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# Jamming with Social Media: How Cognitive Structuring of Organizing Vision Facets Affects IT Innovation Diffusion

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# Appendix A

## Our Grounded Theory Approach

We conducted our study in two stages. In Stage I, aimed at discovering organizational actors' meanings of social media, we focused on category emergence. In Stage II, aimed at developing causal insights around those meanings, we focused on relationships among categories surfaced at Stage I. In Table A1, we map our methods to the methodologies specified by the two main grounded theory proponents: Strauss and Corbin (2007) and Glaser (1992).

**Table A1. Study Methods Relative to Grounded Theory Methodologies**

| Strauss and Corbin Stage | Glaser Stage | Study Stage |
|---|---|---|
| | | I.A: Coding for justificatory principles |
| Open Coding | Substantive Coding | I.B: RCA |
| Axial Coding | Substantive Coding | I.C: Analysis of schemas and business use cases |
| Axial Coding | Theoretical Coding | II.A: Identification of four vision facets |
| Selective Coding | Theoretical Coding | II.B: Examination of bivariate relationships |
| Selective Coding | Theoretical Coding | II.C: Theoretical elaboration |

### *Stage I: Discovering Meanings Attributed to Social Media*

Our choice to use Boltanski and Thévenot's (1999, 2006) "orders of worth" framework to study justification departs from some grounded theorists' sentiment that the investigation should be grounded purely in data, blind to prior theories. Nonetheless, Strauss (1987, p. 306) said "there is no reason not to utilize extant theory from the outset." Strauss (p. 306) articulated three conditions under which using prior theory is permissible, even desirable: first, "that it too [i.e., the prior theory] was carefully grounded in research," that is, empirical data; second, that "entry into the research field follows immediately, or at least before a commitment is made to the research project"; third, that the researcher "be immediately sensitive to the new data and their potentials for new coding, conceptual densification, and integration." Boltanski and Thévenot grounded their framework in decades of ethnographic and statistical investigations of how people justify distinctions among people and explain injustices in scientific, business, and lay contexts, thereby satisfying Strauss's first condition. Our initial objective was to understand the meanings organizational actors attributed to social media. About two months into the study, after we had coded 541 texts from the first 15 Fortune companies, we elected to focus on understanding actors' justifications for social media use. We therefore satisfy Strauss's second condition. Finally, through the entire coding process, we remained alert to the possibility that the data might suggest novel justificatory principles not addressed by Boltanski and Thévenot. Although we were unable to discover any novel principles, our vigilance meets Strauss's third criterion for acceptable use of prior theory by the grounded theory researcher. This approach is consistent also with Urquhart's (2013, p. 29) labeling of the expectation that researchers investigate phenomena without invoking their prior knowledge as a "myth" and Urquhart and Fernandez's (2013, p. 230) recommendation of a "phased literature review," with the "understanding that the generated grounded theory will determine the relevance of the literature, never the converse." Finally, as noted in Table F1, our grounded theory endeavors began *after* we developed the dataset of 1,183 initiatives and the signaling rates for the six principles across those initiatives. This is consistent with Suddaby's (2006, p. 636) perspective that "in a grounded theory study, content analysis is only one of multiple contexts for acquiring data." Thus, whereas we imposed Boltanski and Thévenot's framework on the initial data, concepts other than principles and relationships among the concepts emerged through our engagement with the data.

Our second methodological choice at this stage (i.e., to use RCA) also may appear somewhat inconsistent with conventional grounded theory paradigms. Because of the connectionist structure of schemas (Strauss and Quinn 1997), discovering them can be an extremely complex task. For example, permitting signaling rates for the six principles to be either a 0 or a 1, there are 63 possible combinations of the principles or 63 possible schemas. With signaling rates varying continuously between 0 and 1, an *infinite* number of possible schemas exist. To deal with such complex phenomena, researchers have advocated leveraging advanced computational techniques in grounded theory research (e.g., Birks et al. 2013; Goes 2013).

RCA is particularly well suited to grounded theory as it performs constant comparisons at two stages of the procedure. First, computing relationality coefficients entails comparing the vector of values for all variables for each observation with the vector of values for all variables for every other observation (Goldberg 2011). Second, identification of relational clusters necessitates comparing each observation's relationality coefficient with every other observation's relationality coefficient (Goldberg 2011). In this fashion, RCA automates the process of constant comparison by leveraging advanced computational techniques.

