472	Sum	101.5394
Std Dev	0.125367	Variance	0.015717
Skewness	-0.19943	Kurtosis	-0.72844

Quantiles (Def=5)			
100% Max	0.926819	99%	0.920275
75% Q3	0.785398	95%	0.87553
50% Med	0.67962	90%	0.845435
25% Q1	0.584077	10%	0.508248
0% Min	0.353487	5%	0.472796
		1%	0.389361
Range	0.573331		
Q3-Q1	0.201321		
Mode	0.472796		

Table 29: Distribution of the Second Canonical Correlation, 4-D Data

Reliability: the QAP Estimates

The time1-time2 data for both the Szawlowski and HSTS data were compared using QAP to obtain a correlational index of matrix similarity (CORR) and the Z transform of this variable (ZQAP). Based on the mean permutation correlation and the empirically-derived standard error of the mean correlation, an approximate Z was also obtained (ZR), along with the permutation p value (P) which represents the proportion of permuted coefficients that exceed the observed value. Although MDS procedures can estimate missing values and

Moments			
N	149	Sum Wgts	149
Mean	0.440574	Sum	65.64548
Std Dev	0.142711	Variance	0.020366
Skewness	0.182504	Kurtosis	-0.2925
Quantiles (Def=5)			
100% Max	0.841525	99%	0.765901
75% Q3	0.539035	95%	0.671328
50% Med	0.433165	90%	0.632293
25% Q1	0.340859	10%	0.253791
0% Min	0.131848	5%	0.197179
		1%	0.137711
Range	0.709677		
Q3-Q1	0.198225		
Mode	0.283064		

Table 30: Distribution of the Third Canonical Correlation, 4-D Data

Moments			
N	149	Sum Wgts	149
Mean	0.14849	Sum	22.12496
Std Dev	0.108106	Variance	0.011687
Skewness	0.788765	Kurtosis	0.33736
Quantiles (Def=5)			
100% Max	0.520587	99%	0.430936
75% Q3	0.207269	95%	0.367812
50% Med	0.142572	90%	0.294338
25% Q1	0.059113	10%	0.019101
0% Min	0.001095	5%	0.010545
		1%	0.003352
Range	0.519492		
Q3-Q1	0.148156		
Mode	0.028715		

Table 31: Distribution of the Fourth Canonical Correlation, 4-D Data

therefore can handle cases where correlations are missing from the matrix, QAP has no such feature. As well, the effect of missing data on QAP solutions is not well understood. Therefore, this analysis was restricted to those cases which had 7 or more projects, less than 10% missing data, and no non-estimable correlations. This resulted in the selection of 78 cases from the HSTS data, and 101 cases from Szawlowski's dataset.

The randomization estimates of P are summarized in Table 33a for each study. It is clear that a great number of cases had very few, if any permutations that randomly exceeded the observed correlation, although the 90th percentile of the HSTS data is noticeably higher than that of the other dataset. To compare the reliability estimates over the short-interval (Szawlowski) and long-interval (HSTS) data collection periods, an arbitrary cutoff of .05 was assigned to the randomization P-values and a 2x2 chi-square table was constructed (Table 33b). The chi-square test indicated a significant difference in the proportion of cases whose P-value exceeded this criterion (65.4% of the HSTS data, compared to 87% of Szawlowski's cases, $\chi^2 = 12.124$, $p < .001$).

An additional feature of QAP analysis is that a mean permutation correlation and an empirical standard error (i.e., the standard deviation of the permutation statistics) is provided directly. According to Hubert (1987) these will follow an approximately normal distribution. The implication of this is that the direct computation of a Z-score from (Observed correlation - mean permutation correlation)/(standard error) will follow a Gaussian distribution. To test this aspect of QAP, the Z-scores were computed for each case, and the corresponding probability was computed using the SAS system (SAS, 1996). The plot of the empirical versus the computed p-values in Figure 33 reflects the correlation of .9978 ($p < .0001$) between the computed and empirical estimates, supporting Hubert's argument.

1st Can. Corr., 4-D cases

Figure 29: 1st Canonical Correlation, 4-dimensional cases at time 1

2nd Can. Corr., 4-D cases

Figure 30: 2nd Canonical Correlation, 4-dimensional cases at time 1

3rd Can. Corr., 4-D cases

Figure 31: 3rd Canonical Correlation, 4-dimensional cases at time 1

4th Can. Corr., 4-D cases

Table Figure 32: Canonical Correlations, 4-dimensional cases at time 1.

Normal Approximation

Figure 33: Computed vs. Randomization-based p-values from QAP analyses

High School Data			
Moments			
N	78	Sum Wgts	78
Mean	0.474205	Sum	36.988
Std Dev	0.152094	Variance	0.023133
Skewness	0.467047	Kurtosis	0.022755
USS	19.32112	CSS	1.781219
CV	32.07355	Std Mean	0.017221
T:Mean=0	27.53596	Pr> T	0.0001
Num ^= 0	78	Num > 0	78
M(Sign)	39	Pr>= M	0.0001
Sgn Rank	1540.5	Pr>= S	0.0001
W:Normal	0.971147	Pr<W	0.2441

Quantiles (Def=5)			
100% Max	0.879	99%	0.879
75% Q3	0.548	95%	0.759
50% Med	0.463	90%	0.692
25% Q1	0.377	10%	0.284
0% Min	0.173	5%	0.246
		1%	0.173
Range	0.706		
Q3-Q1	0.171		
Mode	0.246		

Szawlowski's Data			
Moments			
N	101	Sum Wgts	101
Mean	0.452307	Sum	45.683
Std Dev	0.176939	Variance	0.031307
Skewness	-0.3389	Kurtosis	0.167643
USS	23.79348	CSS	3.130737
CV	39.11921	Std Mean	0.017606
T:Mean=0	25.69038	Pr> T	0.0001
Num ^= 0	101	Num > 0	100
M(Sign)	49.5	Pr>= M	0.0001
Sgn Rank	2573.5	Pr>= S	0.0001
W:Normal	0.980873	Pr<W	0.5706

Quantiles (Def=5)			
100% Max	0.864	99%	0.819
75% Q3	0.567	95%	0.714
50% Med	0.471	90%	0.669
25% Q1	0.358	10%	0.178
0% Min	-0.055	5%	0.143
		1%	0.031
Range	0.919		
Q3-Q1	0.209		
Mode	0.399		

Table 32: Table of QAP correlations by study.

High School Data			
Quantiles (Def=5)			
100% Max	0.747	99%	0.747
75% Q3	0.084	95%	0.426
50% Med	0.0225	90%	0.273
25% Q1	0.004	10%	0
0% Min	0	5%	0
		1%	0
Range	0.747		
Q3-Q1	0.08		
Mode	0		

Szawlowski's Data			
Quantiles (Def=5)			
100% Max	0.826	99%	0.606
75% Q3	0.006	95%	0.205
50% Med	0	90%	0.076
25% Q1	0	10%	0
0% Min	0	5%	0
		1%	0
Range	0.826		
Q3-Q1	0.006		
Mode	0		

Table 33a: Randomization probability levels for QAP reliability indices in each study:
Time1 - Time 2 estimates.

	p < .05	p ≥ .05	Total
HSTS	53 (65.4%)	28 (34.6%)	81 (100%)
Szawlowski	88 (87.1%)	13 (12.9%)	101 (100%)
Total	141	41	182

$\chi^2 = 12.124$, $p < .001$

Table 33b: Cases exhibiting reliability coefficients with $p < .05$, by study.

Results: Within- and Between-Subject Variation Across Two Settings.

The QAP values for the 45 comparisons are presented in Table 34. Column A contains the re-test QAP values for the 15 Time 1 HSTS cases. Column B contains the comparison between the Time 1 matrices from the Column A comparisons and a random matrix from the combined Time 1 and Time 2 HSTS data. Column C is much the same as column B, except that the data were drawn from the Szawlowski data at either Time 1 or Time 2. Following each row of data are entries in each of three columns, one for each of the

Elements of Models:						
A<B and A >C implied by "within > between" hypothesis						
B>C implied by "Ecology Induces Similarity" hypothesis.						
A	B	C				
Re-test	Random case	Random case				
(HSTS data)	(same study)	(different study)				
.306	.396	.097	A<B*	A>C	B>C	
.314	.368	.236	A<B*	A>C	B>C	
.336	.467	.255	A<B*	A>C	B>C	
.399	.299	.094	A>B	A>C	B>C	
.407	.457	.118	A<B*	A>C	B>C	
.414	.410	.169	A>B	A>C	B>C	
.435	.493	.246	A<B*	A>C	B>C	
.469	----- .253 -----	.010	---- A>B -- A>C -- B>C ----			Median
.512	.622	.479	A<B*	A>C	B>C	re-test
.515	.092	.113	A>B	A>C	B<C*	value
.527	.472	.236	A>B	A>C	B>C	
.533	.223	.058	A>B	A>C	B>C	
.626	.477	.296	A>B	A>C	B>C	
.740	.365	.364	A>B	A>C	B>C	
.759	.339	.188	A>B	A>C	B>C	
Total Hits (by column)			9	15	14	
Total Misses			6	0	1	(by column)

* asterisk denotes a 'miss'.

Table 34: Within- and between-subject relationships among QAP coefficients

implications described above (i.e., that the entry in Column A will be larger than the entry in either Column B or Column C, as per the reliability hypothesis, and that the entry in Column B will be larger than the entry in Column C as per the "homogeneous ecology" hypothesis).

The simple reliability model states that $A > (B \text{ and } C)$. This provides $9+15=24$ hits and $6+0=6$ misses, for an IOF of $(24-6)/(24+6)=0.6$. The "homogeneous ecology" model produces $9+15+14=38$ hits and $6+0+1=7$ misses, for an IOF of .69. The third "constrained reliability" model ignores column A as "unpredictable" and gives us $15+14$ hits and $0+1=1$ miss, for a much better IOF of .93. The final "individual emergence" model takes the totals for the two rightmost columns, and only considers those cases that fall below the median in column A as "unpredictable", giving a revised total of 7 hits and 1 miss for that column from the "predictable" group. This results in a total of $7+15+14=36$ hits, and $1+1=2$ misses, for the best IOF of the four models, at .95. Consistent with Model 4, the Spearman rank-order correlation between the entries of Columns B and C was .74 ($p < .002$).

A Supplementary Exercise: MDS vs. QAP estimates and Stability

Since the 3-D and 4-D scaling solutions (at time 1) produced 3 or 4 canonical correlations (respectively), the relationship between ZQAP and the ZCAN series of indices was assessed through separate multiple regressions. Table 35 presents the univariate correlations between the measures, and the multiple regression results for the 3-D cases. Table 36 presents the results of the same analyses for the 4-D cases. Tables 37 through 39 present univariate correlations among the various indices broken down by study and optimal dimensionality at each of the two time points for cases that had either a 3- or 4-dimensional solution at times 1 and 2, and which stayed at the same OD at time 2. No 4-D cases from the HSTS dataset were observed to have an OD of 4 at time 2. A clear relationship between the two QAP indices ZQAP and ZR is apparent, with nearly all coefficients exceeding .90. As well, the QAP indices are most highly correlated with the first canonical index. With the exception of a blip on the ZCAN2 and ZCAN3 columns of the HSTS 3/3 correlation matrix, the relationship declines monotonically over the second, third and fourth (where applicable) canonical index.

Simple Statistics						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
ZQAP	48	0.6383	0.3319	30.6389	0.0310	1.3758
ZCAN1	84	1.2888	0.3816	108.2583	0.4558	2.1460
ZCAN2	84	0.7077	0.3311	59.4478	0.0703	1.5328
ZCAN3	84	0.2059	0.1917	17.2997	0.0017	1.0850

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0
/ Number of Observations

	ZCAN1	ZCAN2	ZCAN3
ZQAP	0.76306 0.0001 48	0.57420 0.0001 48	0.30123 0.0375 48

Regression Model Relating ZQAP to Canonical Z-Indices
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	3.20314	1.06771	23.814	0.0001
Error	44	1.97274	0.04484		
Total	47	5.17588			

Root MSE	0.21174	R-square	0.6189
Dep Mean	0.63831	Adj R-sq	0.5929
C.V.	33.17240		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	-0.195490	0.10337320	-1.891	0.0652
ZCAN1	1	0.525212	0.09145030	5.743	0.0001
ZCAN2	1	0.112489	0.12070240	0.932	0.3564
ZCAN3	1	0.200556	0.15673464	1.280	0.2074

Table 35: Relationship of QAP index to Canonical indices for 3-D solutions at Time 1.

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
ZQAP	79	0.4437	0.1900	35.0503	-0.0551	1.0010
ZCAN1	111	1.3946	0.3299	154.8003	0.6451	2.3359
ZCAN2	111	0.8487	0.2496	94.2110	0.3530	1.5151
ZCAN3	111	0.4696	0.1884	52.1213	0.1326	1.0103
ZCAN4	111	0.1495	0.1119	16.5981	0.001095	0.5771

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0
/ Number of Observations

	ZCAN1	ZCAN2	ZCAN3	ZCAN4
ZQAP	0.60764 0.0001 79	0.39551 0.0003 79	0.35411 0.0014 79	0.08269 0.4688 79

Regression Model Relating ZQAP to Canonical Z-Indices

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	4	1.10320	0.27580	11.919	0.0001
Error	74	1.71235	0.02314		
Total	78	2.81555			
Root MSE	0.15212	R-square	0.3918		
Dep Mean	0.44368	Adj R-sq	0.3589		
C.V.	34.28586				

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > T
INTERCEP	1	-0.050056	0.07648929	-0.654	0.5149
ZCAN1	1	0.287467	0.06036814	4.762	0.0001
ZCAN2	1	0.049120	0.08531406	0.576	0.5665
ZCAN3	1	0.157068	0.11477185	1.369	0.1753
ZCAN4	1	-0.128420	0.17497771	-0.734	0.4653

Table 36: Relationship of QAP index to Canonical Indices for 4-D solutions at Time 1

Within every grouping of univariate correlations in Tables 37 to 39, a substantial and statistically significant relationship exists between stability on the first and second canonical indices. In the Szawloski data, with the single exception of the fourth canonical stability index, the univariate correlations between the z-transformed QAP index and the several canonical indices were statistically significant for both the 3/3 and 4/4 dimensionalities. For the small number of HSTS cases, the correlation of .39 for ZQAP and ZCAN1 was not significant, although statistical power may be at the bottom of that non-result. The same can be said of the non-significant correlation in that matrix between ZCAN1 and ZCAN3. However, in the regression analysis presented in Table 40, only the first canonical index (ZCAN1) contributed significantly to the prediction of ZQAP after applying statistical control for dimensionality at each of the two points in time and a dummy variable assigned to study (STUDYDUM), suggesting that the variation captured by the first canonical variate is what is being detected by QAP..

Simple Statistics						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
ZQAP	19	0.6705	0.2819	12.7394	0.1013	1.3089
ZCAN1	19	1.5281	0.3773	29.0336	0.6938	2.1460
ZCAN2	19	0.9365	0.3478	17.7935	0.3429	1.5328
ZCAN3	19	0.2390	0.2293	4.5403	0.0143	0.9068

Pearson Correlation Coefficients / Prob > R under Ho: Rho=0 / N = 19				
	ZQAP	ZCAN1	ZCAN2	ZCAN3
ZQAP	1.00000 0.0	0.77343 0.0001	0.63607 0.0034	0.45262 0.0517
ZCAN1	0.77343 0.0001	1.00000 0.0	0.47174 0.0414	0.25669 0.2888
ZCAN2	0.63607 0.0034	0.47174 0.0414	1.00000 0.0	0.53743 0.0176
ZCAN3	0.45262 0.0517	0.25669 0.2888	0.53743 0.0176	1.00000 0.0

Table 37: Correlations among stability indices, Szawloski's data, 3-D solutions at time 1, 3-D solutions at time 2.

Correlation Analysis

4 'VAR' Variables: ZQAP ZCAN1 ZCAN2 ZCAN3

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
ZQAP	14	0.5395	0.2179	7.5527	0.2289	0.9661
ZCAN1	14	1.1790	0.2897	16.5054	0.7373	1.6531
ZCAN2	14	0.5780	0.2764	8.0922	0.2042	1.2816
ZCAN3	14	0.1574	0.1368	2.2042	0.0156	0.5278

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / N = 14

	ZQAP	ZCAN1	ZCAN2	ZCAN3
ZQAP	1.00000 0.0	0.39245 0.1652	-0.07644 0.7951	0.08258 0.7790
ZCAN1	0.39245 0.1652	1.00000 0.0	0.73654 0.0027	0.46995 0.0900
ZCAN2	-0.07644 0.7951	0.73654 0.0027	1.00000 0.0	0.06458 0.8264
ZCAN3	0.08258 0.7790	0.46995 0.0900	0.06458 0.8264	1.00000 0.0

Table 38: Correlations among stability indices HSTS data, 3-D solution at time 1, 3-D solution at time 2.

Correlation Analysis

5 'VAR' Variables: ZQAP ZCAN1 ZCAN2 ZCAN3 ZCAN4

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
ZQAP	30	0.4128	0.1460	12.3829	0.0872	0.6625
ZCAN1	30	1.5498	0.4051	46.4947	0.9292	2.3359
ZCAN2	30	0.9238	0.2489	27.7150	0.5040	1.5908
ZCAN3	30	0.5503	0.2063	16.5091	0.1998	1.2264
ZCAN4	30	0.1516	0.1094	4.5468	0.003973	0.4610

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / N = 30

	ZQAP	ZCAN1	ZCAN2	ZCAN3	ZCAN4
ZQAP	1.00000 0.0	0.70260 0.0001	0.53979 0.0021	0.32136 0.0833	0.10550 0.5790
ZCAN1	0.70260 0.0001	1.00000 0.0	0.52448 0.0029	0.36177 0.0495	0.23120 0.2190
ZCAN2	0.53979 0.0021	0.52448 0.0029	1.00000 0.0	0.64786 0.0001	0.13135 0.4890
ZCAN3	0.32136 0.0833	0.36177 0.0495	0.64786 0.0001	1.00000 0.0	0.10960 0.5643
ZCAN4	0.10550 0.5790	0.23120 0.2190	0.13135 0.4890	0.10960 0.5643	1.00000 0.0

Table 39: Correlations among stability indices, Szawloski data, 4-D solution at time 1, 4-D solution at time 2.

Pearson Partial Correlation Coefficients / Prob > |R| under H₀:
Partial Rho=0 / N = 126

	ZR	ZQAP	ZCAN1	ZCAN2	ZCAN3
ZR	1.00000 0.0	0.87009 0.0001	0.52160 0.0001	0.35881 0.0001	0.19213 0.0325
ZQAP	0.87009 0.0001	1.00000 0.0	0.52747 0.0001	0.41056 0.0001	0.22393 0.0124
ZCAN1	0.52160 0.0001	0.52747 0.0001	1.00000 0.0	0.55678 0.0001	0.23422 0.0088
ZCAN2	0.35881 0.0001	0.41056 0.0001	0.55678 0.0001	1.00000 0.0	0.47066 0.0001
ZCAN3	0.19213 0.0325	0.22393 0.0124	0.23422 0.0088	0.47066 0.0001	1.00000 0.0

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	6	2.26212	0.37702	12.380	0.0001
Error	119	3.62411	0.03045		
Total	125	5.88623			

Root MSE	0.17451	R-square	0.3843
Dep Mean	0.51485	Adj R-sq	0.3533
C.V.	33.89555		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H ₀ : Parameter=0	Prob > T
INTERCEP	1	1.000418	0.18851307	5.307	0.0001
DIMENS	1	-0.199827	0.03941344	-5.070	0.0001
DIMENS2	1	-0.063959	0.04310240	-1.484	0.1405
STUDYDUM	1	-0.058628	0.04412816	-1.329	0.1865
ZCAN1	1	0.264994	0.05675828	4.669	0.0001
ZCAN2	1	0.087594	0.07319105	1.197	0.2338
ZCAN3	1	0.088377	0.08996615	0.982	0.3279

Table 40: Intercorrelations among stability indices, with main effects of study and dimensionality controlled.

