DISCRETIONARY EFFORT: "CAN WE REALLY ACCOUNT FOR PERFORMANCE SURGE?"

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Abstract: When variables are measured on the same set of individuals, the statistics detailing the degree of association between them are vital for inference. Such statistics help to reveal the causal effects and conceptual structures among the underlying variables and can be used as instruments for developing and validating conceptual models. We seek to demonstrate that, by carefully constructing work –effort-related hypothetical structures through statistical measures, a Discretionary Effort model can be realized and fitted. Using empirical data from a survey in professional networks, we tested two models emerging from different sets of expectance variable combinations, with a sample of 1548 primarily managers from various sectors.

The first model was based on valence, instrumentality, and expectance (VIE), whereas the second included these three variables and self-affirmation (VIEA). Analysis of construct validities revealed that VIEAs were better fitted than VIE. Structural measures using covariates were able to explain that VIEA is an improved version of VIE.

Keywords; covariance, latent, expectance, discretionary, professional networks.

Introduction

Discretionary effort (DE) is an appended actionable force that manifests itself only under the right circumstances. DE is thus highly anthropocentric, virtually latent, and not easily exercised in the workplace. Although, many business attempts have been made to heighten the importance and the need to gauge DE with reference to changing organizational competitive needs, very little practical work has surfaced (Morrison, 1994). Yet, the challenges of sustaining and growing businesses are becoming bigger and more complex. When employers start to ask, genuinely, for more and more effort than is designated by job description, employees should know it is time to explore their own untapped potential. Nor should it be surprising to the employees when employers attempt to estimate the degree to which workers create value for the organization that exceeds mere reciprocity.

It appears obvious that, in a dynamic economy, performance measures alone are turning out to be inadequate (Kath, 1964) to account for the intended workforce value-creating capacity (Aldag & Reschke, 1997). Even where these traditional performance measures have been judiciously applied, there is inherent room for discrepancy, largely because business influencer factors such as technological innovations, and now the highly tactical business processes including business intelligent agents (Levitt, & Jin, 1998) and the rapid shift to a service-oriented economy have had polarizing effects on such metrics (Ray, 1997). Business leaders can attest to the fact that it is no longer the systems or external forces or conditions that matter the most, but latent components of human assets' becoming central to organizational competitiveness and ultimate business survival (Lee, Miller, 1999) (Barnard, 1938, Katz, 1964, Katz & Kahn, 1978) (Berman & Katoma, 2006).

Moreover, in an economy that has become highly knowledge intensive, technologically sophisticated, and increasingly reliant upon manager leadership style, it is essential to begin focusing on measuring the surge in performance. Unlike the managerial approach, which is often limited to managing systems and processes, the leadership approach demands that people not be managed, but be led; thus, the inherent difficulty of accounting for every performance measure can be reduced by accounting for the surge in performance. Besides, in organizations where conversional measures have been repeatedly used and even benchmarked, the systematic approach to DE can enhance such measures. One critical benefit of this continuum is the provision and alignment of methodologies and careful definition of lower and upper bounds as delimiters. By attaining these measurement levels, specific elevated performance value domains can then be targeted.

Although, it seems that there is a need to generate new theories, failure to first apply the current theories is derailing sound scientific advancement in this area (Haire, 1954). What is critical here is to first establish DE variables and methodologies in the corporate repository and quickly convert the theory from storage and representation into paradigm development and then into practice.

Hence, we first introduce the conceptual level of work behaviors and then discuss modeling strategies necessary for investigating behavior constructs of DE. We then propose a rigorous approach to defining and treating DE variables. This process is essential because DE variables, like other latent variables, require modeling to explicate the information they contain. Second, we illustrate how data classification is vital for DE variable selection. We then discuss a conceptual model of DE and finally demonstrate two different aspects of DE emerging from different variable combinations as a way of investigating the following hypotheses:

Hypothesis 1: The expectancy model (VIE) fits well in a professional network when self-affirmation (A) is included as one of the core components with valence, expectance, and instrumentality.

Hypothesis 2: Employees (personal level) have stronger DE views than those they perceive the organization (organizational level) to have.

Conceptual Model

Hypothetical constructs are often criticized for placing too much emphasis on the claim that they correspond to real-world events (Togerson 1958, Goldberger 1972) (Durham, 1975). On the contrary, it is hard to convey any meaningful information, certain knowledge, and theoretical laws without hypothetical structures (Gross, 1968) (Cronbach, 1955). Nor does there seem to be a more profound process of illuminating and providing insight from isolated theories than by developing hypothetical structures that are subsequently indirectly measured with latent variables (Gay, 1996). We believe that controversy over the use of hypothetical constructs emerges when complex phenomena are given naïve attention, for example, by carrying out research designs that are limited to non-progressive research boundaries and scope. Such practices have tended to confine well-intended facts of theory to misguided principles that have been obscurely used and thus blocked the path to understanding. Research that is primed to address complex hypothetical constructs must make its aims and methods readily understood. This antecedent highlights also the concern that research that is framed on psychological premises, such as self-esteem, personality, life-satisfaction, expectance, and self-affirmation, be given an epistemological status (Messik, 1981). Thus, rather than limiting findings to a set of constrained theory and hypothesis, a dynamic and process-oriented research approach can enrich and embolden scientific advancement in DE, at the same time seeking to maximize meaning and optimize measurement (Peterson el at., 1982).