As an inductive, discovery approach, RCA may invite criticism that the knowledge discovered is incomplete (i.e., that saturation has not been attained). Mindful of this possibility, we conducted the analyses in stages to ascertain whether adding data changed our findings. Table A2 summarizes data and findings across analysis iterations, with the last two iterations adding firms and texts for April–December 2012, which was missing from the first two iterations.

As will be apparent from the table, the firms sampled became increasingly heterogeneous in industries represented, revenue, and profitability across the iterations. Discounting the first iteration, for which very little data was available, we observe two things. First, concomitant with increased sample heterogeneity, we see a steady decline in the average relationality coefficient, suggesting decreasing schematic similarity in the sample. Second, despite increasing sample and schematic heterogeneity, both the schemas identified and the relative distribution of initiatives across schemas remain consistent across the last three iterations. We therefore were satisfied that the social media schemas discovered were sufficiently comprehensive.

Having discovered the four schemas through RCA, we examined the graphs produced by RCA (see Appendix B, Figure B2) *and* initiatives associated with each schema for similarities and differences. This constant comparison of RCA output with the texts describing the initiatives enabled us to understand and label the schemas as well as identify the business use cases associated with the oppositional preferences patterns nested within the schemas.

## Stage II: Discovering Effects of Different Meanings on Social Media Diffusion

We began our theoretical coding by retracing the constant comparisons performed at Stage I. Revisiting how the schemas identified at Stage I differed from each other led us to identify two concepts: coherence and continuity. Reconsidering how the initiatives associated with a business use case differed from the ideal specification of a business use case led us to identify the concept of vision clarity. Recognizing that community members socially constructed different versions of the vision by appropriating different business use cases in different ways at any given point in time, we identified the concept of vision diversity.

**Table A2. Summary of RCA Findings Across Analyses**

| Sample Characteristics and Findings | | Iteration: First | Second | Third | Fourth |
|---|---|---|---|---|---|
| Fortune firms sampled | | Top 15 | Top 30 | Top 40 | Top 50 |
| Firms with social media initiatives | | 14 | 26 | 36 | 46 |
| Number of texts coded | | 541 | 1,557 | 1,898 | 2,276 |
| Number of initiatives | | 213 | 675 | 929 | 1,183 |
| Industries represented | | 10 | 16 | 22 | 25 |
| Range of firms per industry | | 1-3 | 1-5 | 1-5 | 1-5 |
| Average reputation score† | | 6.39 | 6.44 | 6.48 | 6.43 |
| Variance (range) in reputation | | 1.10 (4.53-7.93) | 0.96 (4.53-8.10) | 0.88 (4.53-8.42) | 0.83 (4.53-8.42) |
| Average revenue* | | $172,273.20 | $130,531.98 | $114,075.18 | $101,989.08 |
| Variance in revenue* | | $8,461,602,847.31 | $5,962,986,659.89 | $5,268,669,534.21 | $4,793,317,698.47 |
| Average profitability* | | $10,412.20 | $7,013.77 | $6,955.38 | $6,209.19 |
| Variance in profitability* | | $109,602,434.89 | $87,535,743.18 | $74,518,283.79 | $61,957,880.51 |
| Bootstrapped Average Relationality Coefficient (SE) | | 0.45 (0.0015) | 0.60 (.0088) | 0.56 (.0091) | 0.53 (.0088) |
| Schemas | *Efficiency-Engineer* | 53% of initiatives | 50% of initiatives | 55% of initiatives | 54% of initiatives |
| | *Brand-Promoter* | -- | 7% of initiatives | 7% of initiatives | 8% of initiatives |
| | *Good-Citizen* | -- | 10% of initiatives | 9% of initiatives | 10% of initiatives |
| | *Master-of-Ceremonies* | 47% of initiatives | 32% of initiatives | 29% of initiatives | 28% of initiatives |

*in millions †Fortune reputation score for 2012

Then, deciding to focus on how these four facets influence diffusion, we examined diffusion across four quarterly windows. These disparate windows afforded us multiple indices of our core theoretical construct (i.e., diffusion), one way in which quantitative grounded theory undertakes constant comparison (Glaser 2008). Specifically, by observing consistent relationships between the four vision facets and diffusion across the four diffusion indices while examining bivariate relationships and during theoretical elaboration, we could conclude that the facets influenced diffusion consistently in the short- to the medium-term. Using EDA techniques such as scatterplot matrices to examine bivariate relationships further enabled constant comparison of focal concepts. Similarly, tabular comparisons of partial correlations across the four diffusion metrics enabled constant comparison during theoretical elaboration.