Predictors of Stability

In order to examine predictors of stability, the normalized canonical correlation-based stability indices for the first three dimensions of all 3- or 4-D cases were used as dependent measures. Fisher's *r*-to-*Z* transformation was applied to them, producing three new variables, ZCAN1-ZCAN3 (and ZCAN4 where applicable). The relationship between these indices of stability and the five major NEO dimensions of Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness was examined through the use of canonical correlation. To ensure that variance attributable to dimensionality and study were allowed to be factored in, the STUDYDUM variable was entered along with a dummy variable coding OD (as 3 or 4) at times 1 and 2.

Results are summarized in Table 41. The first canonical correlation was large and statistically significant ($r=.61$, $p < .0001$). The standardized canonical coefficients were all near zero on the first variate except for dimensionality at time 1 ($\beta = .92$), dimensionality at time 2 ($\beta = .28$), and Openness ($\beta = .19$) on the predictors side, and ZCAN3 on the outcome side ($\beta = 1.04$). The second correlation was also significant ($r=.34$, $p < .026$). The second variate for the predictors was composed primarily of the Study dummy variable ($\beta = -1.07$), Openness ($\beta = .59$), and dimensionality at time 2 ($\beta = -.53$). The outcome variate involved ZCAN2 ($\beta = .97$) and to a lesser extent ZCAN3 ($\beta = -.50$). The third canonical correlation was non-significant ($r=.20$, $p > .36$). Redundancy analysis indicated that 20% of the standardized variance in the canonical stability coefficients was accounted for by the first two variates, and so, by implication, study and dimensionality differences.

Examination of univariate patterns indicated that high openness to experience has a small association ($r = .19$, $p < .015$) with stability based on the second canonical correlation index, while high agreeableness predicts high stability on this measure. STUDYDUM was correlated with ZCAN1 ($r = -.202$, $p < .001$) and ZCAN2 ($r = -.195$, $p < .01$), while time 1 dimensionality correlated .21 with ZCAN2 ($p < .008$) and .56 with ZCAN3 ($p < .0001$). Time 2 dimensionality correlated .23 with ZCAN3 ($p < .003$). Thus, it would appear that openness to experience is the only personality measure that has an overt, albeit small, relationship with canonical indices of stability of Project Spaces.

Canonical Correlation Analysis

	Canonical Correlation	Adjusted Canonical Correlation	Approx Standard Error	Squared Canonical Correlation
1	0.606386	0.576178	0.049678	0.367704
2	0.343128	0.285792	0.069317	0.117737
3	0.202161	0.145597	0.075356	0.040869

Eigenvalues of $INV(E) * H$
 $= CanRsqr / (1 - CanRsqr)$

	Eigenvalue	Difference	Proportion	Cumulative
1	0.5815	0.4481	0.7676	0.7676
2	0.1334	0.0908	0.1761	0.9438
3	0.0426	.	0.0562	1.0000

Test of H_0 : The canonical correlations in the
current row and all that follow are zero

	Likelihood Ratio	Approx F	Num DF	Den DF	Pr > F
1	0.53505295	4.4263	24	441.4475	0.0001
2	0.84620586	1.9033	14	306	0.0255
3	0.95913079	1.0937	6	154	0.3687

Multivariate Statistics and F Approximations

Statistic	S=3 Value	M=2 F	N=75 F	Num DF	Den DF	Pr > F
Wilks' Lambda	0.53505295	4.4263		24	441.4475	0.0001
Pillai's Trace	0.52630951	4.0957		24	462	0.0001
Hotelling-Lawley Trace	0.75759587	4.7560		24	452	0.0001
Roy's Greatest Root	0.58153666	11.1946		8	154	0.0001

NOTE: F Statistic for Roy's Greatest Root is an upper bound.

Standardized Canonical Coefficients for the 'VAR' Variables

	V1	V2	V3
ZCAN1	0.0179	0.2706	-1.1926
ZCAN2	-0.0949	0.9711	0.9290
ZCAN3	1.0394	-0.5003	-0.0746

Standardized Canonical Coefficients for the 'WITH' Variables

	W1	W2	W3
NEUR	0.0249	-0.0882	0.4299
OPEN	0.1879	0.5915	0.3034
EXT	0.0219	0.0925	0.5515
AGREE	0.0017	-0.1705	-0.6262
CONS	0.0470	-0.1422	-0.0064
STUDYDUM	-0.0049	-1.0691	0.3836
DIMENS	0.9208	0.2054	-0.0549
DIMENS2	0.2757	-0.5287	0.1046

Table 41: Canonical analysis of Stability indices and Personality, with Study and OD.

Standardized Variance of the 'VAR' Variables Explained by					
Their Own Canonical Variables			The Opposite Canonical Variables		
	Proportion	Cumulative Proportion	Canonical R-Squared	Proportion	Cumulative Proportion
1	0.4206	0.4206	0.3677	0.1547	0.1547
2	0.4107	0.8313	0.1177	0.0484	0.2030
3	0.1687	1.0000	0.0409	0.0069	0.2099

Standardized Variance of the 'WITH' Variables Explained by					
Their Own Canonical Variables			The Opposite Canonical Variables		
	Proportion	Cumulative Proportion	Canonical R-Squared	Proportion	Cumulative Proportion
1	0.1349	0.1349	0.3677	0.0496	0.0496
2	0.0976	0.2325	0.1177	0.0115	0.0611
3	0.1152	0.3477	0.0409	0.0047	0.0658

Table 41 (cont.)

Discussion

QAP and Canonical Indices of Stability

Both the QAP and canonical methods provide good evidence that individual project spaces tend to exhibit stable solutions over both time and changes in the projects rated. As we would expect intuitively, rating the same projects after a short period tends to provide more similar pairs of Project Spaces than does rating different projects after a longer period of time. However, the magnitude of this difference does not appear to be very large.

The relationship between the QAP index of global matrix similarity and the canonical indices of stability is fairly substantial but noticeably imperfect. For more complex (i.e., higher-dimensional) solutions, lower concordance would be unsurprising, and this is precisely what was observed. For the three-dimensional solutions, the canonical indices accounted for 62% of the variance in the ZQAP index, compared to 39% for the 4-dimensional cases.

On further reflection, this is not surprising. As a result of its use of Pearson correlation, QAP depends on the existence of a linear pattern of relationships among the elements of the correlation matrices. MDS makes no such assumption, and takes advantage of monotonic but not-necessarily-linear similarities between the matrices. Thus, a pattern that is at least monotonic will be scaled to maximize a linear fit and minimize squared error, whereas QAP will only pick up on squared deviations from a line without scaling to correct deviations within the bounds of monotonicity constraints.

Limitations

The results from this section suffer some limitations. From a technical perspective, the relationship between QAP and canonical indices appears to be constrained by the fact that QAP depends on the linear features of the entries in the correlation matrix, while nonmetric MDS can "straighten" lines in its non-metric scaling phase. Furthermore, there is a problem that arises from the result noted above, wherein only 70% of the variance in the badness-of-fit of 1-dimensional solutions (i.e., the linear position of features on a scale, which is what QAP detects) is accounted for by badness-of-fit of higher-dimensional solutions. This suggests that an attenuation factor may exist for pairs of matrices due to QAP's dependence on linearity (i.e., what amounts to an assumed 1-dimensional solution) in contrast to the ability of MDS to fit the data in multidimensional space. Reliable dimensions higher than the first will improve the overall canonical reliability using information unavailable to QAP..

Models of Apparent Stability

QAP has apparent limitations with respect to the amount of information that is used in determining and describing Project Spaces. The MDS analyses give more finely-differentiated information, as well as structure coefficients that (as will be shown below) have a clear substantive interpretation that links cleanly to a theoretical model, and so are to be preferred. For this reason, QAP analysis is omitted from further consideration in this dissertation.

In spite of this limitation of some of the evidence presented in this chapter, there is nevertheless a clear indication that the best way of looking at the phenomenon of the apparent stability of Project Spaces is from the point of view of a joint project space which is, on the whole, comparable across individuals and which may even be recoverable from data not clustered within individuals. Although it is logically not necessary, it remains an open empirical question as to the extent of commonality between individual structures based on single project spaces, and the structure of data aggregated at a higher level of analysis [*contra* Simpson's Paradox], such as project system means or even random assortments of project category profiles.

The fact that between-study and between-dimensionality differences are more strongly associated with stability indices than are personality measures raises some interesting psychological questions that could be pursued in future research. One would anticipate that low openness to experience would result in higher stability, as a homogeneous set of projects and persistent (even if problematic) ways of looking at them should tend to produce similar results. However, the opposite seems to be the case. This suggests that openness to new experiences may be a by-product of having an established, yet somewhat adaptive way of looking at things. Low openness to new experiences would be typical of a person who has a fixed way of construing projects that is persistently being invalidated by experience. The attempt to "experiment" with new ways of construing may result in more ad-hoc ratings of projects over time (and thus less "reliable" Project Spaces) as social-ecological factors force unwanted modifications to projects over time. However, this speculation must be framed in terms of the small magnitude of the relationship, and the existence of a Joint Project Space which seems to be at the bottom of much of what was observed in this chapter.

Having established that there appears to be a fair degree of at least *apparent* reliability in Project Spaces, we must now go further into the questions raised in this chapter by the "individual emergence" model. The existence of a clearly-identifiable joint space that is shared by most people across time and place would confirm that the observed reliability is actually an artefact of the existence of a larger phenomenon which has clearly recognizable features that apply to many, if not most cases.

Chapter 8: The Joint Project Space

In this chapter, results are presented which establish the existence of a joint space derived from the available cases in SEABANK. It will be shown that this common Project Space is stable over time for cases which exhibit OD's of both 3 and 4, and is essentially invariant under changes in choice of similarity coefficient. Furthermore, it is unrelated to NEO-PI personality measures, and Project Spaces derived from intact single-case data are shown to be virtually indistinguishable from Project Spaces that are based on projects patched randomly together from various cases.

Characteristics of the Common Project Space

While intrinsically interesting, separate solutions do not tell us a great deal about people in general. In order to obtain a "joint space," individual differences scaling (or "INDSCAL") must be used. All non-problematic 3-D or 4-D cases with data on the 17 standard PPA dimensions were subjected to this analysis using the SAS module PROC MDS (SAS Institute, 1996), which produces output analogous to the ALSCAL procedure (Young, Takane & Lewyckyj, 1983). Initially, the joint space was obtained by requesting a 4-dimensional solution for all cases, and weirdness coefficients were obtained for all cases. However, because (as seen above) the optimal dimensionality for each individual case appears to vary, the Project Spaces were broken down according to optimal dimensionality based on the results from the separate MDS analyses, and as a secondary analysis, joint spaces were obtained within each group. To examine the impact of solving in a higher or lower dimensionality than is optimal, the correlation between the within-cluster weirdness and overall-solution weirdness was obtained within each group. To test the hypothesis that the solutions obtained using the Pearson coefficient that was assumed above are not different than those obtained using other measures of similarity, the analyses were replicated with the

Kendall tau and Spearman rho substituted for the Pearson r , and the obtained solutions were compared via canonical correlation analysis.

RELIABILITY OF JOINT SPACE INDICATORS

As with the reliability of single-case structural measures, it is possible to obtain indicators from INDSCAL solutions examine the stability not only of the structure of the joint spaces, but of the dimension coefficients and “weirdness” (or “salience” ; Davison, 1992) coefficients. Therefore the data from each of the two points in time (according to the study) were subjected to INDSCAL analysis and a 4-dimensional solution was requested. Canonical correlations between both structure and weirdness coefficients for time 1 and time 2 were computed to discern the reliability of these indicators.

FACTORS ASSOCIATED WITH JOINT SPACE INDICATORS

Not all subjects provided the same number of projects. A small number of cases had four projects available, and at the upper extreme, 17 projects were recorded. Similarly greater or lesser amounts of missing data were possible, which would create minor imbalances in the number of projects contributing to each correlation coefficient. Since the standard error of the correlation coefficients will be affected by the number of projects being used to delineate the Project Space, the possibility that the number of projects is related to some of the joint space indicators was considered. Therefore the relationships between number of projects used, quantity of missing data and joint space indicators was examined to determine if cases should be eliminated due to insufficient data, or whether a larger number of projects is to be recommended in future studies that explore the Project Space at the individual level.

Generalizability: Between-Study Differences in Dimensionality and Dimension Weights

The optimal dimensionality for a given case may arise from factors peculiar to the place and time in which a study is conducted. The simplest approach to examining this factor is a simple one-way ANOVA on the optimal dimensionality of the cases at hand. However, it is also possible that in the joint space, between-study differences exist in the emphasis placed on particular dimensions by subjects, and so a one-way MANOVA was performed on the dimension coefficients within each grouping of optimal dimensionality. In order to maximize

the number of cases available, analyses were run on the Time 1 data of studies which followed subjects across more than one point in time.

Interesting Questions

Given that we have found support for a model that posits the existence of a joint space, it is necessary to attempt to establish this feature of the model. There appears to be a good deal of reliability in Project Spaces, on the whole, and so now we must consider whether this is attributable to individuals who construe consistently within their own set of projects, or the presence of a more global structure which is common to most individuals, but from which some individuals deviate to some extent.

Given that a 3- or 4- dimensional solution fits the great majority of cases (and is in part a function of the qualitative content of the projects included in the matrix from which the Project Space was derived), the time 1 data for all cases were analyzed within each of these two levels of optimal dimensionality. Structure coefficients for the two joint spaces were compared using both canonical analysis and graphical methods, and between-study differences on dimension coefficients (or “weirdness coefficients”) were examined. The question of what happens when cases with an OD of 3 are solved in four dimensions was also explored.

The relationship between INDSCAL weirdness and badness-of-fit for the MDS solutions of various dimensionalities is also one that can be anticipated, because the salience of higher dimensions *should* be related to their importance in solving single spaces. It is merely a question of assessing the strength of the relationship and the patterns involved. Since INDSCAL weirdness will be to a certain extent a function of dimensionality, and because separate solutions are being run for the 3-D and 4-D cases, within each group the original MDS S-Stress values may be compared to the weirdness coefficients to explore the strength of the relationship. It is not expected to be substantial, but should nevertheless allow us to estimate the degree to which problems with solving single cases may be related to deviations from the typical Project Space.

The relationship of measures of aberration to personality variables is of particular interest. The reflection of “weirdness” as defined by having an aberrant Project Space

(relative to the joint space) in personality measures would provide a link between ways of construing projects and other more global aspects of the manner in which a person interacts with the world. Thus, those cases where NEO-PI data existed were analyzed for linear and non-linear relationships between the INDSCAL-derived weirdness coefficients and the NEO-PI variables that were collected. In order to refer “weirdness” to a broader base, the INDSCAL solution was found for all available non-problematic cases irrespective of the presence of NEO data, and then merged after the solution was obtained. Furthermore, given that personality differences seem to be reflected to some degree in the optimal dimensionality of the solution for a given case, and cases have been grouped according to this initial feature, it is best to assume that different relationships may hold within the different groupings.

Given that an indirect relationship between personality, project category and S-Stress has been observed, it is of interest to examine the extent to which project category relates to weirdness coefficients on the various dimensions for the two main groups of interest (the 3-D and 4-D cases). Once again, Poisson regression will be used to examine this relationship.

The choice of a measure of similarity has thus far been limited to Pearson’s correlation coefficient, a computationally efficient and familiar statistic that indexes the association between two variables. In order to explore the sensitivity of the solutions we are looking at to the choice of a measure of association, the 3-D and 4-D cases were re-analyzed using Spearman’s rho and Kendall’s tau coefficients in place of Pearson’s r . On the one hand, because criticisms of the use of Spearman’s coefficient are based in part on its similarity to Pearson’s (e.g., Roberts & Kunst, 1990), while tau remains distinctly nonparametric, it may be that the overall similarity of both structural configuration coefficients and weirdness coefficients will be greater for Spearman’s statistic than for Kendall’s statistic. On the other hand, the smaller discrepancies between converted taus and Pearson r ’s (relative to converted Spearman rho’s) noted by Rupinski & Dunlap (1996) predict the opposite effect. While it is possible to compare the relative similarity of solutions obtained under both conditions, the fact that both of these measures can be converted quite readily to an approximate Pearson’s statistic for the purposes of meta-analysis (Rupinski & Dunlap, 1996) implies that the

canonical correlations between both structure and weirdness coefficients will be extremely large for either choice of coefficient.

Since the 3-D cases have been defined as such on the basis of parsimony, it is also interesting to examine exactly what happens when they are solved in four dimensions. It is expected that since among these cases the relationships that define the fourth dimension are not strong enough to warrant the additional vector when solving individually, the weakness of these links will result in lower weirdness coefficients on the fourth dimension when solving jointly. Since the MDS routine will be able to capitalize on smaller residual values (the bulk of the work having been done by the first three dimensions), the 3-D cases on the whole will not require multiplication by as large a weight in order to fit the joint space. As well, because of the greater complexity of the Project Spaces in the 4-D cases, these will exhibit higher weirdnesses on the third dimension than the 3-D cases.

As a test of the possibility that cross-cultural differences (possibly confounded by linguistic differences) may be at work in structuring Project Spaces, the Chinese and Canadian data from Xiao (1986) were subjected to a separate INDSCAL. Any other differences in study design are therefore controlled, limiting any observed differences in emphasis on one dimension as opposed to another (i.e., weirdness) to these factors.

Another intriguing question arises as to the importance of within-subject clustering of projects. To explore the importance of having projects from the same person when solving for a joint space, an additional analysis was performed on the available data wherein they were randomly separated into two groups. Half of the data were kept intact, while the other half were randomly ordered into "synthetic" project spaces composed of groups of 10 projects drawn from up to 10 different cases, potentially from a variety of different studies. This tested the prediction that if the structure of the Project Space is peculiar to an individual, then the pattern of weights on the various dimensions should permit clear differentiation between real and synthetic Project Spaces. If, on the other hand, clusters of projects reflect a more general pattern which is interpretable irrespective of whether the clusters were drawn from the same individual, then little, if any difference should be apparent. The implication of this latter point is that a general Project Space may be defined on the basis of Personal Projects

themselves, irrespective of within-subject clustering. This would be even stronger evidence for the existence of a joint space from which individuals may deviate to a greater or lesser degree.