Discretionary and Covariance Structures

We began by positioning DE as a latent variable that is caused by other latent variables, namely, expectancy, instrumentality, self-affirmation, and valence, which were measured by manifest variables from the survey instrument.

In mathematical terms, the relationship between the latent construct and the observed indicators is normally modeled with a common factor model (Spearman, 1904):

$Y_{ij} = \quad + \quad {}_i X_j + \quad {}_{ij}$ so that Xi is the latent variable or common factor (in this case the aforementioned DE) representing the hypothetical construct, i the factor loading for i, and ij a unique factor representing specific aspects of item i and measurement error. On the other hand, specific latent variables listed as expectance, instrumentality, valence, and self-affirmation would represent the true scores of continuous variables measured with error.

For continuous items or measures yj for unit j, the measurement model from classical theory (Lord & Novick, 1968) can be written as yj = xj + , where xi is the true score and j is the measurement error. The measurement errors have zero means and are uncorrelated with each other and the true scores. In fact, the true score is defined as the expected value of the measurement variable or item for a subject xj = E(yj), over imagined replications (Lord & Novick, 1968).

Modeling Fundamentals

At this juncture, we acknowledge, in line with Skinner's assertion (1953, p.35), that human behavior variables are derived from a complex mixture of theories and behavior systems. In psychology they are best understood when associated with special measurements and mappings, evident in such endeavours as performance measures. Bentler (1978) and Bagozzi (1980) argue that complex structures and construct validities should necessarily be investigated by means of structural equation modeling. In modeling processes, variable measurements and causal determination are further perceived as based on information contained in the variables and on how variables interact and are related. It has to be noted that, although we discuss modeling with measure on manifest and latent variables, measurability is better defined when variables are discussed as information about events in the context of set fields. We introduce sets of fields as a family of sets closed under complementation and finite unions. A measurable space is a pair of sets S and ∑, expressed as (S, ∑, μ), where S is a set and ∑ a sigma filed on S (Kolmogorov, Fomin, S.V, 1975). The elements of ∑ are called measurable sets and μ a measure. More important, if À is a family of a set S, then μ(À) is a filed algebra generated by À, that is, the smallest filed algebra σ(S) on S which contains À. Roughly speaking, μ(À) is the class of all events that can be decided given that we know the status of the events in À. Thus, when Xi and Yi variables are first treated appropriately as sigma sets and defined as manifest and latent variables, entry into measure space is almost obvious. This is a strategy aimed at underpinning facts and information in a way that best facilitates explication of results and pulls results together into a cohesive yet statistically supported anecdote (Dubin, 1969). Our focus is most importantly aimed at establishing objects that can be codified without loss of generality.

Storage and Structuring

A concrete corporate memory is vital to business processes and instrumental to any significant shifts in business strategies and innovation. Codified data are not only easy to access but crucial for inference, especially data that is based on history on which Bayesian methods can be used. We propose that corporate memory must therefore include segments with well-defined DE objects, variables, and experimental data. With such structures and data, business would learn the procedure of determining DE or at least begin to be more pragmatic about the philosophy behind DE, rather than merely urging employees to do more than what is proportionally allotted to them. The other purpose here is to empirically demonstrate where we stand in providing principles and generalization of the theory in discourse. Although, it would be naïve to point to some sort of DE benchmark at this moment, it is fairly reasonable to assert that these are among the achievements companies will eventually seek.

Much of the investigation in this paper is based on the premise that DE is derived from expectations placed on the outcome of an action (Leonard, 1995). It is also guided by the assumption that DE depends on the variance of the outcome and its instrumentality, that is, if a person took a particular action, a certain outcome would follow (Scholl, 2002) (Vroom, 1064). Even though this supposition forms the central theme of much of the existing framework about DE, different perspectives abound. This is simply because emerging business processes tend to be inclusive and encompass a large set of influencer factors such as trust, perceived leadership support, and continuance commitment, all critical in professional networks. April (2006) posited, for instance, that DE is also highly dependent on self-affirmation. We recall also that, when Vrooms (1964) first postulated the likely interrelationship among the aforementioned DE variables as VIE, different researchers attempted to produce DEs with different variable combinations. However, most of the results measured job satisfaction more than they measured DE, which nonetheless paved the way for further investigation and refinement of the measurement instruments and criteria. From these positions, construct validities have shown that, indeed, DE models are not only obtainable but also scalable.