With quantitative grounded theory, the benchmark is novelty and coherence of insights rather than statistical rigor. Glaser and Strauss (1980, p. 200) said, "Testing the statistical significance of an association between indices presents a strong barrier to the generation of theory…[and] direct attention away from theoretically interesting relationships that are not of sufficient magnitude to be statistically significant." They said, "In place of making tests of significance, the sociologist can establish working rules to fit his particular situation" (p. 201). Because statistical significance is a recognizable heuristic and because we do not believe using the heuristic caused us to overlook otherwise-meaningful relationships, we retained the heuristic, but were careful to qualify its relevance in a grounded theory study.

# Appendix B

## Unpacking Schematic Similarity

The premise underlying schematic similarity is that people with *diametrically opposed attitudes* toward a set of stimuli may have *shared understanding* about those stimuli because they organize their cognitions about the stimuli based on the same underlying rules (Goldberg 2011). In Table B1, Alex and Jamie clearly are schematically similar, given their preference for vegan foods. Bill and Bobby, who like foods associated with a country breakfast (eggs, bacon, and biscuits) also clearly are similar. The schematic similarity of Dean, who *dis*likes foods associated with a country breakfast and likes foods *not* associated with a country breakfast, to Bill and Bobby is less clear. Dean, who grew up with Bill and Bobby, organizes the foods into groupings identical to Bill and Bobby, retaining the cultural meanings associated with the foods, if not the taste for them. Thus, while individuals *sharing the same preferences are schematically similar*, individuals with *oppositional patterns of preferences also are schematically similar*.

Kelly and Mac, with shared preferences, are schematically similar to Sam and Taylor, with *oppositional* preferences, because all four manifest the same evaluation rule regarding the foods: *protein versus carbs*. In contrast, Alex and Jamie's evaluation rule is whether or not the foods are *vegan* and Bill, Bobby, and Dean's evaluation rule is a *country breakfast* meal. Thus, patterns of these nine individuals' food preference reveal how their cognitions about the six foods are related to each other, revealing their underlying *schemas* about food.

**Table B1. Example of Surfacing Schematic Similarity/Dissimilarity**

| Foods | Alex | Jamie | Bill | Bobby | Dean | Kelly | Mac | Sam | Taylor |
|---|---|---|---|---|---|---|---|---|---|
| Eggs | – | – | + | + | – | + | + | – | – |
| Bacon | – | – | + | + | – | + | + | – | – |
| Biscuits | + | + | + | + | – | – | – | + | + |
| Bean salad | + | + | – | – | + | + | + | – | – |
| Granola | + | + | – | – | + | – | – | + | + |
| Strawberries | + | + | – | – | + | – | – | + | + |
| Schema | Vegan | | Country Breakfast | | | Protein versus Carbs | | | |

# Appendix C

## Explanation of Relational Class Analysis

Relational class analysis (RCA), advanced by Goldberg (2011) to detect shared understandings, is a knowledge discovery, rather than a hypothesis testing, technique that is useful in developing theories about meanings. Detecting schemas through RCA requires the researcher identify stimuli that are the building blocks of schemas. The foods in Table B1 are one type of schematic building block. The schematic building blocks in Goldberg's study were musical genres. In our study, the focal stimuli were Boltanski and Thévenot's (2006) six principles. Then, understanding how social entities organize those building blocks into schemas requires that the researcher elicit some *signal of the meaning attributed* to the individual stimuli (e.g., food or musical genre preferences). We derived signals from firms' texts related to social media by coding for the different principles firms used to justify social media. Each text contained one-to-many initiatives and initiatives could be discussed across multiple texts. The resultant signaling metric was the rate at which each principle appeared across texts discussing each initiative. This metric fulfilled Goldberg's requirement that the signaling metrics for the different variables be comparable, ordinal, equidistant, and scaled between zero and one. Figure C1 depicts signaling rates for five sample Ford initiatives.