Results: The Joint Space

Three-Dimensional Solution

From the available data, 279 cases were drawn from 7 different studies on the basis of having been solved in 3 dimensions in the previous analyses, and having more than 7 projects with less than 10% missing data. The overall S-Stress for the solution was .35, and the configuration is plotted in Figure 34. As a check, 100 samples of 279 cases were randomly generated using SAS, and project spaces were computed and submitted to INDSCAL analysis. The obtained value for the S-Stress of the three-dimensional solution was normally distributed with a mean of 0.4454 (standard error= 0.000164). No value fell below 0.444991, indicating $p < .01$ for the obtained solution. However, relative to the simulated distribution, the observed value was over 581 standard error below the mean.

A one-way MANOVA was performed on the dimension coefficients to establish the extent to which these coefficients may be associated with between-study effects. No significant differences were observed on any of the three dimensions (Wilks' Lambda= .97, $p > .947$).

Four-Dimensional Solution

For the 4-D analysis, 338 cases were drawn from 7 studies on the basis of having been solved in 4 dimensions in the previous analyses, and having no problems with number of projects or proportion of data that were missing. The overall S-Stress for the solution was .35, and the first three dimensions of the configuration are plotted in Figure 35, which bears a striking resemblance to the 3-D space of Figure 34. As a check, an attempt was made to generate 100 samples of 338 cases using SAS, however, this task consistently exceeded the computational resources of a large university UNIX system (even on a Friday night), and so an alternative procedure was employed. The number of 17x17 random pseudo-spaces was varied ($N=2,3,4,5,10,15,20$) and 20 samples were generated for each level of N . INDSCAL

solutions were computed and the final 4 S-Stress values formed a curve that has two key features: a negative exponential bend and marked heteroscedasticity. Nonlinear regression was used (the SAS module PROC NLIN) to estimate the curve from the simulated data, and the regression equation

$$\text{criter} = -.5554418393 + \exp(-.0583375928/N);$$

accounted for 99.9964% of the variance. Assuming that as N becomes large, the curve asymptotes to some value around which the error is virtually zero (as in the 3-D case noted above), we would predict values consistently around

$-0.5554418393 + \exp(-0.0583375928/338) = 0.44439$ with virtually no variability. As with the 3-D data where simulation was possible, the observed S-Stress is well below this level. ⁶

A one-way MANOVA was performed on the four dimension coefficients in order to determine whether these coefficients are associated with between-study effects. A significant multivariate effect was observed for study (Wilks' Lambda = 1.82, $p < .0095$). Statistically significant but substantively trivial effects were noted on the first dimension coefficient ($F_{6,331} = 3.88$, $p < .0009$; $R^2 = .066$) and the fourth ($F_{6,331} = 2.67$, $p < .0151$; $R^2 = .046$). Least squares means were computed and pairwise t-tests are presented in Table 56. Keeping in mind the fact that no a priori differences are expected, we apply an Bonferroni-corrected alpha of .0024 and find that the differences are attributable to the fact that the highest group (from Benton's 1987 data) differed from the lowest three groups (the HSTS data, Pychyl's 1986 data and those of Xiao, 1986) on the first dimension. Applying the same criterion in the case of the fourth dimension coefficient, it appears that the result is attributable to a high weirdness for cases drawn from Pychyl's (1986) data, which is markedly higher than the data from the four lowest groupings (Benton's 1987 data; the HSTS data (Lecci, 1990); and those from Szawlowski (1987).

The First Three Dimensions

To examine the degree of this similarity between the joint spaces for the two groups of interest, the configurations were obtained for the 4-dimensional and 3-dimensional cases and compared via canonical correlation analysis and graphical procedures. Table 42 presents the full canonical analysis, which revealed three significant canonical correlations of 0.992,

0.967 and 0.841 in that order. Redundancy analysis revealed that each set of variables accounted for between 87% and 88% of the other set, indicating that the first three dimensions of the 4-D cases are substantially the same as the first three dimensions of the 3-D cases. The locations of the variables on each of the first three dimensions for the two groups are plotted in Figures 36 through 38. Clearly, the Stress/Challenge/Difficulty triad dominate one end of the first dimension of both solutions, standing out as not only similar to one another but distinct from the remaining variables. The the second dimension of both solutions would appear to be driven by the negative relationship between Negative Impact and Positive Impact, while the third appears to depend on the associations between Others' View of Importance, Visibility, Outcome, Progress and Time Adequacy at one end, and the distinct grouping of Enjoyment, Absorption, Value Congruency and Self-Identity at the other end.

3-D Joint Space

Figure 34: Joint Space from 3-D cases' INDSCAL solution

4-D Joint Space

Figure 35: Joint Space from 4-D cases' INDSCAL solution

Correlations Among the 'VAR' Variables					
	DIM31	DIM32	DIM33		
DIM31	1.0000	-0.0323	-0.0262		
DIM32	-0.0323	1.0000	0.0343		
DIM33	-0.0262	0.0343	1.0000		
Correlations Among the 'WITH' Variables					
	DIM41	DIM42	DIM43		
DIM41	1.0000	0.0324	0.0150		
DIM42	0.0324	1.0000	0.0018		
DIM43	0.0150	0.0018	1.0000		
Correlations Between the 'VAR' Variables and the 'WITH' Variables					
	DIM41	DIM42	DIM43		
DIM31	0.9128	0.3210	0.1783		
DIM32	-0.1486	0.8058	-0.2467		
DIM33	-0.2668	0.2539	0.8825		
Canonical Correlation Analysis					
	Adjusted Canonical Correlation	Approx Canonical Correlation	Squared Standard Error	Canonical Correlation	
1	0.992033	0.990179	0.003968	0.984129	
2	0.967229	0.965446	0.016117	0.935532	
3	0.841835	.	0.072829	0.708685	
Eigenvalues of INV(E)*H = CanRsqr/(1-CanRsqr)					
	Eigenvalue	Difference	Proportion	Cumulative	
1	62.0097	47.4980	0.7854	0.7854	
2	14.5117	12.0790	0.1838	0.9692	
3	2.4327	.	0.0308	1.0000	
Test of H0: The canonical correlations in the current row and all that follow are zero					
	Likelihood Ratio	Approx F	Num DF	Den DF	Pr > F
1	0.00029805	81.0590	9	26.92172	0.00
2	0.01878034	37.7824	4	24	0.00
3	0.29131454	31.6253	1	13	0.00

Table 42: Relationship of 1st three dimensions of 4D and 3D Joint Spaces

Multivariate Statistics and F Approximations

S=3 M=-0.5 N=4.5

Statistic	Value	F	Num DF	Den DF	Pr > F
Wilks' Lambda	0.00029205	81.0590	9	26.92172	0.0001
Pillai's Trace	2.62834732	30.6456	9	39	0.0001
Hotelling-Lawley Trace	78.95410245	84.8026	9	29	0.0001
Roy's Greatest Root	62.00971199	268.7088	3	13	0.0001

NOTE: F Statistic for Roy's Greatest Root is an upper bound.

Standardized Canonical Coefficients for the 'VAR' Variables

	V1	V2	V3	
DIM31	0.9090	0.2194	-0.3365	Dimension 1
DIM32	0.3381	0.1741	0.9381	Dimension 2
DIM33	-0.2819	0.9581	-0.0513	Dimension 3

Standardized Canonical Coefficients for the 'WITH' Variables

	W1	W2	W3	
DIM41	0.8642	-0.0740	-0.4976	Dimension 1
DIM42	0.4998	0.4591	0.7345	Dimension 2
DIM43	-0.1606	0.8834	-0.4403	Dimension 3

Canonical Structure

Correlations Between the 'VAR' Variables and Their Canonical Variables

	V1	V2	V3	
DIM31	0.9051	0.2194	-0.3642	Dimension 1
DIM32	0.2995	0.1741	0.9381	Dimension 2
DIM33	-0.2819	0.9581	-0.0513	Dimension 3

Correlations Between the 'WITH' Variables and Their Canonical Variables

	W1	W2	W3	
DIM41	0.8642	-0.0740	-0.4976	Dimension 1
DIM42	0.4998	0.4591	0.7345	Dimension 2
DIM43	-0.1606	0.8834	-0.4403	Dimension 3

Table 42 (cont.)

Canonical Structure

Correlations Between the 'VAR' Variables and Their Canonical Variables

	V1	V2	V3	
DIM31	0.9051	0.2194	-0.3642	Dimension 1
DIM32	0.2995	0.1741	0.9381	Dimension 2
DIM33	-0.2819	0.9581	-0.0513	Dimension 3

Correlations Between the 'WITH' Variables and Their Canonical Variables

	W1	W2	W3	
DIM41	0.8642	-0.0740	-0.4976	Dimension 1
DIM42	0.4998	0.4591	0.7345	Dimension 2
DIM43	-0.1606	0.8834	-0.4403	Dimension 3

Correlations Between the 'VAR' Variables and the Canonical Variables of the 'WITH' Variables

	W1	W2	W3	
DIM31	0.8979	0.2122	-0.3066	Dimension 1
DIM32	0.2972	0.1684	0.7897	Dimension 2
DIM33	-0.2797	0.9267	-0.0432	Dimension 3

Correlations Between the 'WITH' Variables and the Canonical Variables of the 'VAR' Variables

	V1	V2	V3	
DIM41	0.8573	-0.0716	-0.4189	Dimension 1
DIM42	0.4958	0.4440	0.6183	Dimension 2
DIM43	-0.1593	0.8544	-0.3707	Dimension 3

Table 42 (cont.)

STUDY		DIM1 LSMEAN	LSMEAN Number
XIAO		1.03664261	1
HSTS		1.04590196	2
LECCI		1.06388193	3
SZAWLOWSKI		1.06673706	4
PYCHYL		1.03834074	5
BENTON		1.08705863	6
DILLON		1.06511980	7

Pr > |T| H0: LSMEAN(i)=LSMEAN(j)

i/j	1	2	3	4	5	6	7
1	.	0.4653	0.0639	0.0234	0.9106	0.0007	0.0541
2	0.4653	.	0.1075	0.0237	0.5197	0.0003	0.0885
3	0.0639	0.1075	.	0.8083	0.0661	0.0857	0.9267
4	0.0234	0.0237	0.8083	.	0.0218	0.0876	0.8916
5	0.9106	0.5197	0.0661	0.0218	.	0.0005	0.0556
6	0.0007	0.0003	0.0857	0.0376	0.0005	.	0.1060
7	0.0541	0.0885	0.9267	0.8916	0.0556	0.1060	.

STUDY		DIM4 LSMEAN	LSMEAN Number
XIAO		0.96665411	1
HSTS		0.96598042	2
LECCI		0.95559396	3
SZAWLOWSKI		0.95809227	4
PYCHYL		0.98347154	5
BENTON		0.94798039	6
DILLON		0.95278350	7

Pr > |T| H0: LSMEAN(i)=LSMEAN(j)

i/j	1	2	3	4	5	6	7
1	.	0.9433	0.3128	0.3862	0.1369	0.0906	0.2083
2	0.9433	.	0.2127	0.2500	0.0467	0.0328	0.1171
3	0.3128	0.2127	.	0.7762	0.0074	0.4487	0.7797
4	0.3862	0.2500	0.7762	.	0.0061	0.2544	0.5493
5	0.1369	0.0467	0.0074	0.0061	.	0.0007	0.0034
6	0.0906	0.0328	0.4487	0.2544	0.0007	.	0.6349
7	0.2083	0.1171	0.7797	0.5493	0.0034	0.6349	.

Table 43: Between-study Differences: Least-squares means and p-values for pairwise t-tests for 4-D data where differences exist - 1st and 4th Dimension Coefficients.

Figure 36: Relationship of 1st 3 dimensions of 4-d and 3-d joint spaces - Dimension 1

Figure 37: Relationship of 1st 3 dimensions of 4-d and 3-d joint spaces - Dimension 2

Figure 38: Relationship of 1st 3 dimensions of 4-d and 3-d joint spaces - Dimension 3

The Fourth Dimension

Examination of the coordinates of the 17 project features on the fourth dimension obtained for the 4-D cases revealed that at one extreme, Absorption and Visibility were grouped together. At the other extreme, Control, Initiation and Outcome were together, with Control and Initiation being particularly extreme. From a structural point of view, partialling out the fourth dimension when running a canonical correlation between the 3-D joint space and the first three dimensions of the 4-D space also improves the fit markedly ($r = .992$; $r = .974$, and $r = .954$, in that order). The canonical redundancies go up to .95 from the high .8 range on either side once the additional dimension has been controlled, suggesting that the relationship is latent but not strong in the 3-D structure, and that correcting for it there makes for a better mapping of the spaces. This view is confirmed by the univariate correlations of the first and third dimensions of the 3-D solution to the fourth dimension of the 4-D solution ($r = -.02521$ and 0.4485 , respectively). It correlated near zero with all other variables in the solution.

The Choice of a Similarity Index

In this section the re-analysis of the 3-D and 4-D joint spaces using Kendall's tau and Spearman's rho in place of Pearson's r as a similarity measure is reported. The four analyses were referred to the original analyses, with dimension coefficients analyzed separately for the joint space as well as for the weirdness coefficients that were obtained.

THE 3-D CASES: KENDALL'S TAU

The INDSCAL for the 3-D cases described above was replicated, with the difference that Kendall's tau was used in lieu of Pearson's r. For the structural coefficients of the 17 project features, the three canonical correlations between the obtained solution and that arrived at through the use of Pearson's coefficient were 0.9998, 0.9970 and 0.9914, respectively (asymptotic $p < .0001$ for all), with total canonical redundancies in excess of .99 on either side. For the weirdness coefficients on each of the three dimensions, the canonical correlations were 0.9484, 0.9010 and 0.8113 (in that order), with canonical redundancies of approximately .84 on each side.

THE 3-D CASES: SPEARMAN'S RHO

The use of Spearman's rho did not change the results by very much. For the structure coefficients, the set of values for $r_{cc} = (0.9997, 0.9981, 0.9896, \text{asymptotic } p < .0001 \text{ for all})$ with redundancies above .99. For the weirdness coefficients, $r_{cc} = (0.9534, 0.9072, 0.8227, \text{asymptotic } p < .0001 \text{ for all})$, with redundancies of approximately .85.

THE 4-D CASES: KENDALL'S TAU

The INDSCAL for the 4-D cases was also replicated, with Kendall's tau in place of Pearson's r. For the structural coefficients of the 17 project features, the four canonical correlations between the obtained solution and that arrived at through the use of Pearson's coefficient were 0.9998, 0.9996, 0.9992, and 0.9858 respectively (asymptotic $p < .0001$ for all), with total canonical redundancies in excess of .99 on either side. For the weirdness coefficients on each of the four dimensions, the canonical correlations were 0.9446, 0.9371, 0.8943 and 0.8294 (in that order), with canonical redundancies of approximately .86 on each side.

THE 4-D CASES: SPEARMAN'S RHO

Once again, very comparable results were obtained with the Spearman coefficient. For the configuration of the 17 project features, $r_{cc} = (0.9999, 0.9995, 0.9988, 0.9911, \text{asymptotic } p < .0001 \text{ for all})$ and redundancies of 0.9948 on either side. For the weirdness coefficients, $r_{cc} = (0.9508, 0.9351, 0.8980, 0.8330, \text{asymptotic } p < .0001 \text{ for all})$ and redundancies of approximately 0.866 on either side were observed.

What Happens to 3-D Cases in 4-D?

When 509 non-problematic cases that had an OD of either 3 or 4 at time 1 were solved jointly using INDSCAL with a 4-dimensional solution requested, stepwise discriminant function analysis revealed statistically significant but substantively small differences in the weirdness coefficients for the weirdness coefficients for the third and fourth dimensions. The total r^2 for the model was 0.0541, $p < .0001$ with both the 3rd and 4th dimension coefficients included. The partial r^2 values for each predictor were significant but small ($r^2 = .0434$ for

the 3rd dimension and $r^2=.0112$ for the fourth, both $p < .05$). On both measures, the 3-D cases had lower weirdness, with a standardized univariate effect size of .43 standard deviations on the 3rd dimension, and of .27 on the fourth.

Reliability of Joint Space Indicators

Two hundred and thirty five cases on whom complete, non-problematic data were collected at a second point in time (as well as time 1) were analyzed using INDSCAL to derive a second set of structural and weirdness coefficients. One hundred and eleven cases came from the HSTS data, and 124 from the Szawłowski dataset. The results of the requested four-dimensional solution were linked to the 4-D INDSCAL results for the 509 cases reported in the preceding section. The relationship between INDSCAL indices at the two time points were analyzed using canonical correlation.

STRUCTURE COEFFICIENTS

The coefficients for the seventeen project features exhibited marked stability from time 1 to time 2. The first three canonical correlations were in excess of 0.99, and the last was equal to 0.88 ($p < .0001$ for all four). This is in spite of the fact that almost half the data were based on different projects (the HSTS set). Interestingly, while the first and second dimension coefficients had univariate correlations with absolute values in excess of 0.94, the fourth dimension at time 1 was most highly correlated with the third at time 2 ($r=0.85$) and vice-versa ($r=0.93$). Redundancy analysis indicated that 93.8% of the standardized variance in the time 2 structure was accounted for by the time 1 structure.

WEIRDNESS COEFFICIENTS

There are a couple of ways of looking at the stability of weirdness coefficients. Because just over half of the data represent the same projects rated a second time, a global correlation between weirdness coefficients may mask a difference between the HSTS and Szawłowski data. For the sake of completeness, both the global analysis and separate analyses by study were performed. Overall, four significant canonical correlations were obtained ($r = 0.42, .031, 0.25$ and 0.22 , $p < .0006$ for all), with approximately 12% of the variance of either set accounted for by the first variate of the other. When broken down by study, only the first canonical correlation emerged as significant ($r=.78$, $p < .0003$, redundancy

of time 2 coefficients with time1=18%) within the HSTS data. Examination of the canonical structure coefficients revealed that the first relationship was primarily attributable to the weirdness coefficients associated with the first and second dimension.

The first two canonical correlations emerged for the Szawlowski data ($r = .54$, $p < .001$; $r = .49$, $p < .019$, respectively, with cumulative redundancies of approximately 20% for the first two variates on either side). The first variate was composed primarily of the coefficients for Dimensions 1, 2 and 3 on the Time 1 side, and Dimensions 1, 2, and 4 on the Time 2 side. The second variate reflected Dimension 4 on the Time 1 side, and Dimension 3 on the Time 2 side, neatly mirroring the reversal in the structure coefficients for dimensions 3 and 4 noted above. In spite of the non-significant 2nd canonical correlation in the HSTS data, this same reversal was also apparent in the structure coefficients for the 2nd canonical variates.

Relationship to S-Stress Measures

The first three or four measures of S-Stress that were obtained in the MDS solutions in the first set of analyses were compared via canonical correlation to the 3 or 4 dimension coefficients obtained in the two INDSCALs run on the 3-D and 4-D cases. Within the 3-D cases, only the first canonical correlation was significant ($r = .33$, $p < .0067$). The standardized coefficients indicated that BADFIT1 had a substantial negative loading on the first variate, while BADFIT3 had a substantial positive loading. On the opposite side, the loading for weirdness on dimension 1 had a loading almost triple that of the second largest value (that of the dimension 2 coefficient). Redundancy analysis indicated that approximately 8% of the standardized variance in weirdness could be accounted for by the linear combination of S-Stress measures.