Segmentation and Variable Groupings

Expectancy theory tends to be motivational in nature, in part, due to the grounding work reflected in VRoom’s (1964) work on VIE, which we do not question here, but build upon. Motivation itself is a wide and complex concept in the psychology of human behavior. Without dwelling much on the subject of behavior, our stand is, however, that DE draws from motivational and non-motivational groups and classes of variables. Corporate memory should therefore be designed with DE constituents containing classes of these human behavior sets of variables. A great deal of effort should therefore be focused first on variable definitions and storage and second on variable classification, paradigm development, and then practice. Storage in this view is defined as the physical and logical representation of concepts, but with clear semantics attached to their hierarchical and ontological orientation. For instance, the VIE group is composed of three sets defined categorically as valence, instrumentality, and expectancy. Each of these sets has elements such as skill base, aspiration levels, and work reward options. Remember that, while there has been a race to convert hypothesis or at least codify knowledge in many aspects of research including complex phenomena such as knowledge management processes, little, if any, information points to DE systems. The question then arises: what is the use of theory if it cannot readily translate into practice.

For business entities, it is in fact the usage part that is most sought. Although synergy may occur between concept and usage when the paradigm feeds directly into usage, it is unlikely that pieces of concepts alone will be adequate and accurately used for most of the intended purposes. Thus, isolated concepts and visual portrayal alone of the underlying causal relationships among DE variables may not be enough without systematic storage and clear hypothetical and tested constructs of DE models.

Classification

Measurement models are usually specified with continuous latent variables, for instance Xj. Such models are called factor models when the observed variables are continuous and otherwise noted as item response models when the measures are categorical (Skrondal & Rabe-Hesketh, 2004). Sometimes the true variable (manifest) is instead construed as categorical, a typical example being medical diagnosis (ill versus not ill). The measurement is, in this case, usually also categorical, with the same number of categories as the true variable. Measurement modeling can thus be used to assess measurement quality, especially in cases where ambiguities can be problematic and when high accuracy levels are required.

When the true variable is continuous, measurement quality is typically assessed in terms of the reliability of individual measures (Skrondal & Rabe-Hesketh, 2004). If the true variable is categorical, measurement quality is typically formulated in terms of the misclassification rate, sensitivity, and specificity. The categorization process is very critical in dealing with the variables according to the sets that represent them effectively, in light of their being motivational or non-motivational and nested groups. Whether they are probabilistic or not and Boolean or not are some of the important records required. In business it is common to classify customers into market segments. For example, Magidson & Vermont (2002) used latent class to classify bank customers as value seekers, conservative savers, and investors. In psychology, Prochaska & DiClemente (1983) looked at social classes, revealing stages of change in patient behavior such as trying to quit smoking. In sociology, one would investigate the social classes of particular types of people.

In total, we derived four classes from VIE and VIEA, two from VIE and two from VIEA. Classification was based on the individual and work perspectives of expectance, valence, and instrumentality and within the affirmation variables. The measurement instrument was further subdivided into two parts. the first ten questions focusing on expectancy variables and the remaining eight questions focusing on expectancy constructs, as illustrated later in the factor class analyses.

Value Domain

Latent variables are synonymous with business objects. They possess attributes as secondary objects or manifest variables. Storage of discretionary variables therefore should be defined around business data objects, purposed to capture outer and measurable elements in order to induce measurement of the inner latent variables. The main objects in the data model of a corporate memory database could be the *source* (from which the discretionary variable emanated, typically a human or a published work), the *snippet* (for instance, a posting or message, usually one fact or idea about discretionary constructs), and the *file* (representing either the creator's own work or a reference s/he found concerning the viability of the expectance construct). Each of these objects can be specialized, depending on how the discretionary framework is realized in a particular system and environment. For example, an implementation of the framework may distinguish snippets posted as motivational and non-motivational variables and items related to valence and instrumentality.

Each of the three main types of object or latent variables, for instance, expectancy, instrumentality, and valence, can be associated with secondary objects that add value to that object – *ratings* given by respondents on the measurement instrument, *comments* made by readers, and system *metadata* collected such as the individuals' perception of the meaning, which class category it is likely to fall into, and who entered it into the system and the date on which this was done. These secondary objects all are useful in computing manifest variable scores. Recent research at Shell International (Hendrix, 2007) revealed that, in a professional network where employees are explicitly seen to exercise their DE through sharing and helping others, several variables need to be considered. The most apparent drivers of DE in that platform included perceived leadership support (at the organization level), sense of community, and perceived usefulness of the system.

Objects in the model are associated with each other via directional links. Any secondary object can be related to any source of effector variables and can reference any other object in the model. Every object has an individual concept associated with it and specific constraints and definitions of how that object can be used. The descriptions of the operations on the variables and value ratings are consistent with the basic metadata registry model for data semantics, as illustrated below:

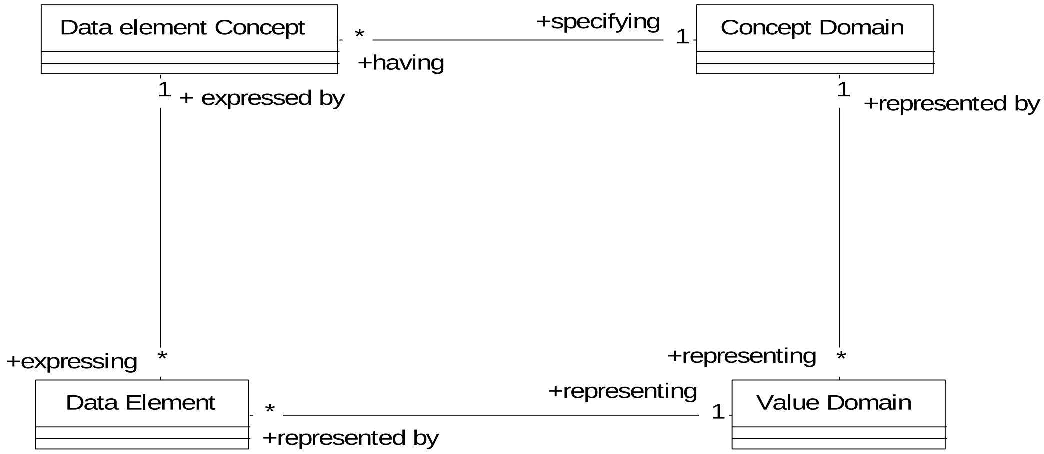

Figure 1. Overview of the metadata registry (ISO03)

The diagram above has two levels, namely, the conceptual level and the syntactical level. Conceptual level constitutes the "data element concept" and the "concept domain" classes, while the syntactical level is composed of "data element" and "value domain." Data elements such as ratings in the data model are represented by manifest variables; x1, x2, x3,……xn and are defined by the data element concept. The data element concept describes the data type (ISO95), for example, real numbers. The value domain assigns the data elements with permissible values, for instance, the value 1 as true and 0 as false or 0 and 1 for negative and positive values, respectively. Expectancy that, for example, spans a range of 0 and 1 is purely probabilistic.

Table 1: Value domains

Class description	General description
I. Conceptual Domain A set of value meanings, for example, probability values.	Value domains are not necessarily related to any data element. Two value domains that share all the value meanings are conceptually equivalent and share the same conceptual domain.
II. Value Domain The set of designations for the classes of a partition determined by a characteristic. A designation is known as a value, the associated class of the partition is described by a concept called the value meaning, and each value and the associated value meaning pair is known as a permissible value (ISO04).	Two value domains that share some value meanings are conceptually related and share the same conceptual domain in a concept system containing each of the conceptual domains.
III. Data Element The containers of data. The term data element is synonymous with the term variable or manifest, as it is understood in programming. Thus, the data type associated with a data element is important.	Many data elements may have the same value domain. For example, the expectance value would be either 1 for high or 0 for low. Expectancy can be expressed as a probability between 0 and 1.
4**. Data element concept** Would define, for instance, real numbers.	A data element concept is related to a single conceptual domain, so all the data elements sharing the same data element concept share conceptually related representation.

An example: A population consisting of objects about the observed data can be given as x1, x2,………xn, and the framework for understanding the data would be as illustrated in the diagram below:

Table 2: Example 1

Population	Set of range of expectancy outcomes
Characteristic	Proportion of valence variables
Partition	{x| 0 <= < 1}
Designation	Real numbers between 0 and 1

Table 3: Example 2

Population	Set of motivational items
Characteristic	Proportion of expectancy variables
Partition	{effort-performance expectancy,.., leading-visibility expectancy}
Designation	EP, IP, EL, LV,NP, IR, MR, NL, PO, TS

Table 4: Example 3

Conceptual domain name	Probabilities or knowledge item categories
Value Domain	All real numbers between and including 0 and 1
Permissible values	< 1, Maximum Positive Outcome> < 0, Minimum Positive Outcome>
Data element	Set of items (variables) on the measurement instrument
Data element concept	Real values

Part of the reason for describing data in a metadata registry is to establish some form of description of a data construct or instances so that operations estimations are maintained in a uniform and prescribed manner. For instance, variable identifiers, quality measures, responsible organizations, and definitions are recorded for every data construct. It is also crucial that in a process with in-depth coverage of concepts from different areas of study, such as human physiology and mathematical modeling, a thorough definition of variables is sought for consistency. This precept is in line with Argyris and Schon (1974), who posited that people use mental mind maps in making decisions and how they actually arrive at those decisions. Even though psychologically based studies often take heuristic stances, increased practical experience and improved measurement tools are providing more ground for strong claims and conclusions. We expect that greater realistic outcomes will be unveiled, for example, in how individuals treat DE issues.