For the 4-D cases, the first four S-Stress measures were on one side, and the four vectors of dimension coefficients were on the opposite side. Only the first canonical correlation was significant ($r = .42$, $p < .0001$). Unlike the case of the 3-D analysis, the standardized coefficients for weirdness on the first variate were more homogeneous, with those of the first two dimension coefficients being somewhat larger than those of the last two. The S-Stress vectors for the 1-D and 4-D solutions appeared to contribute the most on the

opposite side. Roughly 6% of the standardized variance in weirdness was attributable to the S-Stress vectors.

Cross-Cultural Differences and Similarities at Two Levels

A potential problem with the Project Space that has been ignored to this point is that of restriction of range due to mean differences on the various project features. That is to say that it is possible that attenuation of correlations due to extreme responding on some features may play something of a role in the relative emphasis that an INDSCAL solution will assign to a given case on a given dimension. Thus, where substantial mean differences exist between groups at the project system level, differences in subject weights obtained by INDSCAL may also emerge. If this is the case, then attenuation of correlations may be at work in distorting the Project Spaces in groups that respond more extremely than others.

The data due to Xiao (1986) comprises 58 cases, half of which were Canadian undergraduate students, and half of whom were Chinese undergraduates. Using an English PPA form for the Canadian students and a Chinese translation for the Chinese group, Xiao (1986) found significant differences between the groups using stepwise discriminant function analysis. Differences between the Canadian and Chinese groups emerged on Enjoyment, Difficulty, Initiation, Progress, Positive Impact and Importance which accounted for 59% of the variance in group membership. Eighty-six percent accuracy was obtained in classifying the Canadian group, and 97% accuracy was obtained for the Chinese group. A cross-validation sample drawn from archival data produced excellent, if slightly lower classification results.

Despite these marked differences in means, an attempt to discriminate the groups on the basis of weirdness coefficients from an INDSCAL run only on data from this study failed to find any significant predictors among the weirdness coefficients on any of the four dimensions that were requested in the solution. (For this analysis, 3-D and 4-D cases were solved together. Fifty of the 58 cases had an OD of 3 or 4, and among these cases, there was no significant difference in terms of weirdness on dimension 4).

Relationship to NEO Measures

No significant univariate correlations were observed between weirdness coefficients and the five NEO-PI dimensions of Neuroticism, Extraversion, Openness, Agreeableness and

Conscientiousness. The possibility of nonlinear relationships was explored by examining scatterplots for patterns and testing various nonlinear models, none of which appeared to account for much variance in the weirdness coefficients. It would appear that while gross dimensionality of the solution may be indirectly related to personality factors, individual dimension coefficients that arise from the INDSCAL model are unrelated to personality factors in general, in so far as they are measured by the NEO-PI.

Weirdness and Project Category

Fourteen Poisson regressions were run to study the relationship between the seven project categories noted above and weirdness coefficients on the dimensions obtained for each of the 3-D (N=138) and 4-D (N=269) groups for whom project category information was available. In spite of the great opportunity for chance to provide a result that could at least be described as “a trend,” no p-value for the parameter associated with any dimension dipped below 0.11 when predicting any project category.

Discriminating Synthetic from Intact Project Spaces

One hundred and seventeen cases that exhibited an OD of 3 at time 1 were randomly selected from the non-problematic PPA data in the dataset on the basis of having provided ten projects with little or no missing data. These were randomly assigned to the intact (N=58) or synthetic (N=59) condition. After randomizing the order and creating artificial ID's for the synthetic data, the datasets were set back together with a variable to code whether the Project Space was synthetic or not. Stepwise Discriminant Function Analysis (DFA) failed to discriminate the real from the artificial on the basis of the three weirdness coefficients provided ($p > .11$ for the best predictor, DIM1).

One hundred and seventy-five cases that exhibited an OD of 4 at time 1 were randomly selected from SEABank on the basis of having provided ten projects with little or no missing data, and were similarly assigned to the real (N=96) or synthetic condition (N=79). A similar randomization was performed on the 'synthetic' group, coded accordingly and submitted to stepwise DFA. The final model selected on this basis comprised the weirdnesses for the first and second dimension, and accounted for 5.99% of the variance in group (Wilks' $\lambda = 0.94$, $p < 0.0049$). The unique contribution of the 2nd dimension coefficient was significant ($p < .005$), however, that of the first dimension was not ($p = 0.0965$). Thus, it

would appear that a statistically significant but substantively trivial difference exists in terms of weirdness on the second dimension for the 4-D cases which did not emerge for the 3-D cases. Because it emerged on the second dimension and not the fourth, however, it may be considered most parsimoniously as a failure to replicate the effect from the 3-D group, rather than a possible moderated effect due to optimal dimensionality, or one which only emerges for more complex solutions. This interpretation is further justified by the striking similarity of the joint spaces described above.

Discussion: The Joint Project Space

There are both technical matters and more substantive issues that arise from the preceding analyses. These will be addressed in this section.

TECHNICAL CONCERNS

Key technical features of the analyses have indicated that a) the solutions using Pearson's coefficient are strikingly similar to those obtained using other coefficients; b) the badness-of-fit criteria are much lower than expected by chance; and c) the technical choice involved in selecting a similarity measure is of little import, as essentially identical spaces are obtained, no matter if Pearson's r , Spearman's ρ or Kendall's τ are used. If we view the (1-canonical redundancy) as a sort of $(1-r^2)$ values we find that the method variance is under 15% in most cases or, in a sense, the overall reliability coefficients generally exceed .90 . There is no clear pattern of substantial differences that would lead to a conclusion that either Spearman's or Kendall's coefficient should be preferred. Lastly, from a reliability perspective, the joint space seems essentially unchanged over time, and the weirdness coefficients associated with individuals' Project Spaces relative to the joint space are also somewhat stable.

The S-Stress values for the Pearson solutions (to which we will refer from here on) are markedly better than those for random data. They are to some extent related to the single-case MDS badness-of-fit measures, although the magnitude of the relationship is not

substantial. They are unrelated in any direct way to NEO-PI measures. This brings us to speculate as to the reason for this lack of relationship. Perhaps the most obvious explanation is the robustness of the structure that was recovered in the joint space, and the restriction of range that ensues from that phenomenon. Relative to the structural constants, variation around those constants tends to be small. While it appears that there are some links between personality measures and project category, and project category and complexity of solutions, the link between complexity of solutions (as indexed by the badness-of-fit measures) and overall weirdness relative to the joint space is not strong.

SUBSTANTIVE ISSUES

It is important at this juncture to underscore the *key* feature of the INDSCAL spaces that were obtained, which is the *interpretability* of the obtained solutions, particularly with respect to the theoretical model expounded by Little (1989). Four of the five theoretical facets emerge in distinct subregions of the three-dimensional spaces of both groups. The Stress triad (Stress, Difficulty and Challenge) is clearly defined, and the clustering of four of the five **Meaning** variables (Value Congruency, Self-Identity, Enjoyment and Absorption) makes intuitive sense. Only Importance is absent, clustering more closely with the **Community** variables (Others' View of Importance and Visibility), which themselves occupy a distinct space. The **Efficacy** variables (Outcome and Progress) are nicely matched as well, and in fact share the upper end of the third dimension with Community, suggesting that people anticipate greater success on more visible projects that others see as important.

Notably, the **Structure** variables (Control, Initiation, Negative and Positive Impact and Time Adequacy) are less clearly defined, occupying the centre of the space and extending towards the various other facets in interpretable ways. Time Adequacy appears in the part of the space occupied by the Efficacy variables, which makes sense, because time constraints will certainly affect one's estimate of successful completion for entirely practical reasons. Control and Negative Impact appear high on the second dimension with Initiation, forming a distinct grouping from this facet, while Positive Impact emerges on the opposite end of the second dimension with Importance, Others' View of Importance and Value Congruency. The Positive/Negative Impact distance appears to define the second dimension, and it would

appear that Control and Initiation load in the opposite direction to Positive Impact. Time Adequacy also appears to be closer to the “negative” aspects of Structure.

The content of the fourth dimension that was required for the 4-D cases suggests that on the one hand, the Structure variables Control and Initiation are strongly related for some people. On the other hand, Absorption and Visibility correlate highly for this group as well, but appear to be rated somewhat independently of Control and Initiation. This suggests a tendency to become absorbed in public projects irrespective of the extent to which one is responsible for the inception and conduct of the project. However, conversion of the correlation coefficients to “zipsative” measures revealed no significant linear or curvilinear relationships with NEO-PI measures.

Lastly, these results imply that large differences may exist in the means of the project feature columns between identifiable groups, despite an absence of differences in the Project Spaces of individuals in the groups. The failure to distinguish Xiao’s Chinese and Canadian students on the basis of dimension weights in the presence of substantial between-group differences at the project feature *mean* level is significant for two reasons. First, it shows that restriction of range effects that arise from the type of rating scale used in PPA do not markedly affect the covariance structure of the Project Space, as some measurement model techniques [e.g. structural equation modeling] might imply. Furthermore, it shows that at the very least, the 17 standard project features which generate an identifiable joint Project Space in English have a corresponding structure in Chinese which does not appear to be affected by the translation (which we must assume was quite good).

Chapter 9: Structural Models

This chapter will further underscore the idea that the apparent reliability of single cases is actually a manifestation of a stable structure that undergirds *all* Project Spaces, but from which some individuals deviate. The focus in this chapter will be on linking the former feature of the individual emergence model with extant results, with an emphasis on crossing the “boundary” between mean-level and project-level analysis. Various analyses are used to establish the relationships between theoretical models as discussed briefly in Chapter 1 and the joint Project Space. The reliability of the joint space indicators will be elucidated, and factors associated with them explored. Finally, in order to explore the origins of the underlying structure, a four-dimensional joint space will be constructed for some generated Project Spaces based on mean project profiles across content categories and compared with the actual joint space.

Artefactual Reliability?

The high reliability of most individual Project Spaces over both time and changes in projects rated, when coupled with the remarkable structural similarity of the first three dimensions of the 3-D and 4-D cases suggests that the overall joint space in which people construe their projects is quite similar across people and time and possibly even cultures. This leads back to the question raised in Chapter 7 of whether or not the apparent reliability is but an artefact of an underlying structure that accounts for most Project Spaces. It is possible that a global model might fit the data quite well, even when within-subject clustering of projects can be ignored as contributing fairly little to the configuration. Therefore, a factor analysis may be performed on the raw project data themselves, and the resultant factor pattern matrix may be compared to the INDSCAL solutions. Little’s (1989) proposed five-factor model was tested in this manner.

Four sets of vectors were compared. The set of vectors that define the configuration of project features from the 3-D and 4-D joint spaces obtained as part of the preceding analyses

were compared with the factor pattern loadings that resulted from a five-factor solution to all available data. Similarly, a set of five dummy vectors were compared to these loadings. As a reference point, the significance of the obtained values were estimated by reference to simulated distributions of the canonical correlations of the data to models drawn from a 3-dimensional sphere of random points or permutation distributions of the simple coded vectors.

Generality of the Joint Space and Project Profiles Across Category

It is possible that the global features of projects in different categories contain most of the information about the way that projects are construed in general. To explore this possibility, a mean profile was taken across the seven categories used in PPA within each of the studies that used the standard codings. A large number of synthetic project systems were generated from these simple profiles, and subjected to INDSCAL analysis. To offset the apparent restriction of this limited number of profiles, this procedure was repeated by taking profiles within each study that provided data on project category. This introduces additional variance due not only to between-study effects, but also due to between-rater effects on the categorization of projects.

Results: Structural Models

Factor Analysis of All Available Data

Seven thousand and seventy-one projects which had complete data on all 17 standard project features were subjected to factor analysis. Only the first five factors resulted in an eigenvalue greater than 1, and so these were retained. The varimax rotated pattern matrices are presented in Table 44.

The Joint Space and the Factor Space: Three-Dimensional Cases

The relationship between the factor pattern matrix and the joint space matrix of INDSCAL coordinates was very strong, with a first canonical correlation of .997, a second canonical correlation of .974 and a third canonical correlation of .947. P-values of 0.0001 were obtained for all three correlations in the actual canonical analysis, and all values exceed the simulated values from the technical appendices and other runs described above. The redundancy analysis revealed that the first correlation accounted for 32% of the variance in

	FACTOR1	FACTOR2	FACTOR3	FACTOR4	FACTOR5	
IMP	0.38036	0.45900	0.33656	0.07428	-0.26640	IMPORTANCE
FNJ	-0.32364	0.03090	0.72971	-0.03134	-0.08087	ENJOYMENT
DIFF	0.77494	-0.12441	-0.10888	-0.09116	0.00688	DIFFICULTY
VIS	0.15136	0.63644	0.17080	-0.06057	0.01843	VISIBILITY
CONT	-0.32671	0.21885	0.01022	0.63740	-0.11368	CONTROL
INI	0.15961	-0.09581	0.27550	0.79094	-0.04076	INITIATION
STRESS	0.74542	0.21027	-0.17411	0.00647	0.08886	STRESS
TA	-0.16483	0.54003	0.11887	0.31645	0.14576	TIME ADEQUACY
OUT	-0.37595	0.46395	0.23263	0.37407	-0.11867	OUTCOME
SELFID	-0.08069	0.14257	0.69861	0.20356	0.04225	Self-Identity
OV	0.27112	0.65335	0.02834	-0.14373	-0.26077	OTHER'S VIEW
VC	0.14819	0.24185	0.58126	0.14205	-0.25352	VALUE CONGRUENCY
NI	0.25236	0.14541	0.04188	-0.17922	0.77525	NEGATIVE IMPACT
PI	0.26562	0.31009	0.27006	-0.07891	-0.56958	POSITIVE IMPACT
PROG	-0.18385	0.58798	0.28584	0.18657	0.05540	PROGRESS
CHALL	0.76443	0.06151	0.20013	-0.06299	-0.05432	CHALLENGE
ABS	0.16676	0.31814	0.64540	0.10632	0.02499	ABSORPTION
	FACTOR1	FACTOR2	FACTOR3	FACTOR4	FACTOR5	
Variance	2.6114	2.3140	2.3010	1.4612	1.2018	
Explained						
Eigenvalue	3.8530	2.8132	1.1688	1.0514	1.0030	

Table 44: Rotated Factor Pattern for All Projects at Project Level

the factor pattern. The first two correlations accounted for 46%; the first three, 59%; the first four, 67.36%, with a total of 67.36% (rounded to two decimals). Remaining variance is unaccounted for due to the imbalance between the number of vectors on either side of the equations. Conversely, the factor pattern provided a total redundancy of 88.2% of the three INDSCAL vectors.

To check on the possibility that a violation of assumptions may have biased the results, another simulation was run in which a set of three uncorrelated vectors of normal deviates was generated for each project feature, providing one thousand 5×17 matrices. The median canonical correlations between the factor structure and these random models were $r_{cc1} = .741$ (100% maximum = .964), $r_{cc2} = .526$ (100% maximum = .844) and $r_{cc3} = .271$, (100% maximum = .648). All observed canonical correlations were substantially larger than the largest simulated value, implying $p < .001$ for all three, relative to random models.

The order in which factors were extracted did not exactly reproduce the order of the dimensions from the INDSCAL solution. The first two factors had substantial univariate correlations with the coordinates of the first INDSCAL dimension ($r = -0.80$ and 0.94 , respectively), while the fourth factor was the one that best reflected the second dimension ($r = .68$) and the third factor best reflected the third dimension ($r = .86$). This suggests that the factor-analytic approach can pick up on key features of the joint project space, but that the emphasis is somewhat different.

The Joint Space and the Factor Space: Four-Dimensional Cases

In like manner, the coordinates for the four - dimensional solutions of 4-D cases were compared to the overall five-factor model. Once again, substantial canonical correlations were observed, with values of 0.990, 0.981, 0.967 and 0.799 (in that order; $p < .0001$ for the first three, and $p < .0037$ for the fourth). The total proportion of variance in the 4-D structure that was accounted for by the factor structure was 88.2%, with a redundancy of 86.4% of the factor structure due to the 4-D structure, indicating substantial overlap. A comparison to a simulated distribution of 1000 random 4×17 matrices was made. The distributions for the first through fourth canonical correlations had median values of 0.802 (100% max = 0.966), 0.612 (100% max = .873), 0.396 (100% max = .700) and .177 (100% max = 0.591), respectively. All simulated p-values were therefore less than $p = 0.001$.

The Theoretical Model and the Factor Space

To code the theoretical five-factor model from Little (1989), five dummy vectors were set up to reflect the loadings on the posited factors (meaning, structure, stress, efficacy and community). These were related to the actual factor pattern observed, and five canonical correlations were observed (0.983, $p < .0001$; 0.852, $p < .025$; 0.792, n.s.; 0.645, n.s.; and

0.006, n.s., respectively). The cumulative canonical redundancies for the proportion of variance in the factor pattern accounted for by the model were (respectively) 20%, 38%, 51%, 57% and 57% (rounded off).

Once again, a simulation was run comparing the canonical correlations for five random vectors of normal deviates to the factor pattern. The distributions for the first through the fifth simulated canonical correlations had median values of 0.857 (100% max=0.985), 0.690 (100% max=.896), 0.492 (100% max = .770), 0.287 (100%max = .647) and .077 (100% max= 0.402), respectively. In this case, the first correlation was above the 99th percentile, but not above the maximum ($p < .01$), while the second was above the 95th percentile ($p < .05$). The third exceeded all observed simulated values ($p < .001$) while the fourth fell above the 99th percentile ($p < .01$). The fifth canonical correlation fell below the median.

Sampling random points from a sphere or hypersphere to construct an arbitrary model may result in a somewhat different distribution than a set of dummy vectors. Thus, the same dummy-coded model was compared to the factor pattern matrix using a permutation technique in which the rows and columns of the matrix were permuted randomly a thousand times. The dummy matrix was permuted randomly by row and by column within rows, and each permuted pattern matrix was correlated with the original factor structure. This kept the number of -1, 0 and 1 values constant in the model matrix while randomly changing the assignment of variables to theoretical factors. In some cases, it resulted in a matrix that was less than full rank (i.e., one of the columns contained zero variance or a liner combination of other columns), which could result in a canonical correlation taking on a value of zero. Substantively, this simply means that a model with fewer than five factors was being tested on that particular permutation, and a comparison with a slightly more parsimonious model is a substantively valid comparison. Therefore the cases where a zero-variance vector (or a less-than-full-rank matrix) was included and resulted in a near-zero correlation on a higher pair of canonical variates were not dropped from the simulation.

One thousand of the 4.27×10^{16} possible permutations were generated. The first canonical correlation of .98 exceeded all but one of the permutation values (median= .90, 100% max=.984). The second value (.85) fell well above the median (.75) but just below the

95th percentile (.86), while the third (.79) fell above the 99th percentile (median=.54, 99th percentile=.78). The fourth (.65) was also substantial relative to the median (.31) and was exceeded by only one permutation, while the fifth (.01) fell below the first quartile (.03) on a permutation distribution where the zero correlations attributable to non-full-rank matrices comprised at least 10% of the data (median=.074).

It is interesting to note that the permutation distributions of dummy variables had medians that were (with the exception of the fifth canonical correlation) consistently higher than those of the randomly-generated vectors. This may be attributable to the fact that the simplicity of the model results in a good many permutations where 0/0 exchanges occur. As a result of this recycling of combinations with small permutation in many cases, remnants of a very good structure were probably present in many of the permutations as a result of the relatively large number of indistinguishable combinations.