Factor Analysis Scoring Processes

We envisioned that data should be subjected to scoring and classification processes so as to refine our measurement instrument and at the same time pave the way for a more inclusive and learning cycle. We realized early that a modeling process that provided an epistemological status to hypothetical structure constructs could be better positioned and form a good basis for measuring the performance surge values. Value as seen by many business architects is elastic, that is, it embodies large sets of business components, including customer value and an avalanche of the often esoteric variables tied to the service economy continuum.

For the first part of the measurement instrument, variables focused on expectancy items. Factor analyses identified two components (table 4) critical to expectancy measurements. Factor one (EP) defines IP, EL, LV, NL, and PO. Factor two (MR) accounts for NP and IR. TS scored moderately on both factors and thus bridged the two. Expectancy is what employees come to expect in joining a particular network. It is about the process of making certain choices based on certain desires of the individual and those perceived on the part of the workplace. The instrument was therefore framed to reflect views of both the individual and the workplace based on a five-point Likert scale: 1. Effort-performance expectancy (EP). 2. Interpersonal-performance expectancy (IP). 3. Effort-learning expectancy (EL). 4. Leading-visibility expectancy (LV). 5. Network-performance expectancy (NP). 6. Mutual-reciprocity expectancy (MR). 7. Individual-network learning expectancy (NL). 8. Performance-outcome expectancy (PO). 9. Team-sustainability expectancy (TS). The Cronbach's alpha reliability on the items was 0.77 at the individual level and 0.84 at the workplace level. In both cases, the mean difference values were significantly less than 0.05, indicating that there was a high dependence between the variables in each group.

The second part of the measurement looked at specific questions regarding mostly motivational tools and constructs highly varied as instrumental in affecting the way employees were likely to exercise DE, ranging from effort expectancy constructs to team sustainability constructs. The variables are listed as follows: (1). Effort-expectancy constructs (EE) with reliability test of 0.65 for personal and 0.82 for work measures. (2). Performance expectancy constructs (PE) registering a reliability of 0.61 and 0.83 for personal and work ratings, respectively. (3). Achievement of workplace goals (WG) with a personal reliability measure of 0.74 and work reliability measure of 0.85. (4). Emotional orientation for desired outcome (EO) scoring 0.59 and 0.82 for reliability on personal and work measures, respectively. (5). Positive comparison of expectancy with peers (PC) with 0.70 for personal reliability and 0.63 as work reliability score. (6). Self is seen to have capacity for efficacious action (EA) registering 0.63 for personal reliability and 0.80 for work. (7). Team-sustainability expectancy (TS) also scoring higher than the recommended average of 0.70 on both sides. The mean differences were very small in all the group items, far less than 0.05, showing a close dependence in the variables as we anticipated.

Table 4: Rotated expectance factor results

	Component Personal Expectancy		Component Work Expectancy
	1	2	1
EP	.660	.072	.632
IP	.548	.206	.640
EL	.636	.209	.681
LV	.573	.059	.574
NP	.164	.707	.618
IR	.200	.643	.588
MR	.099	.762	.633
NL	.648	.216	.704
PO	.615	.245	.701
TS	.429	.454	.647

The scoring revealed that the first ten variables are better defined as effort-performance and mutual-reciprocity factors but interlinked by team-sustainability variable. Effort-performance is a belief that, towards an individual expended effort, an effective performance outcome is expected. Mutual reciprocity is a give-receive balance employees expect in the work environment. Whatever they give in work, they expect to receive in reward; which is in line with causal performance measures that are based on operation and includes process cost, time, and quantity and quality factors. TS, is the team sustainability component, which serves well as a moderating factor between EP and MR. Whatever the effort and its outcome may be, the team as a whole has to be strengthened for continuity's sake. When factor analysis was conducted, focusing on the work perspective side, only one component emerged as representative of the rest of the variables, namely, the individual-network learning expectancy (NL). While individuals are more likely to derive their DE expectancies from EP and MR, organizations, according to this finding, viewed DE mostly as instituted by network learning (NL) experiences that employees are perceived to acquire through professional networks.

Factor analysis directed at the second class of the questionnaire was proposed to investigate whether employees were frequently provided with what they needed to exercise DE. The two Likert scales were thus defined according to how frequently the tools were provided at the individual level and whether the employee's functions were measured and the level of importance the function had in the work place. Results in the table below illustrate that, at the individual level, six components emerged. First, all the initially defined factors were accounted for without much loss of information.

Table 5. Rotated Factor Analysis Results

	Components: Personal Level						Components: Work Level			
	1	2	3	4	5	6		1	2	3
EE1	.567	.135	.110	.116	.238	-.133	EE1	.300	.158	.684
EE2	.597	.026	.155	.006	.146	.175	EE2	.246	.202	.780
EE3	.253	.307	.075	-.026	.570	-.069	EE3	.176	.345	.657
EE4	.327	.289	.394	.073	.121	-.242	EE4	.296	.356	.545
EE5	.650	.055	.075	.109	.069	.118	EE5	.523	.044	.389
PE1	.536	.180	.116	-.059	.304	.247	PE1	.342	.316	.595
PE2	-.026	.035	.424	.036	.426	.067	PE2	.226	.289	.685
PE3	.349	-.036	.056	.124	.589	.089	PE3	.407	.248	.549
PE4	.593	.109	.144	.264	.086	.044	PE4	.596	.152	.424
PE5	.493	.300	.087	.300	-.020	.001	PE5	.602	.144	.341
WG1	.220	.670	.053	.016	.132	-.066	WG1	.375	.398	.442
WG2	.244	.386	.506	.084	-.213	.074	WG2	.475	.399	.317
WG3	.379	.197	.522	.137	.048	-.090	WG3	.675	.214	.282
WG4	.456	.247	.398	.092	.078	-.088	WG4	.686	.263	.270
WG5	.434	.466	.239	.188	-.050	-.037	WG5	.657	.316	.203
EO1	.319	.020	.539	.103	.074	.239	EO1	.421	.420	.350
EO2	.255	.246	.507	.151	.111	.146	EO2	.440	.494	.325
EO3	-.037	.011	.602	.127	.162	.053	EO3	.193	.575	.180
EO4	-.008	-.037	.232	.233	.435	.387	EO4	.433	.490	.234
EO5	.301	.013	.054	.424	.408	.050	EO5	.462	.474	.300
PC1	.385	.311	.162	.330	.152	-.022	PC1	.470	.497	.278
PC2	.133	.049	.132	.735	.107	-.074	PC2	.503	.428	.257
PC3	.348	.125	.154	.384	-.240	.395	PC3	.521	.402	.173
PC4	.070	.366	.195	.570	.129	.050	PC4	.367	.587	.171
PC5	.374	.161	.382	.443	-.166	.130	PC5	.463	.277	.102
EA1	.040	.174	.092	-.032	.112	.614	EA1	.078	.625	.287
EA2	.141	.494	.211	.208	.233	.146	EA2	.333	.641	.255
EA3	-.069	.683	.100	.050	-.072	.193	EA3	.051	.732	.138
EA4	.366	.438	-.055	-.066	-.010	.481	EA4	.254	.507	.203
EA5	.139	.646	.104	.166	.046	.166	EA5	.348	.615	.207

The classes of sigma algebras (σ) from the table above can be written as σ1. **{EE(.65 commonality)** {**EE1,EE2, EE5, PE1, PE4,PE5**, *PC5, PC1, EE4, WG4, WG5, EA4*}, σ2. **EA(.68 commonality)** {**WG1, EA2, EA3, EA5**, *WG5, PC1, EA4, EE4*}, σ3. **EO(.60 commonality)** {**WG2, WG3, EO1, EO2, EO3,** *PC5, EE4, PE2, WG4*}, σ4. **PC(.74 commonality)** {**PC2, PC4**, *EO5, PC5, PC1*}. σ5. **PE(.59 commonality)** {**EE3, PE3,** *PE2, EO4,EO5*} and σ6. **EA(.61 commonality)** {**EA1**, *EA4, PC3, EO4*}}

It must be noted that the six components are represented by the first two letters preceding each set. The components thus can be clearly denoted as EE, EA, WG, EO, PC, PE, and *EA,* comprising different variables each arising from the different factors. Board letters illustrate variables with higher influence that are not shared by other sets. Simple trend can be seen, showing that the

EE and PE are grouped in one category as factor 1. EA dominates factor 2, while factor 3 is influenced by WG and EO. Factor 4 is moderately represented by PC, and the rest, namely, factors 5 and 6, are weakly represented by PE and EA. This is because PE and EA are well represented in other factors in a more homogeneous manner. Vetting these variables strictly leaves us with 4 factors determined by EE, EA, EO, and PC.