The Theoretical Model and the Joint Spaces

The dummy vectors coded in the preceding analysis were compared to the 3-D and 4-D joint spaces using the same permutation method. In the case of the INDSCAL configurations, the presence of five dummy vectors on the model side of the equation and no more than four on the opposite side almost eliminated the problem of zero correlations that are attributable to less-than-full-rank models being generated. This appears to have occurred twice, in the fourth canonical correlation between the 4-D solution and the theoretical model where two permutations resulted in canonical correlation coefficients below 3×10^{-17} .

For the three-dimensional INDSCAL, the three canonical correlations (and their asymptotic p's) were .98 ($p < .0001$), .83 ($p < .027$) and .54 (n.s.) in that order. The permutation distributions (based on 1000 replications) for the first three canonical correlations had medians of .74 (100% max. =.975), .53 (100% max = .81) and .30 (100% max=.70), implying that the observed values are substantially higher than the median permutation, and significant below the .001 level relative to the permutation distribution.

For the 4-D INDSCAL, the four correlations (and their asymptotic p's) were .98 ($p < .0001$), .86 ($p < .035$), .65 (n.s.) and .40 (n.s.). The permutation distributions (based on 1000 replications) for the first four canonical correlations had medians of .80 (100% max. =.977), .62 (100% max = .88; only two permutations exceeded the observed value), .42

(100%max. = .72, 99th percentile=.64) and .18 (100% max= .52, 95th percentile = .38), implying that the observed values are substantially higher than the median permutation, and the first three are significant near or below the .001 level relative to the permutation distribution. The last appears significant at the .05 level; however, this liberal alpha may be taken with a grain of salt in view of the magnitude of the other results.

The New and Improved Theoretical Model

To explore how the theoretical model might be improved, the dummy-coded vectors used to express the theoretical model were re-coded to allow the Structure variables to load on the facets described in the discussion of the interpretability of the INDSCAL spaces (above). Table 45 presents both the original and revised loadings. On the Structure dummy vector, all variables except Positive impact were given a value of 1, whereas the latter variable was coded as -1 to reflect its apparent opposite sign relative to the others. A code of .5 was assigned where a secondary loading was deemed necessary. Control and Initiation were coded as loading .5 on the Meaning vector, while Negative Impact was coded on the Stress vector. Positive Impact as +.5 on the Community vector, and Time Adequacy was allowed to load on the Efficacy vector.

For the 3-D solution, this model resulted in canonical correlations of .981 (asymptotic $p < .0001$), .928 ($p < .0001$) and .778 ($p < .014$), all of which are substantially higher than those obtained by the original model, indicating a marked improvement in goodness-of-fit over the values reported above. The permutation method described above was applied to these new vectors. The first correlation was exceeded by only one permutation (median=.827, 100% max= .985). The second exceeded all permutation values (median=.604, 100% max. = .888), as did the third (median=.323, 100% max. = .743).

For the 4-D solution, the model provided correlations of .984 (asymptotic $p < .0001$), .949 ($p < .0003$), .766 ($p < .0772$) and .384 ($p > .416$), of which all save the last exceed those of the preceding analysis. In testing against a permutation distribution, the first canonical correlation was exceeded by only one permutation (median=.84, 100% max=.985). The second was above the maximum value obtained (median=.676, 100% max=.866). The third

<u>Original Loadings</u>						
FACTOR	_NAME_	MEANING	STRESS	STRUCTUR	COMMUN	EFFICACY
Comm.	OV	0	0	0	1	0
Comm.	VIS	0	0	0	1	0
Eff.	OUT	0	0	0	0	1
Eff.	PROG	0	0	0	0	1
Meaning	ABS	1	0	0	0	0
Meaning	ENJ	1	0	0	0	0
Meaning	IMP	1	0	0	0	0
Meaning	SELFID	1	0	0	0	0
Meaning	VC	1	0	0	0	0
Stress	CHALL	0	1	0	0	0
Stress	DIFF	0	1	0	0	0
Stress	STRESS	0	1	0	0	0
Struc.	CONT	0	0	1	0	0
Struc.	INI	0	0	1	0	0
Struc.	NI	0	0	-1	0	0
Struc.	PI	0	0	1	0	0
Struc.	TA	0	0	1	0	0

<u>Revised Loadings</u>						
FACTOR	_NAME_	MEANING	STRESS	STRUCTUR	COMMUN	EFFICACY
Comm.	OV	0	0	0	1	0
Comm.	VIS	0	0	0	1	0
Eff.	OUT	0	0	0	0	1
Eff.	PROG	0	0	0	0	1
Meaning	ABS	1	0	0	0	0
Meaning	ENJ	1	0	0	0	0
Meaning	IMP	1	0	0	0	0
Meaning	SELFID	1	0	0	0	0
Meaning	VC	1	0	0	0	0
Stress	CHALL	0	1	0	0	0
Stress	DIFF	0	1	0	0	0
Stress	STRESS	0	1	0	0	0
Struc.	CONT	0.5	0	1	0	0
Struc.	INI	0.5	0	1	0	0
Struc.	NI	0	0.5	1	0	0
Struc.	PI	0	0	-1	0.5	0
Struc.	TA	0	0	1	0	0.5

Table 45: Original and Revised Loadings on Theoretical Dimensions

was exceeded by only one permutation (median=.447, 100% max=.788), while the fourth fell well above the median (.197) but below the 95th percentile (.406).

Redundancy analysis is particularly informative in this respect. The total canonical redundancy between the original model and the 3-D solution was .64, while the revised model provided a value of .81. Likewise, for the 4-D solution, the original model provided a redundancy of .58, which increased to .66 with the revised model. The new model thus seems to be “improved” in a statistical sense. When coupled with the reasoning given above, the substantive interpretation also seems better.

The New Model and the Factor Structure

Following the same procedures, the factor pattern matrix was compared to the new theoretical model, resulting in five canonical correlations of which the first two had significant asymptotic p-values ($r=.970$, $p < .0010$; $r=.946$, $p < .0024$; $r=.826$, $p > .12$; $r=.427$, $p > .71$; $r=.049$, $p > .87$). With respect to the permutation distribution ($N=1000$), the first canonical correlation fell above the 95th percentile; the second was not exceeded by any permutation; the third was exceeded by one permutation; the fourth fell below the 90th percentile and the fifth fell below the median. The redundancy analysis revealed that 31% of the variance in the factor pattern was accounted for by the first correlation, 50% by the first two, 64% by the first three and 66.04% by the first four. Overall, 66.07% of the variance in the factor pattern was accounted for by the model. This reveals a consistently higher redundancy than the original model across all canonical correlations.

Generated Project Spaces from Category Means

Means were obtained on all 17 project features for the seven project categories described above, using 9,187 projects for which category information was available. Those from Szawlowski's data were re-categorized using the same algorithm employed in the previous analyses of project category. Cases with missing data were not excluded, to leave in error variance which reflects real-life data. From these seven profiles, and a group of 728 synthetic project systems (from a possible 5040) were generated to mimic the original INDSCAL solutions studied above. A 4-D solution was requested, and the resulting configuration was compared to that obtained through INDSCAL analysis of the 4-D cases

above. Four significant canonical correlations were obtained ($r = .98, .84, .75$ and $.55$, respectively; $p < .009$ for the first three, and $p < .0405$ for the last), with standardized canonical redundancies of $.64$ for the generated variables and $.64$ for the original solution, suggesting a substantial similarity between the solutions.

TAPPING INTO MORE VARIANCE: PROFILES WITHIN STUDIES

Somewhat better results were obtained when instead of generating project systems from only 7 profiles, the profiles were obtained by computing means within each study. The resulting 21 profiles were then bootstrapped in similar manner, with 4 dimensions requested from 728 synthetic systems. They were then compared with the four dimensions from the 4-D cases' results. The four canonical correlations were $.97, .91, .83$ and $.39$ (respectively; $p < .005$ for the first three, $p > .16$ for the fourth. Redundancy analysis indicated that 74% of the variance in the generated structure was accounted for by the actual structure, with 66% of the latter accounted for by the former.⁷

Discussion: Theoretical Models

Allowing some cross-loadings and modifying the Structure dimension to place all variables except Positive Impact on one end improves the fit of the theoretical model substantially, increasing the canonical correlations obtained and the overall redundancy. The changes are interpretable and reflect other modifications to the model, such as the setting free of Challenge to cross-load in Little's (1988; SSHRC) LISREL analysis.

A key implication of these findings is that Simpson's paradox does not appear to be at work in PPA. Correlations at the single-case level share the same patterns as do those obtained at the project system level. This result is important because it suggests that generalizations may be made about the likely impact of changes to the project system that are derived from extant results. Specific predictions that are amenable to experimental and clinical tests may be generated. For example, we may hypothesize that dropping a difficult and challenging project which has substantial negative impact on other projects may result in lower stress for the individual concerned.

Chapter 10: The Analysis of the Single Case

From the preceding results, it appears that a robust structure undergirds personal project ratings, and that personality factors may indirectly affect the Project Space in so far as they are expressed in the choice of projects, which in turn relates back to the dimensionality of the solution. Nevertheless, within a single case variability may arise due to both the specific set of projects sampled as well as changes in the same project over time. In order to understand the extent of this variation, it is instructive at this point to consider several individual cases, and establish a technique for estimating the degree to which variability may occur due to the specific set of projects sampled. As a further attempt to give classical traits an opportunity to relate themselves with respect to Project Space differences, some extreme cases (in NEO-PI terms) will be compared on the assumption that while individual differences in Project Spaces may not be large, they may yet be interpretable with respect to such variables.

It would appear from the preceding analyses that project content relates to at least some of the key features of an MDS solution to a Project Space, and that project content may be to some extent predictable from personality measures. To examine the impact of varying project content given only the data from a single individual, the exact content of the system can be varied by bootstrapping the data and computing a set of intercorrelations for each bootstrap replication. This will result in variation among the correlation coefficients which will in turn perturb the interpoint distances estimated by MDS. Differences in personality may be emphasized by deliberately sampling extreme cases based on NEO-PI profile scores.

Fingerprinting Project Spaces

The bootstrap procedure (Efron & Tibshirani, 1993) has gained a foothold in the statistical literature as a procedure for obtaining empirical estimates of standard errors of many common statistics. Bootstrapping involves simple random sampling from the observed data *with replacement*. Because the Project Space as we have conceived it thus

far is reliant upon the correlation coefficient, which has been shown to have a standard error that is estimable by the bootstrap technique, it is a simple generalization to infer that the multivariate structure of the Project Space may be estimated by the bootstrap method and by extension, the scaling solutions obtained by solving those spaces with an MDS procedure. To the extent that the interpoint distances are variable, the estimates of those distances should be variable around the the best estimate.

One method for examining the stability of the different project features across bootstrap samples is to simply solve each bootstrap sample separately and examine the extent to which the point “jiggles” in the configuration. However, since individual MDS solutions have arbitrary signs on the dimensions, solving the bootstrapped Project Spaces from a single case separately can result in “reflections” where a feature that is high on a given dimension in one solution may be equally low (i.e., have a negative sign) on other solutions. This is the effect that would produce the bias discussed in Chapter 5 (see Eq. 1.5 *et seq.*). This may result in some “mirroring” for features that are consistently extreme on a given dimension, but are arbitrarily scaled opposite to other solutions because doing so minimizes S-Stress. One solution to this problem is to use the original model as an input set of parameters around which estimates may be derived, which should force the signs to be the same in most, if not all solutions.

Because mirrored values will bias both mean and median, a graphical approach to the single case is advocated here which will summarize the results of a BPS. What we shall call a “smudge plot” was used. This method places the name of the project features on the Y-axis of a plot, and the location on each dimension from the MDS solution is marked with a tick on the X-axis. In general, bootstrapped configuration coefficients for the 17 features will hover around a central value, plus or minus some standard error. When the features are identified on the Y-axis, a “smudge” will appear in the area of highest density, which fades away in either direction (i.e., to the left or to the right). This creates a “fingerprint” of sorts which should be directly interpretable with respect to the relative importance of each feature on each dimension. This plot also allows visualization of the extent to which “mirroring” has gone on in the MDS solutions, and

features which are extreme on a given dimension are likely to have a small number of points “reflected” in the vicinity of -1 times the centre of the main smudge.

Two Cases

In order to provide some substantive material on which to reflect, two cases were non-randomly selected from SEABank. The first had the highest score on NEO-PI Neuroticism that was available among cases that had project category information. The second had the highest Extraversion score. In the entire dataset (N=398), Neuroticism and Extraversion correlated $-.25$ ($p < .0001$).

Results

The raw data for both Case #1 and #2 are presented in Table 46, and the smudgeplots for dimensions 1 through 4 for Case #1 are presented in Figures 39 through 42. The smudgeplots for dimensions 1 through 3 for Case #2 are presented in Figures 43 through 45.

Case #1

Case #1 was an 18 year old male from the HSTS dataset who had a NEO-PI Neuroticism Z-score of 2.70 and an Extraversion z-score of $-.60$. This individual reported on five administrative/maintenance projects, three intrapersonal projects, one leisure project and one interpersonal project. Notably, three or more intrapersonal projects were reported by only 3.2% of cases. The original MDS configuration ($OD=4$) produced an S-Stress value of .052. The bootstrapping procedure used 200 replications and produced a mean S-Stress of .03 (std. Dev. = .013, 98% C.I.=.004 to .059). The smudgeplot for the first dimension reveals marked structure with very little mirroring, possibly due to the homogeneity of the project system (i.e., 5 of one kind and 3 of another comprising 80% of the projects). The Stress/Difficulty/Challenge triad is partially evident, with Negative Impact loading more highly than Stress. However, Value Congruence, Self-Identity and Absorption also seem to form a distinct structure with the Difficulty/Challenge pair, thus splitting the usual Meaning dimension. Importance and Enjoyment standing well away from this set, along with the Efficacy variables Progress and Outcome, as well as Control and Time Adequacy.

On the next dimension, Stress and Negative Impact share a space with Value Congruency, Outcome and Progress (which was less clearly defined on dimension 1 and remains fuzzy on second dimension). Initiation and Progress are the most distinct features on the lower end of the second dimension.

The third dimension in this case does not appear to have any variables that are distinctly differentiated from zero on most dimensions, and this is similar to what is observed on the fourth.

Case #2

Case #2 was a 19 year old male from the Szawlowski dataset. He had a NEO-PI Extraversion Z-score of 2.76 and a Neuroticism Z-score of -2.2. This individual reported four administrative/maintenance projects, two leisure and two occupational/academic projects, one interpersonal project and one health/body project.

C B N K I D	P							S T R E S		S E L F					P R O G				C H A L		A B S
	C A T	I M P	E N J	D I F F	V I S	C O N T	I N I	T A	O U T	I D	O V	V C	N I	P I							
38	6	10	8	9	9	7	6	9	3	6	8	10	8	7	7	4	10	9			
38	4	9	6	9	9	7	6	10	3	6	8	10	8	7	7	4	10	9			
38	6	7	6	8	7	7	6	6	2	5	5	5	8	7	7	0	10	6			
38	6	7	8	7	8	7	5	6	2	6	7	3	8	7	7	4	7	8			
38	5	5	8	8	7	7	5	8	2	5	5	2	8	8	2	2	8	7			
38	6	7	7	9	7	3	0	8	3	8	6	5	8	8	2	0	7	6			
38	4	4	0	10	8	0	5	6	0	1	10	10	8	10	10	0	10	10			
38	6	6	8	8	5	7	6	6	5	7	2	4	7	6	2	4	7	3			
38	4	4	0	10	5	0	5	7	0	0	10	0	8	10	10	0	10	10			
38	3	2	0	10	5	0	4	5	0	1	10	1	8	7	1	2	10	10			
412	2	4	5	0	4	5	10	0	2	1	2	2	4	0	10	2	0	2			
412	1	10	0	2	5	10	0	2	3	10	10	10	10	0	2	10	0	0			
412	6	5	2	0	0	10	10	0	0	10	10	5	10	0	10	10	4	0			
412	6	1	8	8	0	0	10	5	0	0	10	0	4	0	5	0	10	0			
412	5	0	9	0	7	10	10	0	2	7	8	2	8	6	0	10	0	5			
412	1	10	7	0	8	10	10	0	5	10	10	10	10	5	10	10	0	10			
412	6	3	3	0	0	10	10	0	1	10	7	10	4	0	0	10	0	2			
412	6	2	4	0	0	10	10	0	1	10	7	10	4	0	0	10	0	2			
412	3	8	8	7	5	5	10	2	4	4	8	0	8	0	0	5	5	10			
412	5	10	10	4	10	10	10	0	8	10	10	0	10	10	0	0	0	10			

Table 46: Raw Data for Two Sample Cases

Smudgeplot – Dim 1

Figure 39: Smudgeplot for Dimension 1, Case #1

Smudgeplot - Dim 2

Figure 40: Smudgeplot for Dimension 2, Case #1

Smudgeplot - Dim 3

Figure 41: Smudgeplot for Dimension 3, Case #1

Smudgeplot - Dim 4

Figure 42: Smudgeplot for Dimension 4, Case #1

The initial MDS solution (3 dimensions) produced an S-Stress of .092, and 200 bootstrap iterations produced an average S-Stress of 0.069 (std. dev.=.029). The smudgeplot for the first dimension places the Stress/Difficulty/Challenge triad on the upper end, with a slight tendency for the Meaning dimensions of Enjoyment and Absorption to share that space. On the lower end, the two Efficacy variables appear with Control and Others' View of Importance. Value Congruency leans towards the lower end of this dimension.

The second dimension places Visibility, Absorption, Enjoyment, Negative Impact and Time Adequacy at one end, with Positive Impact, Challenge and Progress leaning most towards the opposite end. The third dimension in this case is a little clearer than in Case 1, with Initiation tending clearly away from the other features in the lower direction, and Self-Identity and Importance moving away in the opposite direction. A tendency for Time Adequacy and Visibility towards the upper end is also discernable, although not as marked as the effect for Importance.

Just One More Case

Perhaps the most unusual case in the available data was that of an 18-year old male from the HSTS data (Time 1, Case #69). A smudgeplot is not presented, because only a small number of correlations were non-missing (which accounts for the exclusion of this case from the preceding INDSCAL analyses, as well). Table 47 presents the profile of PPA feature means and a most extraordinary NEO profile of z-scores *all in excess of +2 standard deviations*. Although no missing data were present for any of the features, 12 of them had zero variance. Of those twelve, one was as a result of all zeroes (Negative Impact), eight were due to all 10's being given (Visibility, Control, Initiation, Outcome, Self-Identity, Positive Impact, Challenge and Absorption) and three were attributable to all 5's in the column (Time Adequacy, Value Congruency and Others' View of Importance). This was one of two cases that exhibited the aberrant DIFGUTT pattern 10111 noted above. Of particular note is the fact that no strange pattern was observed in terms of project content. Five different categories were represented, with two occupational/ academic projects, two leisure projects, four interpersonal projects, and one each from the health and intrapersonal projects domains. appears to share the lower end with Initiation and to a certain extent Positive Impact. While

the upper end is not clearly defined, Value Congruency and Negative Impact seem to lean in that fourth dimensions do not appear to be clearly interpretable.