At the work level, however, only three components were evident, namely; **EE, EA,** and **WG**. The first two components **EE** and **EA** were consistent with those extracted at the personal level or individual components but it can be clearly seen that WG was in fact representative of EO and PC. Generally, the factors were not very significantly different but were fewer than the previous class. One important conclusion is that, from the first group, the factors reduced to half when compared at both individual and work levels. The same trend was apparent for the second group according to the results from the two classes. In the second survey, we will either restructure or rearrange the questions whose measures have been identified to have fallen in unexpected factors. Alternatively, it would be easier to establish a functional measure that would transform such variables in order to have a refined instrument. This is, however, left for future work.

What is of interest, again, is the EP, MR, and TS variables identified earlier, as they seem to significantly influence expectancies. Another important result is that, as revealed by the sets above, EE and PE are the determinants of instrumentality and fall in the same sigma algebra set σ1. WG and EO are the main influencers of valence and belong to one sigma algebra σ3. Self-affirmation is determined by PC and EA.

Modeling with Classes

The modeling process was conducted with Lisrel Software. The main aim was to test whether and how VIE and VIEA models would fit our data and inductively validate the measurement instrument, at the same time making the case that the hypothetical constructs on DE are worthwhile exploring. Tables 1 and 2 constitute classes A (VIE) and B (VIEA) forming group 1 of variables derived from factor analysis. Tables 3 and 4 compose classes C and D, which is group 2, with variables exactly the same as in classes A and B (group 1). Group 1 represents the effect of personal perspective of employees on the measurement instrument, while group 2 expresses the work perspective of the employee or how companies perceived DE.

Table 6: (Class A)

Personal without A (VIE).								
Measurements Equations								
	EP	MR	EE	PE	EO	WG	R^2	t-statistic
E	0.656						0.112	5.256
E		1.000					0.125	14.465
I			1.000				0.663	9.789
I				0.894			0.581	17.691
V					0.706			
V						1.000	0.541	10.895
Structural Equations								
	E	V						
I	0.452						0.841	0.935
I		0.586						2.494
E		0.462					0.660	6.227

As seen in Table 1, load factors were high, consistent with the factor analysis results that the endogenous variables significantly influence the latent variables. R^2 values were also significant, indicating that the variances in relationship between the manifest and latent variables were largely accounted for. The least accounted for variances occurred between EP and E (0.112) and between MR and E (0.125). The t-statistics were highly significant, greater than the recommended 1.96 except for the causal relationship between E and I (0.935), as shown in the structural equation part of the table.

For the models to be considered adequate as fitting the sample data, goodness of fit indices (GFI) were used. From class A, the degree of freedom (df) was 6 and chi-square was 13 (p = 0.0333). The root mean square (RMSEA) was 0.0431, less than 0.05, a very good achievement. The goodness of fit index was 0.993, and the normed fit index (NIF) was 0.990. These are significantly adequate and acceptable results.

Table 7: (Class B)

Measurement Equations with A (VIEA)										
	EP	MR	EE	PE	EA	PC	EO	WG	R^2	t-statistics
E	0.627								0.111	3.478
E		1.000							0.135	9.243
I			1.000						0.655	7.143
I				0.906					0.594	12.477
A					0.656				0.315	8.368
A						1.000			0.733	3.782
V							0.739		0.391	9.945
V								1.000	0.505	8.656
Structural Equations										
	V	I	E	A						
V	0.258 (0.042)									

	6.176			
I	0.212 (0.025) 8.317	0.210 (0.028) 7.600		
E	0.129 (0.031) 4.181	0.117 (0.026) 4.465	0.096 (0.052) 1.827	
A	0.293 (0.033) 8.915	0.221 (0.026) 8.614	0.112 (0.030) 3.684	0.352 (0.052) 7.076

In Class B, the R^2 values are significantly high, except for the relationships between EP and E, (0.111) as well as between MR and E (0.135). The t-statistics in this class are all highly significant, illustrating that all the relations between the variables in this class are strong and important. The load factors are very significant considering that there are more variables measured in Class B than in Class A. The t-statistics measuring the effects among the latent variables are all highly significant shifts from class A, consistent with fundamental regression analysis claims that the more variables at play the better the representation of the causal structures, as more information is elicited.

It can be deduced that the affirmation aspect (Class B) reveals more causality among the underlying variables. The variable self affirmation (A) is therefore a justifiable influencer on DE, with t-statistics of 8.368 and 3.782 on the measurement equation and t-statistics of 8.915, 8.614 and 3.684 in the structural equation.

Class B had 13 degrees of freedom and a chi-square of 7 ($p = 0.878$). The Root Mean Square was 0.0, with both GFI and NFI at 0.994 as well. There was a slight improvement in all these measurements compared with the results of Class A, showing that the model fit in the same group was very close.