Discussion: Case Studies

While these cases were presented primarily as an exposition of a proposed method for studying individual cases, there are some noteworthy features of both which bear discussion. First of all, the Stress/Difficulty/Challenge triad is clearly defined for the second of the first two cases, but was split on the other. In the case where it split, we observed on the one hand very high Neuroticism, and on the other, associations between the Stress feature and Negative Impact, Value Congruency and Outcome. The usual pattern for Difficulty and Challenge is partially dissolved, and these features are most strongly associated with Negative Impact, Value Congruency, Self-Identity and Absorption. This suggests that some very personal meaningfulness for this individual is associated with difficult and challenging projects. Similarly, the split of the Meaning dimensions also places Enjoyment and Importance with Control, Time Adequacy and to a lesser extent, Stress. The striking dissociation between Enjoyment and Importance as opposed to Value Congruency and Self-Identity might suggest valuable lines of clinical inquiry to an experienced practitioner. The construal of important, enjoyable projects as stressful, efficacious and under control seems to function independently of the construal of difficult and challenging projects as value-congruent, absorbing and self-prototypical. Further research could reveal that this dissociation may be characteristic of individuals high on Neuroticism.

Smudgeplot - Dim 1

Figure 43: Smudgeplot for Case #2, Dimension 1

Smudgeplot - Dim 2

Figure 44: Smudgeplot for Case #2, Dimension 2

Smudgeplot - Dim 3

Figure 45: Smudgeplot for Case #2, Dimension 3

PPA Feature Profile:

Variable	Number of Projects	Mean	Std Dev
IMP	10	8.000000	2.054805
ENJ	10	8.200000	2.394438
DIFF	10	7.500000	2.635231
VIS	10	10.000000	0
CONT	10	10.000000	0
INI	10	10.000000	0
STRESS	10	4.733333	3.650807
TA	10	5.000000	0
OUT	10	10.000000	0
SELFID	10	10.000000	0
OV	10	5.000000	0
VC	10	5.000000	0
NI	10	0	0
PI	10	10.000000	0
PROG	10	3.500000	2.415229
CHALL	10	10.000000	0
ABS	10	10.000000	0

Neo Profile Z-Scores:

NEUR	EXT	OPEN	AGREE	CONS
2.68	2.55	2.18	2.13	2.58

Table 47: A Remarkable Case

The Stress/Difficulty/Challenge triad was not split in the second case, where we observed high Extraversion. In this case, Enjoyment was positively associated with Stress. The other end of the first dimension for this case suggested that social concerns pertaining to Others' View of Importance and degree of Control were associated with ratings of Efficacy (i.e., Progress and Outcome), in keeping with what would be expected of an Extravert. This contrasts nicely with Case #1.

For Case #1, the Outcome/Progress/Enjoyment/Importance/ Time Adequacy/Control structure at the top of the first dimension and the Progress/Initiation relationship on the second suggest that the most efficacious projects are self-initiated and personally meaningful, while a sense of meaninglessness is associated with less efficacious projects initiated by others. The Meaning variables all emerge strongly, albeit in peculiar fashion, for this case. For the Extraverted individual, however, the Meaning variables emerge only on higher dimensions with less clear differentiation than they do

for our Intravert.. In Case #2, the smudgeplot for Dimension 1 suggests that the central concerns in this case are not so much Meaning and Stress as they are Stress and Efficacy. This difference in construing may, in future research, provide a basis for differentiating among Neurotic and Extraverted individuals.

Lastly, there is a suggestion in the unusual case described above that other atypical patterns of response may require further refinements in the analysis of Project Spaces in order to fully rule out the existence of more subtle links between the Project Space and personality. This is of particular note due to the heterogeneity of the projects provided. That such a range of activities would be truly indistinguishable on so many features strains credulity - rather, a peculiar form of response bias and self-presentation may well be at work, especially given the truly odd NEO-PI profile. Cases such as this one suggest the urgency of obtaining measures of response bias (e.g., the Balanced Inventory of Desirable Responding; Paulhus, 1991) along with PPA data to explore variance-constraining patterns and their relationship to such factors. Presumably, a tendency to respond in extreme ways on the NEO-PI and PPA measures suggests a more global tendency that could be measured in this way.

Having explored ways in which we might develop an approach to the single case which can take into account both normative results and individual idiosyncrasies, we may proceed to review the results obtained and examine the bigger picture of where the present research fits into the field.

Chapter 11: Summary and Future Directions

The research undertaken as part of this dissertation underscores some important facts about Personal Projects Analysis, and contains the seeds of future research projects that will exploit the full range of individual and normative-level data that can be obtained via PPA. First, interpretable results emerge from the analysis of single cases, and the stability coefficients obtained by the analysis of longitudinal data on both the same and different projects imply that the error associated with these solutions cannot be as large as one would expect, given the small number of projects that are rated in any given case.

Secondly, it is significant that Simpson's Paradox does not appear to be strongly at work in PPA analyses, particularly with respect to cross-cultural differences. As we have seen, the individual-level Project Space does not differ markedly from the joint space, even for a Chinese translation of PPA. This means that on the whole, we can extend our research hypotheses to a very concrete level which may provide even richer clinical data. We can derive and test predictions about specific patterns and associations that emerge from interesting groups, and explore in a confirmatory way the indirect link between personality, project content and complexity of Project Spaces. Even more intriguingly, the fact that system-level measures can discriminate between cultural groups while underlying patterns of intercorrelations are the same is quite valuable in so far as it suggests that the mean-level differences are *not* attributable to differences in construal, but reflect less artefactual processes such as social ecological differences. As a cautionary note with respect to generalizing extant results, this finding also demonstrates that even where there is a self-similarity of structure across levels of analysis, the relationships that obtain from analyses at different levels are not *necessarily* the same. Thus, we must still view our hypotheses as tentative and subject to empirical disconfirmation.

Third, the technical developments in this work suggest several things. First, as a global measure of similarity of two correlation matrices, QAP lacks the subtlety of MDS approaches. It appears to capture only the more global features of the Project Space. Given the ease of derivation of MDS solutions to Project Spaces, common availability of canonical correlation routines, and the computational power that is now available to bootstrap and simulate, the more refined combination of the latter techniques is to be preferred, especially in view of the interpretability of the output.

It is important that the relationship between project category and MDS indices manifests itself in different ways, as these relationships bear on substantive links to other variables (e.g., personality). The relationship of S-Stress measures in varying dimensionalities to frequency of projects in certain categories is one such phenomenon. However, the fact that optimal dimensionality is somewhat stable for longitudinal data collected on the same projects but utterly unreliable for longitudinal data collected on different projects suggests two things. One, that this aspect of the MDS solution is highly contingent on the particular combination of projects. Two, the relatively small relationship even for the same projects over time is suggestive of the idea that something more than ordinary unreliability of ratings is at work. This is amplified by the apparent instability of the weirdness coefficients that was observed in Chapter 8, and the instability of OD even for the same projects over a short period of time. It would appear that changes in the projects themselves due to differences in stage of completion and relevance to other projects may be giving rise to the apparent changes in complexity. This underscores the underlying assumption of PPA that systemic influences are at work. If an individual is embedded in a local ecosystem, and that ecosystem is dynamically changing, then the context of an individual's projects as well as the projects themselves will be subject to local sources of variation.

Optimal Dimensionality and Cognitive Complexity

The issue of optimal dimensionality initially suggested an analogy to literature on cognitive complexity (Bieri, 1955, 1966). In this literature, the degree of differentiation of a personal construct system was taken to be essentially an individual differences variable that could be measured by the extent to which different constructs were used

independently of one another in construing people (Adams-Webber, 1981). Such complexity has been shown to be related to accuracy in predicting which constructs will be used by other people (Adams-Webber, 1969). While this may be true of the construal of *persons*, optimal dimensionality of Project Spaces is not a stable characteristic once the projects in the system are changed, nor is it even remarkably stable over the same projects across a short period of time. This is possibly due to the fact that constructs pertaining to people are based on relatively enduring aspects of individual behaviour, while projects are themselves intrinsically more dynamic, more likely to change under situational constraints (we hope!) and so require more adaptation from one day to the next.

The implication of this is that complexity is largely tied up with the objects being construed. This is consistent with the observations in the preceding section regarding sources of variation. In fact, a limitation of the present study is that it provides no definitive answer to the question “Is there a single optimal dimensionality of the Joint Project Space?” While it appears that at least three dimensions are defensible and are similar to those found within 4-D solutions, the necessary and sufficient conditions for the emergence of the fourth dimension in so many single cases is a phenomenon that requires further investigation. It may be that a peculiar form of response bias can reduce the apparent dimensionality of a case by constraining the variances and covariances on which we base our estimates.

It is nevertheless possible that at the individual level measures of cognitive complexity (which themselves may be somewhat dynamic in so far as changing the persons construed will change the complexity score) will relate to the degree of differentiation in a given project space. A desire for black-and-white differences between projects may result in stronger correlations in the matrix used to derive the Project Space, while an acceptance of less well-differentiated projects may result in a more complex solution. This “project style,” if you will, may be reflected in such measures, which may in turn be related to affect.

The existence of a “project style” would not be inconsistent with the finding of indirect relationships between project categories represented in the PPA data matrix and

NEO-PI indices. Once again, there may be a complex and indirect relationship between differentiation among features, project category and optimal dimensionality or some of the various weirdness coefficients associated with deviation from the joint Project Space at a given point in time. It is possible that only extensive longitudinal data will provide definitive answers for us.

Constraints on Future Research

Future research will be subject to the limitations expressed in this dissertation with respect to several factors: Excessive missing data at the project level; missing values in the Project Space itself that arise from the presence of ZVF's; and possible links between these factors and personality factors. In addition to these constraints, the general lack of substantial individual differences relative to the strength of the joint Project Space indicates that restriction of range effects will likely be at work, and will require substantial sample sizes to compensate for this technical factor.

More generally, the applicability of this line of "ipsative" reasoning may extend to NEO-PI scores themselves. The ipsative approach to reliability suggested by Gee (1997a) may be applied to these measures to explore whether the degree of consistency in ratings on the NEO-PI is reflected to any degree in PPA. It is possible that "average" people are merely extraordinary in different ways that have not been anticipated by we, the test designers. Just as a mean of 5 can be achieved with 10 fives, or five zeroes and five 10's, a NEO score may contain additional information through which more subtle "fingerprinting" of specific types of individual may be obtained.

Project Spaces and Personality at Large

The field of personality does not appear to require a substantial reorganization. Rather, the specific subregion of the Personal Construct System that we have identified as the Project Space does not appear to show sufficient variation that marked relationships to standard personality features could be found. There may be other variables that have not been studied in relation to Project Space indices which would produce substantial results or control apparent biases, however, we cannot discuss data that we have not obtained. For example, socially-desirable responding can be measured (e.g. the Balanced Inventory of Desirable Responding; Paulhus, 1991) and it has been

shown to both inflate and deflate correlations among evaluative scales similar to the NEO-PI (Paulhus, Bruce & Trapnell, 1995). A study relating such measures to PPA ratings could clarify how distortions of the project space may be typical of some response styles, perhaps by relating them to weirdness coefficients.

The present analyses suggest that the extent to which different types of people focus more on certain types of projects is related to complexity of the individual Project Space. However, the day-to-day existence of most people comprises a multitude of projects, not all of which are clearly expressive of who we are, and which change in terms of both content and stage of completion over time. If neurotics seem to select projects in which a degree of self-absorption is allowed, we must recall that no neurotic listed 10 intrapersonal projects. If extraverts seem to avoid these projects, it is worth pointing out that of the 55 cases who had Extraversion scores one standard deviation above the mean or greater, fully 25% of them reported at least one intrapersonal project, and slightly over 5% reported 2 or 3 such projects.

While a monomaniacal obsession with a certain kind of project might (depending on the context and content) be viewed as pathological, out of all the cases observed for whom category data were available only 1.1% reported two categories. The remaining 98.9% reported three or more. It is possible that personality measures and Project Space measures could be two independent sources of variation that are associated with quality of life. While the strength of the underlying joint space suggests that a large sample might be required to offset range restriction effects, patterns of project appraisal may be guided by, and may in turn influence, appraisals of life satisfaction. To the extent that project variety and affective measures may affect distortions of the common space, it appears that the study of the Project Space at the individual level may result in a deeper understanding of how we select and appraise our Personal Projects.

Theoretical Implications for PPA

It is necessary at this point to revisit some of the basic elements of PPA as originally conceived. First we may consider the trade-off between a Personal Construct Theory kind of understanding of idiosyncratic construing and comparability across cases through the use of “provided” dimensions. Cameron (1984) has already shown that most

of the PPA dimensions used have counterparts in the personal construct systems of participants, and these results were very much propaedeutic to the establishment of the Joint Project Space. This study is, in part, an extension of this work in so far as it establishes a common *structure* shared, it would appear, almost universally. Not only are the constructs (i.e., project features) commonly used, but they appear to covary in similar ways irrespective of the individual, to the point where individual differences almost appear to vanish. Thus, that line of reasoning has been taken to its logical conclusion.

The key study (Xiao, 1986) that was used to test the possibility of distortions in Project Space that arise from cross-cultural differences does have a limitation which it shares with many of the other studies included in the data. Specifically, it is based on undergraduates. This limits the generalizability of several of the key studies used in this work (e.g., Lecci, 1986, 1990; Szawlowski, 1986; Xiao, 1986). It may be that intelligence is a factor, and sampling from a population which has effectively been pre-selected for above-average intelligence limits the degree of relative differentiation of the Project Spaces obtained.

For example, in the general population, an OD of 1 or 2 (or 5 or 6) may not be so unusual as the present results would indicate. The ‘weirdness’ of university students relative to a norm based on a truly random sample might actually distinguish them as a group, particularly given the fact that lifestyle factors of the young and educated might produce more homogeneous collections of project categories. For instance, for this group occupational/academic projects probably consist more of the latter group than the former group, and a more precise coding scheme might allow us to see a difference between a group of “frosh” and a group of senior managers. Indeed, it is plausible that certain clusters of project categories that are typical of various personality types (within given social ecologies) may exist, but the univariate analyses conducted above failed to detect the multivariate patterns. Determining whether 1,2, 5 or 6-D solutions are more common in the population at large is a viable direction for future research to take.

PPA attempts to bring in the kind of personal meaning that Kelly would expect from a measure (Adams-Webber, 1981a), while providing a technique for the integration of individually-salient data with higher-level data at the normative level. The Project

Space is, I believe, a foundational element in the theoretical structure in so far as it opens the individual case to greater exploration and appreciation, all the while retaining a solid empirically-demonstrated Joint Space to which individual Project Spaces may be referred. Furthermore, there is a practical basis for a fuller realization of the clinical potential of PPA through the use of smudgeplots. The development of software which enables the generation of these fingerprints through an interactive program that elicits clients' projects and performs the required analyses could open a new door for clinicians as well as researchers who wish to build their models from cases, rather than hope that many cases conform to their personal constructs regarding how people work.

Persons, Personality and Individual Differences: Lamiell's Critique

The broader implications of this study for the broader field of personality may be examined by answering a recent and scathing critique of the individual differences model by Lamiell (1997). He traces a line of argument he has been developing for some time, which asserts that "*the study of individual differences is fundamentally and irremediably ill-suited to the task of advancing personality theory*" [emphasis in original] (Lamiell, 1997, p. 117). He argues from two theses which bear restatement here:

Thesis 1: Any theory of personality is a conceptual framework designed to provide explanations for and hence an understanding of individual behavior psychological functioning.

Thesis 2: Except under hypothetical conditions never realized in practice, the reliability and validity coefficients and other statistical indices generated by studies of individual differences variables (alone or in combination with "situational" or "treatment" variables...) bear no legitimate interpretation of any kind whatsoever at the level of the individual.

[emphasis in original] (Lamiell, 1997, p. 118). Lamiell argues that the first thesis has never been seriously questioned by personality psychologists since its original statement (in a slightly different form) by Murray. That personality theory aims to predict individual behaviour is a given; however, the second thesis is crucial to his critique, and needs to be addressed.

ON KNOWLEDGE ABOUT INDIVIDUALS VERSUS KNOWLEDGE
ABOUT INDIVIDUAL DIFFERENCES

Arguing from the position that traditional statistical indices have no interpretation except at the aggregate level, he begins by attempting to demolish the individual differences model from a strictly logical perspective. However, this logic relies upon the inadequacy of extant techniques, and fails to consider the possibility of statistical techniques that have an interpretation at the individual level. A demonstration that Cronbach's alpha (one of the statistics which he takes to task) is strongly related to ipsative statistics which are defined for the single case (Gee, 1997a) in fact reveals that aggregate phenomena such as reliability in fact depend on the behavior of individual cases, and that it is possible to study "reliable responding" of an individual as an aspect of that individual which may or may not be a defining characteristic (just as the "individual emergence" model of Chapter 6 does not require that all people retain the same Project Space over time). However, the fact that a person may respond consistently or inconsistently implies that consistency can be construed as an individual differences variable, which contradicts Lamiell's (1997, p. 122) view that "*individual differences variables do not exist for individuals.*"

There is, furthermore, a Kellian argument against this view which arises from the meaningfulness of experimenters' constructs from the point of view of the respondent. It is possible that an instrument which gives no consistent score to a person is an instrument that is simply not meaningful to that person. For example, an inventory given to an ex-smoker about his or her reasons for smoking probably has a very different structure (if any) than the same inventory given to a smoker. Inconsistent responding would be *expected*, simply because the questions may not make much sense anymore unless a specific request is made to respond to the items based on what the historical reasons were for smoking, during the time in which the respondent last smoked. (Of course, this creates a certain validity problem). If we deny that individuals differ on the meaningfulness that they assign to a question, and the consistency with which they answer our questions, then the lack of significance of those questions implies that

knowledge is impossible, even of the individual, by anyone other than the individual.

We arrive at an untenable solipsism.

To view this problem from another angle, we must return to the problem of Simpson's Paradox to fully appreciate Lamiell's Thesis Two. In a deep sense, Lamiell is arguing that because our knowledge is based on measures derived from aggregates of individuals, personality psychology is not about persons, but about groups of people. From the statistical point of view he is quite right, but this does not preclude the study of individual patterns, nor does it preclude the further development of techniques for studying individuals and aggregating those results to see what happens. We merely move down to a lower level of aggregation, in a sense, just as was done in the present research. Instead of aggregating means across individuals, we obtain individual structures from lower-level units (projects) within the individual case, and then look for regularities. This is where PPA comes in as a technique which enables us to link our knowledge at the individual differences level (admittedly about groups, not individuals) to our knowledge at the lower level (i.e., individuals) and consider whether there is a correspondence, or if an ecological fallacy is being committed. However, as seen above, the similarity of structures at neighbouring levels of analysis is an *empirical* problem, and not a *logical* one.

As an example, in the present work, a strong structure was present, and while some distortions of this structure exist within individual cases, neither the fact that one person may be Chinese and another Canadian, nor that one person is highly neurotic while another extraordinarily extraverted bear strongly on the emphasis given to the varying dimensions of the joint Project Space. Furthermore, we are most fortunate that things add up nicely. Stress and Difficulty correlate positively at both the project level (in fact, only 13.5% of non-problematic cases at time 1 exhibited a correlation below zero) and the system-mean level ($r=.47$, $p < .0001$). This means that for people in general, a large number of difficult projects would be expected to produce high levels of stress. However, we also know that if Ryan has a large number of difficult projects, he is feeling stressed. Furthermore, we may predict (and this is a hypothesis that *can* be tested in a clinical setting) that abandoning some difficult projects may reduce stress for him. If it

works for Ryan, then Lamiell cannot argue that we are not making successful predictions about individuals. If it works for many people other than Ryan, then we have built up, on a case-by-case basis, a method that is based on a generalization about people that applies to individuals.

ON DIFFERENCES BETWEEN INDIVIDUALS AND INDIVIDUAL BEHAVIOR

The problem of solipsism and the impossibility of knowledge also apply to a second line of argument that Lamiell (1997) develops. He attempts to make the case that differences between individuals cannot cause individual behaviour, and within the limited range of assumptions that he makes, this seems right. He points out that if we wish to explain the difference between Smith, who is chatty at a party (C) and Jones who is quiet (Q) with reference to their known positions on the individual-differences dimension Extraversion/Introversion (E and I, respectively), then what we are really doing is explaining the difference (C-Q) in terms of the difference (E-I). But since the differences are independent of the individuals described by the contrasting poles of what we shall view as two Kellian constructs (E/I and C/Q), then Lamiell asks how these differences could possibly influence, determine or cause Smith's behavior? While he asserts that the (E-I) difference may exist for an onlooker, Lamiell denies that anything but E exists psychologically for Smith and that anything but I exists psychologically for Jones. But what observer can experience the (E-I) discrepancy without knowledge of E and I separately? Knowledge of both E and I must be present in the observer, which means that it is entirely possible, and in fact, probable, that this knowledge is shared by Smith and Jones.

It is, of course, inconsistent to allow this knowledge to the observers while denying this knowledge to the observed, and it results (by Kelly's sociality and commonality corollaries; see Fig. 1) in the impossibility of shared knowledge and social interaction. Lamiell assumes that the Introversion pole of the E/I construct is non-existent, where it may be either "submerged" (Kelly, 1955) or entirely present. If we return to the thoughts of yet another personality theorist, the Sullivanian "Not Me" is absent in Lamiell's consideration of his Thesis 2. One knows what one is, but also what one is not, and the knowledge of what one is not completes the personal constructs which

have arisen to usefully predict oneself and others, with a greater or lesser degree of success.

Thus, individual differences exist in so far as we perceive differences between individuals. Who does the theorizing and the predicting, and whether theories apply to one person or more than one person, do not lessen the importance of perceived differences and the association between perceived differences on one dimension and perceived differences on another. If one extravert can relate (E-I) to (C-Q) in their own mind where both (E → C) and (¬E → Q), C and Q are mutually exclusive and ¬E → I, then that person has constructed a theory of himself which may or may not generalize to other people. If the person who is theorizing is a psychologist, then the theory of individual differences will surely be called a theory of personality in its own right, particularly if - empirically - it works in a large number of cases.

AN EXAMPLE TO ILLUSTRATE ECOLOGICAL CONSTRAINTS

A further example of this may clarify the line of reasoning, and allow some elaboration. Suppose we have a set of containers with pieces of copper (C) in them, and a set of containers each with some water (W) in them. We observe that dumping the containers of copper on a table does not cause the pieces of copper to change their shape (¬S) but dumping the containers of water does cause the contents to change their shape (S). We formulate a theory that the difference (C-W) appears to correspond to the difference (S - ¬S) *across pairs of observations*, and which makes successful individual predictions every time (and would provide a very high index of ordinal fit; Thorngate, 1992). We try the experiment with Iron substituted for Copper, and gasoline for water. We observe a similar result. Ultimately, we construct a theory of Solids and Liquids, which subsumes the sets (Copper, Iron....) and (water, gasoline...). While this theory does not tell exactly what shape the puddle will take if a liquid falls on a flat surface, a bit of experimentation will reveal that if it lands in a sufficiently large container, it will take on the shape of the container. Lamiell may be interested in the exact shape of the puddle as an individual puddle different from all others; however in scientific research, we are interested in the conditions under which events occur in predictable ways. We

hope that unpredictability is merely due to a lack of knowledge about the relevant variables that affect the behavior of the individual puddle.

The successive elaboration of our mode of construing is perfectly consistent with Kelly's experience corollary as given in Figure 1. The replication of these experiments by another person should produce similar constructs in that other person, and (by the commonality corollary) would result in processes that are psychologically similar. That is, of course, based on the assumption that the ecological constraints on the experiment were much the same. If these experiments were conducted much closer to the sun, many "Solids" would in fact be "Liquids" (or we might even discover "Gases") whereas a scientist from Pluto would find that many "Liquids" are "Solids," due to the environmental variable "Temperature." Thus, ecological constraints work to force us to elaborate our models of how things work, and it is through elaboration that we come to see individuals as differing (e.g. Copper-Water), in spite of many marked similarities among subsets of them (e.g., Iron-Copper).

INDIVIDUAL DIFFERENCES, PPA AND ECOLOGICAL CONSTRAINTS

The preceding defense of individual differences might seem surprising, given that the joint Project Space seems to be a fairly stable entity from which individuals do not appear to differ very markedly, and given that such differences as may exist appear to be only indirectly related to classical individual differences measures. If we return to Smith, Jones and the Big Five Personality features, then we may discern precisely where PPA's integrative and ecologically-representative nature can play a vital role in answering what must ultimately be empirical questions about individuals and how they differ.

Personality is expressed in many ways, and from the present results, the kinds of projects selected may be one such mode of expression, which relates indirectly to the complexity of the set of ratings that are obtained, but not the gross structure (or distortions thereof) of the set of constructs applied. However, from the views expressed above, precise prediction of an individual's behaviour in a given setting requires knowledge not only of general attributes such "Solid," "Liquid," "Neurotic" or "Extraverted," but of the ecological constraints on the expression of solidity, liquidity,

neuroticism or extraversion. If our prediction of Smith's chattiness (based on his Extraversion) were to fail, and we knew that in general, Smith was chatty at parties, then we would be forced either to abandon our model of the relationship between Extraversion and chattiness, or elaborate it, perhaps by asking Smith why he is refraining from chatting. It is likely that some ulterior motive (read "higher-order project") is at work, such as "impressing a potential client," or "getting a date with someone who dislikes excessive chatter." We may, with Lamiell, deny the possibility that our theory could be valid in the case of Smith because we lack information, or we could elaborate our theory by obtaining the relevant information that will specify the conditions under which our predictions should work. If our plausible assumption that (I) exists for Smith (as E exists for Jones) as part of the "Not Me" is valid, then the latter course will ultimately prove more valuable for the elaboration of psychological theories at both the professional and the everyday "man-as-a-scientist" level espoused by Kelly (1955).

Thoughts on the Possibility of Linking Single-Case and Normative

Approaches in Future Research

The construction of generalizations based on observations of individual cases is nothing new. It has perhaps been the complexity of the individual that has led us to start with generalities and attempt to apply them to the specific that has impeded our progress and created the difficulties noted by Lamiell. However, with Lamiell, we can search for an understanding of the individual with reference to specific features of the project system, and perhaps with reference to deviations that affect the estimation of the Project Space such as the existence of zero-variance features, which may imply that a feature is irrelevant for that case (which surely differentiates the case from the normative one). Further research is needed on the applicability of smudgeplots to the single case, and the identification of distinct patterns. The elements of idiographic research methods based on ipsative statistics (or idiographic methods) are available today, and need integration.

For example, a smudgeplot can lead to a set of predictions that can be tested for the single case, and the efficacy of the predictions can be evaluated normatively in spite of differences in the questions used. If a particular pattern emerges that suggests a strong association between Difficulty and Challenge, but Stress is at the far opposite end of the

first dimension, then it is possible to ask the respondent a set of six questions about the pattern:

1) Do you generally find difficult projects to be challenging?	<u>Yes</u>	No	Doesn't matter
2) Do you generally find challenging projects to be stressful?	Yes	<u>No</u>	Doesn't matter
3) Do you generally find challenging projects to be difficult?	<u>Yes</u>	No	Doesn't matter
4) Do you generally find stressful projects to be challenging?	Yes	<u>No</u>	Doesn't matter
5) Do you generally find difficult projects to be stressful?	Yes	<u>No</u>	Doesn't matter
6) Do you generally find stressful projects to be difficult?	Yes	<u>No</u>	Doesn't matter

The answers that would be expected based on the smudgeplot pattern just described are underlined. There are six predictions, and the goodness-of-fit of those predictions can be quantified using Thorngate's (1992) Ordinal Pattern Analysis (described above), which should produce a coefficient distributed noncentrally between 0 and 1 (across a large number of cases) if smudgeplot predictions are valid, even when those predictions vary on a casewise basis. Thus it is again not impossible to assess the efficacy of a technique based on predictions that may be entirely unique to a single case, thus satisfying both the ecological representativeness criterion and the joint normative and ipsative levels of measurement criterion discussed in the beginning pages of this work.

Conclusion

In summary, it would appear that who we are, what we do, and how we think about these matters are intertwined in a complex way, but not one so complex that one person is excluded from any appreciation of another's way of construing the world. In fact, it is within a framework of shared meanings and anticipations that we communicate who we are and what we are up to amongst ourselves. With Kelly (1963), I reject the concept of motivation in the study of humans as a *deus ex machina* that "drives" us. Human beings are in motion, and motivation is a primitive element. To return to the imagery of Chapter One, the channels through which it flows are actually quite well-known to us, at least as regards the simpler aspects of daily life: our Personal Projects.

Lastly, we must consider affect. Sadly neglected in the present work for reasons of space, this domain is nevertheless a vital direction for future PPA research, because

we *do* share a map that enables us to understand when another person is caught on the shoals of stress and meaninglessness, and from this we can empathize. The fact that this map exhibits a rather breathtaking self-similarity across levels of magnification, like frost on a window, is an aesthetic bonus which still raises empirical questions, and which underscores the need to understand not only thought and action, but the ways in which feelings emerge from them and return to guide their complex interplay. I hope that this dissertation moves us towards an integrative research programme that pursues the Personal Construct and Personal Project approaches to personality to a practical level that fully integrates thought, action, behavior, and social context at both the individual and normative levels.

ENDNOTES

1. Gaines & Shaw (1992) point out that *"Kelly introduces the notion of a psychological space as a term for a region in which we may place and classify elements of our experience...He sees us as creating dimensions in personal psychological space as a way of providing a coordinate system for our experience, and emphasizes that the topology of the space comes into existence as it is divided."*

2. The "modularity" criterion (Little, 1989) allows PPA features to be dropped if the seem to be outside the range of convenience of the projects that are to be rated in any given sample. This has resulted in a non-negligible amount of missing data in the SEABank database.

3. The wide availability of tables for this statistic has rendered the back-transform of this function rather obscure. It is derived here because of its anticipated utility in generating random correlation matrices in this study:

$$\begin{aligned} z &= .5 \ln(1+r) - .5 \ln(1-r) \\ 2z &= \ln(1+r) - \ln(1-r) \\ \exp(2z) &= (1+r)/(1-r) \\ \exp(2z)(1-r) &= 1+r \\ \exp(2z) - r(\exp(2z)) &= 1+r \\ \exp(2z) - r(\exp(2z)) - 1 &= r \\ \exp(2z) - 1 &= r + r(\exp(2z)) \\ \exp(2z) - 1 &= r(\exp(2z) + 1) \\ (\exp(2z) - 1)/(\exp(2z) + 1) &= r \end{aligned}$$

The standard error of Z is given by McNemar (1962) as $1/(N-3)^{1/2}$.

4. "Stress" is a measure of badness-of-fit between the obtained solution and the original data, which is (crudely) analogous to $1-r^2$. The term "S-Stress" refers to a standardized badness-of-fit measure and will be used to denote badness-of-fit in this dissertation, so as to avoid confusion with the project feature "Stress." The SAS analyses in the present work made use of Young's S-Stress formula 1 (SAS Institute, 1996). See Kruskal & Wish (1978) for details.

5. It would appear upon reflection, however, that differentiability of the presumed 'link function' is a hidden assumption of nonmetric MDS. The existence of undifferentiable functions in an MDS solution would produce bizarre and unpredictable results when points change slightly over iterations as a result of the scaling procedure, because the differentiation performed in the metric phase of the iterations depends on estimates of slopes that - for undifferentiable functions - will vary wildly under slight changes of scale rather than converge to a value. This is not to say that undifferentiable

functions are of no scientific interest. Even at the level of extensive measurement, Mandelbrot (1983) opines that Nature may have not only a different degree of complexity but a whole different kind of complexity wherein the number of distinct scales of length is virtually infinite.

6. To examine the general relationship between N and dimensionality as predictors of stress, the simulation was run for 1 through 5-dimensional solutions for the same set of values of N. For 17x17 matrices, the general formula

$$E(\text{stress}) = -.669772345 + \exp(0.12818749/N + 0.289780462/D - .062769778/(N \times D))$$

(where D=dimensionality of solution and N=number of matrices analyzed) provides an expected value for stress, and once $N > 20$, the variability around this value is virtually nil. This model accounted for 99.56% of the variability in the set of S-Stress values that was generated. To examine the efficacy of this model in prediction, the model predicts a value of 0.43206 for the 100 cases that were generated for the 3-D data, which we may recall had a mean S-Stress of 0.4454, and was based on a set of random 17x17 matrices generated by the same code that was used to obtain the data on which the model was based.

7. Except for a slight variation in the second decimal place on the fourth dimension ($r=.38$, $p > .20$), these figures are identical to those obtained by the same bootstrapping procedure when inadvertently performed on a smaller run of only 100 cases, suggesting that the bootstrapping will tend to produce consistent approximations to the original intact Project Space.

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Appendix A: Sample Data Collection Forms & Output

PERSONAL PROJECTS ANALYSIS

(Based on those used by Lecci, 1990, at time 1).

We are interested in studying the kinds of activities and concerns that people have at different stages of their life. We call these personal projects. All of us have a number of personal projects at any given time that we think about, plan for, carry out, and sometimes (though not always) complete.

Here are some examples of projects:

- Completing my English essay
- Trying to help Gary get along better with others.
- Overcoming fear of meeting new people.
- Getting more outdoor exercise.
- Try to finish the book Allan gave me.
- Taking a trip to Ottawa.
- Cutting the grass.
- Finding a part-time job.
- Redecorating my bedroom.
- Trying to clarify my religious beliefs.
- Losing ten pounds.
- Making a birthday present for my friend.

We are also interested in finding out how people feel about these personal projects, how enjoyable they are, and so on. We would appreciate it if you could begin by just writing down in the next ten minutes as many personal projects as you can that you are engaged in or thinking about at the present time - remember these are not necessarily formal projects, or important ones - we would prefer you to give us more of the everyday kind of activity or concerns that characterize your life at present.

List of Projects

Please go ahead and write down as many as you can in ten minutes.

[illegible]

Now copy the projects in as brief a form as possible on PAGE 6. Just make your description long enough to keep each project clearly in your mind. As you can see, there is space for 10 projects. If your initial list contains more than 10, select the 10 that you are most likely to engage in over the next month or so. If you wrote down fewer than 10, see if you can think of several months, or break down some of those you listed into several projects. It is important for everyone to try to fill in 10 projects.

In columns 1 to 19 please rate each one of your projects using any number from 0 to 10 on the following dimensions. Remember that numbers between 0 and 10 can also be used.

1. Importance: how important each project is to you at the present time. (Use 10 if the project is very important to you and 0 if it is not at all important to you.).
2. Enjoyment: how you enjoy working on each project (use 10 if you enjoy it a great deal and 0 if you do not enjoy it at all).
3. Difficulty: how difficult you find it to carry out each project. (Use 10 for a project that you find very difficult to carry out and 0 for one that you do not find difficult at all).
4. Visibility: how visible each project is to the relevant people who are close to you, that is, how aware they are that you are engaged in this project (use 10 for a project that is very visible to those around you and 0 for a project that is not at all visible to those around you).
5. Control: how much you feel you are in control of each project (use 10 for a project over which you feel in complete control, and 0 for a project over which you feel you no control at all).

6. Initiation: how much you feel responsible for having initiated each project (use 10 if you feel fully responsible for having initiated a project and 0 if you have taken no part whatsoever in initiating a project).
7. Stress: how stressful it is for you to carry out each project (use 10 if a project is very stressful to carry out and 0 if a project is very relaxing to carry out).
8. Time Adequacy: how much you feel that the amount of time you spend working on each project is adequate (use 10 if you feel that the amount of time spent on a project is perfectly adequate, and 0 if you feel, for one reason or another, that the amount of time you spend working on a project is not at all adequate).
9. Outcome: what you anticipate the outcome of each project to be (use 10 if you think that a project will be extremely successful and 0 if you think that a project will turn out to be a total failure).
10. Self-Identity: to what extent a project is distinctly you; your personal “trademark” as opposed to quite alien to you (use 10 if a project is a distinctive trademark and 0 if a project is decidedly alien).
11. Others’ View: how important each project is seen to be by relevant people who are close to you (use 10 if a project is seen by others as very important and 0 if it is seen as not important at all).

12. Value
Congruency: to what extent is each project consistent with the values which guide your life (use 10 if a project is totally consistent with your values and 0 if a project is totally at odds with them)
13. Positive Impact: how much you feel that each project helps the others. Don't worry whether it hinders or not, we'll get to that on the next dimension (use 10 to indicate that a project greatly increases your chances of working on other projects and 0 to indicate that a project has no positive effect).
14. Negative Impact: how much you feel that each project hinders other projects (use 10 to indicate that a project seriously hinders your chances of working on other projects and 0 to indicate that it does not have any negative effect).
15. Progress: how successful you have been in a project so far (use 10 to indicate that you have been very successful and 0 to indicate that you have had no success at all).
16. Challenge: to what extent each project is demanding and challenging to you (use 10 if a project is most challenging and 0 if it is not challenging at all).
17. Absorption: to what extent you become engrossed or deeply involved in a project (use 10 if you generally get absorbed in an activity and 0 if you tend to be uninvolved when doing it).

Technical Appendix B
The Natural Ability of MDS to Reduce Stress

On the following pages are printouts from Monte Carlo simulations. These simulations have been conducted to determine the extent to which MDS may be able to find apparent structure in random data, and to provide some empirical estimates of the confidence intervals within which unstructured data may vary.

Method

To obtain empirical estimates of the stress levels to which MDS solutions can descend for 10 projects rated on 17 dimensions when none of the dimensions are correlated, random normal deviates were generated in 100 generic PPA 17x10 matrices. Correlation coefficients were calculated and submitted to PROC MDS (SAS Institute, 1995) for processing. Four-dimensional solutions were obtained, then three-dimensional solutions for the same data.

Results

FOUR DIMENSIONS

Figure TA1 plots the decrease of stress (labeled "CRITER" in the output) over iterations (_ITER_) of the algorithm in obtaining a 4-dimensional solution. Final values are described in Table TA1, and a histogram is presented in Figure TA2. Stress is normally distributed in the 95% confidence interval ranging from .086525 to 0.152654. Thus, even for random data, relatively good stress values can be obtained, indicating that a PPA matrix can be viewed as "structured" in four dimensions only when stress is quite low, i.e., below about .08.