Table 8: (Class C)

Work without A (VIE).								
				Measurements Equations				
	EP	MR	EE	PE	WG	EO	R^2	t-statistic
E	0.832						0.258	7.140
E		1.000	0.691				0.261	13.198
I			0.445					3.353
I				1.000			0.841	6.003
V					1.017		0.763	28.230
V						1.000	0.727	12.933
				Structural Equations				
	E	V					R^2	t-statistics
I	-0.0064 (0.109) -0.059	0.983 (0.0556) 17.683					0.875	17.683

I	-------	0.356 (0.0434) 8.203		0.371	8.203
E					

Class C and Class D look at the work perspective of the DE. In the table above, it can be easily observed that the loader factors are significantly high, with the least measurement of 0.445 between EE and I on the measurement questions of table 8. The R^2 reveals that more information was accounted for in the relationships between the variables when compared with both classes A and B. The t-statistics were also consistently high on both the measurement equation and the structural equations. This result also indicates that group 2 was more consistent than group 1, both in relations between the variables and further revealing the internal consistency of the work aspect of items on the measurement instrument.

In Class C, the df was 5 and chi-square was 3 (p = 0.618). RMSEA was 0.0 and GFI was 0.998, with NFI at 0.999. These are more accurate results that those for Classes A and B.

Table 9: (Class D)

Work with A (VIEA)										
Measurement Equations with A **(VIEA)**										
	EP	MR	EE	PE	WG	EO	PC	EA	R^2	t-statistics
E	0.86								0.259	7.128
E		1.000							0.244	13.687
I			0.699						0.712	11.871
E			0.475						-----	3.353
I				1.000					0.824	6.894
V					0.982				0.741	30.238
V						1.000			0.749	13.752
A							1.000		0.705	12.933
A								0.843	0.671	25.398
Structural Equations										
	V	I	E	A					R^2	t-statistics
V	--------	--------	-------	-------						
I	2.079 (0.109) 0.288	-------	0.031 (0.967) 2.145	-1.060 (0.057) -1.196					0.941	2.145
E	0.336 (0.0413) 8.133	-------	-------	-------					0.364	8.133
A	--------	--------	--------	--------						

Class D in group 2 was by far the best represented in terms of loader factors and index measurements of the amount of variances accounted for and the significance of those variables as revealed by the t-statistics compared with the other classes.

When classes are ranked according to how well they revealed the causal validity of DE, class D is ranked first, followed by Class C, then B, and lastly A. Construct validity as illustrated in groups 1 and 2 shows a trend in factor loading between groups. Classification, as well as categorization, of data is therefore highly visible and necessary in this result and also an important result in DE research. This finding is important because DE is a continuum based on the emergence and convergence of different variables often stemming from motivation in human psychology and other non-motivational variables that are equally vital. VIEAs are not only more accurate than VIEs between classes, they are also distinct within groups.

For Class D, the df was 14 while the chi-square was 26 ($p = 0.0240$). The p-value was the lowest of all the classes. RMSEA was at 0.0358, GFI of 0.991, and NFI at 0.995. These are optimal results and highly acceptable. Although other indices suggested that D is slightly less optimal than other classes, the scores are in all the counts higher than the recommended values and the results on the validity in Table 4 reflect that, indeed, Class D is the best-represented class. One interesting finding on Class D is that self-affirmation was not as significant as it was measured on the rest of the classes.

Conclusion

We have described in a general sense the process-oriented approach to defining and treating DE variables. We believe that, when these variables are systematically positioned in any work environment and clearly understood, quick paradigm and system development will naturally follow. We have also demonstrated that the processes of factor analysis and variable classification play an important role, in selection of relevant DE variables, especially in the face of overwhelming theory of ambiguous meaning.

Factor analysis revealed the most critical components of the items in the measurement of DE, while the classification exercise categorized these components into classes for easy comparison and explication of information in the models. We also noted that items which did not score well can be improved upon, a subject reserved for future work.

The modeling process showed that, indeed, DEs are well represented by the current theoretical constructs and are scalable. Therefore, we suggest that the DE measurements based on the variable combinations as proposed by Vroom (1964), VIE and the current suggestion of VIEA, are acceptable. Moreover, our data reveal that VIEA is an improved version of VIE. In the future, we intend to include more variables, based primarily on organization citizenship concepts and others from the work with Shell International, as discussed earlier. This precursor is important because the more variables in the model, the better the estimations and the more information and knowledge that can be explained.

In relation to our hypotheses, the results revealed that VIE in professional networks fits well when self-affirmation is included as one of the core components of the model. At the work level, however, self-affirmation was not reflected in the final class D, probably because the organization did not perceive self-affirmation to be accurately measured as it relates to individuals.

Contrary to our assumption that employees have stronger DE views than does the organization, the results revealed that it was actually the organization that had stronger

DE views, perhaps because of the awareness of the need for DE by organizational management. Yet, we believe that DE should be more actively cultivated at the individual level in order to balance the progressive efforts of both employees and organizations.

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