THREE DIMENSIONS

Figure TA3 plots the decrease of stress over iterations of the algorithm in obtaining a 4-dimensional solution. Final values are described in Table TA2, and a histogram is presented in Figure TA4. Stress is normally distributed in the 95% confidence interval ranging from 0.152057 to 0.238951. The 1% lower bound is around .12. Thus, for random data, relatively good stress values (e.g., below .10) are rarely obtained, indicating that a 17x17 PPA matrix can be viewed as "structured" in three dimensions when stress is moderate to low, i.e., below about .10.

Discussion

The addition of a fourth dimension allows the MDS algorithm to find an arrangement of the 17 points such that stress can appear quite low even for random data. Thus, if some actual Project Spaces are truly 4-dimensional, then it will be necessary to obtain very low stress levels for the 4-D solution.

The three-dimensional results are more encouraging. If, as is quite possible, for any given set of projects only a subset of the dimensions are relevant, and the rest are just "noise," then obtaining stress levels below .10 is a good indication that structure exists

Plot of CRITER*_ITER_. Legend: A = 1 obs, B = 2 obs, etc.

NOTE: 222 obs hidden.

Figure TA1: Plot of stress across iterations for random data, 4 Dimensions

Univariate Statistics			
Variable=CRITER			
Badness-of-Fit Criterion			
Moments			
N	100	Sum Wgts	100
Mean	0.120357	Sum	12.03568
Std Dev	0.01966	Variance	0.000387
Skewness	0.001368	Kurtosis	0.062773
USS	1.486841	CSS	0.038265
CV	16.33485	Std Mean	0.001966
T:Mean=0	61.21879	Pr> T	0.0001
Num ^= 0	100	Num > 0	100
M(Sign)	50	Pr>= M	0.0001
Sgn Rank	2525	Pr>= S	0.0001
W:Normal	0.988023	Pr<W	0.9042
Quantiles (Def=5)			
100% Max	0.173166	99%	0.170059
75% Q3	0.134326	95%	0.152654
50% Med	0.119623	90%	0.143622
25% Q1	0.108291	10%	0.09208
0% Min	0.068716	5%	0.086525
		1%	0.075057
Range	0.10445		
Q3-Q1	0.026035		
Mode	0.068716		
Extremes			
Lowest	Obs	Highest	Obs
0.068716 (	19)	0.152949 (	25)
0.081398 (	55)	0.157002 (	8)
0.083274 (	48)	0.1579 (	61)
0.084005 (	83)	0.166952 (	95)
0.085623 (	70)	0.173166 (	40)

Table TA1: Distribution of stress for random data, 4 Dimensions

Figure TA2: Distribution of stress for random data, 4 Dimensions

NOTE: 84 obs hidden.

Figure TA3: Plot of stress across iterations for random data, 3 Dimensions

Univariate Statistics			
Variable=CRITER			
Badness-of-Fit Criterion			
Moments			
N	100	Sum Wgts	100
Mean	0.194865	Sum	19.48647
Std Dev	0.027041	Variance	0.000731
Skewness	-0.20394	Kurtosis	-0.17681
USS	3.869619	CSS	0.072393
CV	13.87705	Std Mean	0.002704
T:Mean=0	72.06145	Pr> T	0.0001
Num = 0	100	Num > 0	100
M(Sign)	50	Pr>= M	0.0001
Sgn Rank	2525	Pr>= S	0.0001
W:Normal	0.980915	Pr<W	0.5756
Quantiles (Def=5)			
100% Max	0.253043	99%	0.251641
75% Q3	0.21364	95%	0.238951
50% Med	0.196029	90%	0.227441
25% Q1	0.174711	10%	0.161871
0% Min	0.121368	5%	0.152057
		1%	0.12335
Range	0.131675		
Q3-Q1	0.038929		
Mode	0.121368		
Extremes			
Lowest	Obs	Highest	Obs
0.121368(	19)	0.240211(	40)
0.125333(	45)	0.241251(	77)
0.142511(	90)	0.241944(	56)
0.144127(	46)	0.250239(	8)
0.149048(	23)	0.253043(	11)

Table TA2: Distribution of stress for random data, 3 Dimensions

Figure TA4: Distribution of stress for random data, 3 Dimensions

TECHNICAL APPENDIX C: SIMULATED DATA TABLES

Canonical Correlations of Random Data, 3D

Univariate Procedure

Variable=CANCORR1

Moments

N	5000	Sum Wgts	5000
Mean	0.620112	Sum	3100.558
Std Dev	0.119444	Variance	0.014267
Skewness	-0.18226	Kurtosis	-0.23368
USS	1994.011	CSS	71.31966
CV	19.26164	Std Mean	0.001689
T:Mean=0	367.1062	Pr> T	0.0001
Num ^= 0	5000	Num > 0	5000
M(Sign)	2500	Pr>= M	0.0001
Sgn Rank	6251250	Pr>= S	0.0001

Quantiles(Def=5)

100% Max	0.951154	99%	0.873792
75% Q3	0.705187	95%	0.808222
50% Med	0.624279	90%	0.771161
25% Q1	0.537949	10%	0.456411
0% Min	0.220245	5%	0.417098
		1%	0.333065
Range	0.730909		
Q3-Q1	0.167238		
Mode	0.220245		

Extremes

Lowest	Obs	Highest	Obs
0.220245(	3208)	0.92911(	417)
0.22512(	4395)	0.932654(	1226)
0.236178(	3349)	0.94458(	3105)
0.241565(	1404)	0.949825(	1752)
0.249506(	40)	0.951154(	1469)

Canonical Correlations of Random Data, 3D

Univariate Procedure

Variable=CANCORR2

Moments

N	5000	Sum Wgts	5000
Mean	0.356445	Sum	1782.223
Std Dev	0.119812	Variance	0.014355
Skewness	0.16868	Kurtosis	-0.28582
USS	707.0233	CSS	71.75974
CV	33.61297	Std Mean	0.001694
T:Mean=0	210.3672	Pr> T	0.0001
Num ^= 0	5000	Num > 0	5000
M(Sign)	2500	Pr>= M	0.0001
Sgn Rank	6251250	Pr>= S	0.0001

Quantiles(Def=5)

100% Max	0.810932	99%	0.635132
75% Q3	0.437963	95%	0.558123
50% Med	0.353472	90%	0.516693
25% Q1	0.270077	10%	0.200589
0% Min	0.029945	5%	0.164823
		1%	0.108337
Range	0.780987		
Q3-Q1	0.167885		
Mode	0.029945		

Extremes

Lowest	Obs	Highest	Obs
0.029945(	3212)	0.74717(	1226)
0.033964(	189)	0.751676(	2687)
0.045175(	3976)	0.75554(	4557)
0.046677(	3342)	0.770358(	2392)
0.04857(	4122)	0.810932(	4362)

Canonical Correlations of Random Data, 3D

Univariate Procedure

Variable=CANCORR3

Moments

N	5000	Sum Wgts	5000
Mean	0.11401	Sum	570.0523
Std Dev	0.087519	Variance	0.007659
Skewness	1.028338	Kurtosis	0.87615
USS	103.2817	CSS	38.2898
CV	76.76359	Std Mean	0.001238
T:Mean=0	92.11487	Pr> T	0.0001
Num ^= 0	5000	Num > 0	5000
M(Sign)	2500	Pr>= M	0.0001
Sgn Rank	6251250	Pr>= S	0.0001

Quantiles(Def=5)

100% Max	0.531534	99%	0.377815
75% Q3	0.164871	95%	0.285776
50% Med	0.095194	90%	0.238945
25% Q1	0.044844	10%	0.017766
0% Min	0.000018	5%	0.008727
		1%	0.001748
Range	0.531517		
Q3-Q1	0.120027		
Mode	0.000018		

Extremes

Lowest	Obs	Highest	Obs
0.000018(	4846)	0.463064(	3266)
0.000029(	3754)	0.48302(	1169)
0.000035(	2342)	0.501159(	1101)
0.000078(	1697)	0.510526(	3281)
0.000114(	888)	0.531534(	3022)

Canonical Correlations of Random Data, 4D

Univariate Procedure

Variable=CANCORR1

Moments

N	5000	Sum Wgts	5000
Mean	0.749685	Sum	3748.425
Std Dev	0.094028	Variance	0.008841
Skewness	-0.43699	Kurtosis	0.116808
USS	2854.336	CSS	44.19757
CV	12.54235	Std Mean	0.00133
T:Mean=0	563.7755	Pr> T	0.0001
Num ^= 0	5000	Num > 0	5000
M(Sign)	2500	Pr>= M	0.0001
Sgn Rank	6251250	Pr>= S	0.0001

Quantiles (Def=5)

100% Max	0.967283	99%	0.930407
75% Q3	0.818348	95%	0.890863
50% Med	0.75571	90%	0.867227
25% Q1	0.628135	10%	0.627212
0% Min	0.356641	5%	0.585837
		1%	0.498473
Range	0.610642		
Q3-Q1	0.130213		
Mode	0.356641		

Extremes

Lowest	Obs	Highest	Obs
0.356641(	3217)	0.960264(	3496)
0.369174(	40)	0.961854(	104)
0.400855(	250)	0.961981(	3008)
0.4114(	630)	0.965169(	2101)
0.412171(	4492)	0.967283(	2969)

Canonical Correlations of Random Data, 4D

Univariate Procedure

Variable=CANCORR2

Moments

N	5000	Sum Wgts	5000
Mean	0.538379	Sum	2691.896
Std Dev	0.108864	Variance	0.011851
Skewness	-0.14406	Kurtosis	-0.18466
USS	1508.506	CSS	59.24849
CV	20.22077	Std Mean	0.00154
T:Mean=0	349.6932	Pr> T	0.0001
Num ^= 0	5000	Num > 0	5000
M(Sign)	2500	Pr>= M	0.0001
Sgn Rank	6251250	Pr>= S	0.0001

Quantiles (Def=5)

100% Max	0.901259	99%	0.771354
75% Q3	0.618271	95%	0.713498
50% Med	0.542251	90%	0.676792
25% Q1	0.464548	10%	0.396611
0% Min	0.181149	5%	0.350867
		1%	0.278355
Range	0.720109		
Q3-Q1	0.150723		
Mode	0.181149		

Extremes

Lowest	Obs	Highest	Obs
0.181149(	1776)	0.830152(	4029)
0.193125(	3014)	0.844325(	4134)
0.195885(	4239)	0.846555(	1739)
0.20342(	2791)	0.855198(	3849)
0.205601(	2987)	0.901259(	1226)

Canonical Correlations of Random Data, 4D

Univariate Procedure

Variable=CANCORR3

Moments

N	5000	Sum Wgts	5000
Mean	0.316641	Sum	1583.206
Std Dev	0.106138	Variance	0.011265
Skewness	0.152653	Kurtosis	-0.29882
USS	557.6231	CSS	56.31482
CV	33.51987	Std Mean	0.001501
T:Mean=0	210.9515	Pr> T	0.0001
Num ^= 0	5000	Num > 0	5000
M(Sign)	2500	Pr>= M	0.0001
Sgn Rank	6251250	Pr>= S	0.0001

Quantiles (Def=5)

100% Max	0.703635	99%	0.570149
75% Q3	0.389641	95%	0.494948
50% Med	0.313429	90%	0.456147
25% Q1	0.239419	10%	0.177146
0% Min	0.025908	5%	0.148344
		1%	0.093771
Range	0.677727		
Q3-Q1	0.150222		
Mode	0.025908		

Extremes

Lowest	Obs	Highest	Obs
0.025908 (	1650)	0.642637 (	1847)
0.038483 (	551)	0.654312 (	1739)
0.038513 (	189)	0.676505 (	4355)
0.038674 (	1349)	0.700742 (	271)
0.041828 (	1201)	0.703635 (	2840)

Canonical Correlations of Random Data, 4D

Univariate Procedure

Variable=CANCORR4

Moments

N	5000	Sum Wgts	5000
Mean	0.101581	Sum	507.9045
Std Dev	0.077162	Variance	0.005954
Skewness	0.976923	Kurtosis	0.7474
USS	81.35732	CSS	29.76393
CV	75.96114	Std Mean	0.001091
T:Mean=0	93.08796	Pr> T	0.0001
Num ^= 0	5000	Num > 0	5000
M(Sign)	2500	Pr>= M	0.0001
Sgn Rank	6251250	Pr>= S	0.0001

Quantiles(Def=5)

100% Max	0.474456	99%	0.33447
75% Q3	0.147307	95%	0.252929
50% Med	0.086016	90%	0.208392
25% Q1	0.03954	10%	0.015601
0% Min	0.000018	5%	0.007852
		1%	0.001325
Range	0.474438		
Q3-Q1	0.107768		
Mode	0.000018		

Extremes

Lowest	Obs	Highest	Obs
0.000018(	793)	0.397393(	2085)
0.000025(	3835)	0.399377(	4994)
0.000161(	4989)	0.460156(	4909)
0.000174(	1166)	0.467463(	4887)
0.000182(	1873)	0.474456(	3189)

Technical Appendix D: Sample Simulation and Permutation Programs

Cancorr.sim.sas: simulates 5000 canonical correlations

```

options linesize=73 pagesize=54;
data x;
/*input the 3 dimensions for the PROXSCAL, ANTHROPAC and PROC MDS solutions*/
input prox1 prox2 prox3 ap1 ap2 ap3 procmds1 procmds2 procmds3;
do j=1 to 5000;
  fake1=rannor(0);
  fake2=rannor(0);
  fake3=rannor(0);
  output;
end;
cards;
-.553 -.025 -.090 -0.58163673 0.27930167 0.55436260 -1.40 -0.50 0.43
-.925 -.021 .114 1.24603724 -0.35782930 -0.30033329 2.19 -0.30 0.27
-.481 .385 .108 -0.74556524 0.32476822 -0.54425573 -1.01 1.17 -0.46
-.612 -.052 .118 -0.73382860 0.23365296 0.31457490 -1.39 -0.03 0.30
.833 .414 -.288 1.34665251 0.34074157 0.09505078 2.11 1.13 -0.27
.867 .078 -.386 1.33630908 -0.13856523 0.35561687 2.18 0.63 -0.58
-.683 .236 -.129 -1.05998242 0.35683265 0.09375234 -1.69 0.69 -0.28
-.035 -.121 .079 -0.04119423 -0.09027758 0.25817743 -0.14 -0.76 0.42
-.278 -.482 .228 -0.48508194 -0.66906077 -0.25687936 -0.51 -1.25 -0.73
.695 -.023 .283 0.93186378 -0.26541954 -0.50184387 1.70 -0.28 0.45
-.543 .188 -.361 -0.62433535 0.51636958 0.65795332 -1.74 -0.21 0.53
.642 -.104 .054 0.85852498 -0.31185299 -0.18998161 1.62 -0.31 0.22
-.082 .474 .381 -0.10842545 0.68067902 -0.59433846 -0.19 1.24 0.65
-.507 -.306 -.334 -0.90707576 -0.43165720 0.24842387 -0.94 0.30 -1.33
-.323 .139 .316 -0.29127169 0.56901532 0.05957061 -0.79 0.19 1.09
-.346 -.311 -.130 -0.65841317 -0.23056984 -0.08240002 -1.14 -0.44 -0.71
.480 -.469 .050 0.51742280 -0.80612862 -0.16745031 1.14 -1.28 -0.20
;
proc sort; by j;
proc cancorr noprint outstat=canstat red;
var prox1-prox3;
with fake1-fake3;
by j;
run;
proc univariate normal;
var prox1-prox3;
where _type_='CANCORR';
run;
filename gsasfile '/tmp/gsas1.bmp';
goptions gaccess=gsasfile device=imgpaint gsfmde=append
  cback=white colours=(black);
proc gchart;
vbar prox1;
where _type_='CANCORR';
title 'Distribution of Canonical Correlations';
title2 'based on 5000 simulations';
run;
filename gsasfile '/tmp/gsas2.bmp';
goptions gaccess=gsasfile device=imgpaint gsfmde=append
  cback=white colours=(black);

proc gchart;
vbar prox2;
where _type_='CANCORR';
title 'Distribution of Canonical Correlations';
title2 'based on 5000 simulations';
run;

```

```
filename gsasfile '/tmp/gsas3.bmp';
goptions gaccess=gsasfile device=imgpaint gsfmde=append
  cback=white colours=(black);
proc gchart;
vbar pro=3;
where type='CANCORR';
title 'Distribution of Canonical Correlations';
title2 'based on 5000 simulations';
run;
```

dummy.permute.sas: Compare dummy-coded theoretical model with randomly-permuted model

```
options ls=73 ps=55;

proc cancorr data=tmp.compare;
var meaning--efficacy;
with dim31-dim33;
title 'Theoretical model and 3-D structure';
run;

proc cancorr data=tmp.compare;
var meaning--efficacy;
with dim41-dim44;
title 'Theoretical model and 4-D structure';
run;

data real dummy;
set tmp.compare;
posn=_n_;
output dummy;
output real;
run;

data dummy ; set dummy;
drop posn;
run;

data real; set real; drop meaning--efficacy;
run;

data dummy; set dummy;
do j=1 to 1000;
  ranpos=rannor(0);
  output;
end;
run;

proc sort data=dummy; by j ranpos;

data dummy; set dummy; by j;
if first.j then posn=0;
posn+1;
array v(5) meaning--efficacy;
do i=1 to 5;
  old=v(i);
  target=floor(ranuni(0)*4+1);
  v(i)=v(target);
  v(target)=old;
end;
run;

proc sort; by posn;
data mrg;
```

```
merge dummy real;
by posn;

proc sort; by j;

proc cancorr data=mrg noprint outstat=canout;;
var meaning--efficacy;
with dim31-dim33;
by j;
run;

data canout; set canout;
rename meaning=cancor1;
rename stress =cancor2;
rename structur=cancor3;
if _type_='CANCORR' then output; else delete;
run;

proc univariate;var cancor1-cancor3;
title 'Distrib. of permuted model--3D configuration';
run;

proc cancorr noprint data=mrg outstat=canout;;
var meaning--efficacy;
with dim41-dim44;
by j;
run;

data canout; set canout;
rename meaning=cancor1;
rename stress =cancor2;
rename structur=cancor3;
rename commun=cancor4;
if _type_='CANCORR' then output; else delete;
run;

proc univariate;var cancor1-cancor4;
title 'Distrib. of permuted model--4D configuration';
run;
```

Appendix E: Key Abbreviations

PPA Variable Names:

IMP	Importance
ENJ	Enjoyment
DIFF	Difficulty
VIS	Visibility
CONT	Control
INI	Initiation
STRESS	Stressfulness
TA	Time Adequacy
OUT	Anticipated Outcome
SELFID	Self-identity (sometimes known as “self-prototypicality”)\
OV	Others’ view of Importance
VC	Value Congruency
NI	Negative Impact
PI	Positive Impact
PROG	Progress
CHALL	Challenge
ABS	Absorption

Statistical Procedures and Programs

INDSCAL	Individual Differences Scaling
ALSCAL	Forrest Young’s computer program for computing INDSCAL models.
MDS	Multidimensional scaling
QAP	Quadratic Assignment Procedure
OPA	Ordinal Pattern Analysis
SAS	“Statistical Analysis Software,” package from the SAS Institute.

IMAGE EVALUATION TEST TARGET (QA-3)

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