| | Initiative | Texts |
|---|---|---|
| A | Ford Customer Service | 1 |
| B | SYNC | 9 |
| C | Empowering Multicultural Women | 1 |
| D | Amazing Race Road Rally | 2 |
| E | Road Trip | 4 |
| F | Fiesta Movement | 27 |

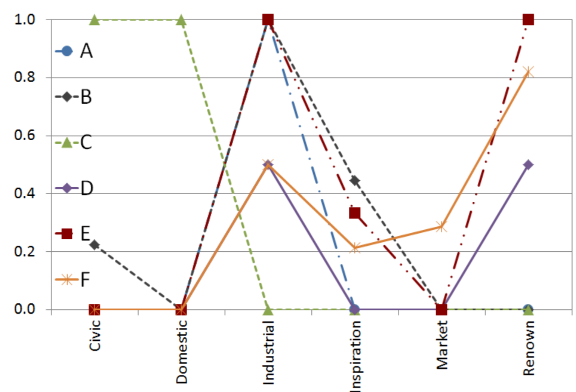



**Figure C1. Sample Ford Initiatives and Signaling Rates for Principles**

### *Step 1: Computing the Relationality Matrix*

RCA begins by computing an $N \times N$ relationality matrix, where N = the number of observations. In this case, N was the 1,183 social media initiatives identified. For each pair of observations, a relationality coefficient is computed as follows (formulas from Goldberg 2011):

$$R_{ij} = \frac{2}{K(K-1)} \sum_{k=1}^{K-1} \sum_{l=k+1}^{K} (\lambda_{ij}^{kl} \cdot \delta_{ij}^{kl})$$

where $\delta_{ij}^{kl} = 1 - \left| |\Delta X_i^{kl}| - |\Delta X_j^{kl}| \right|,$

$$\Delta X_i^{kl} = X_i^k - X_i^l \,,$$

$$\lambda_{ij}^{kl} = \begin{cases} 1 & \Delta X_i^{kl} \cdot \Delta X_j^{kl} \geq 0 \\ -1 & \Delta X_i^{kl} \cdot \Delta X_j^{kl} < 0 \end{cases},$$

$K$ = total number of variables (or cognitive elements that constitute the schemas),
$i, j$ = particular observations (here initiatives),
$k, l$ = particular variables (here principles), and
X = set of data points, each ranging from 0 to 1, for $K$ variables and $N$ observations.

We automated these computations using Excel VBA to produce the $N \times N$ relationality matrix. The lower bound on the relationality coefficient depends on scale granularity and the number of variables, tending toward -1 as each increases, but rarely equaling -1 (in our data, the minimum relationality coefficient was -0.25). Consequently, expected values of relationality coefficients exceed zero. Goldberg therefore recommends ascertaining the significance of the relationality coefficients relative to their bootstrapped means. This was done in Stata (version 10.1) with 1,000 replications of 1,000 observations. As per Goldberg, coefficients with an absolute value significantly higher than the bootstrapped mean of 0.53 (SE = 0.0088) were retained. Using the relationality coefficients' absolute value operationalizes the premise that positively and negatively related observations are schematically similar (Goldberg 2011).

The relationality coefficient bears some resemblance to the Pearson correlation coefficient. Like the correlation coefficient, the relationality coefficient can, in theory, range from -1 to 1. In reality, however, the lower bound on the relationality coefficient depends on scale granularity and the number of variables (i.e., cognitive elements that are organized into schemas), tending toward -1 as each increases. While correlation computes association based on two vectors of data points, treating the data points within each vector as independent, relationality is sensitive to interdependencies between the data points. Correlations are sensitive to differences in use of extreme values and cannot be computed in the presence of zero variance. Relationality, however, is less sensitive to differences in scale usage and can be computed even in the presence of zero variance. Sample relationality and correlation coefficients are shown in Table C1. As per Goldberg, the correlation between relationality and Pearson coefficients is high (r = 0.94 with our data).

**Table C1. Relationality and Correlation Coefficients for Five Ford Initiatives**

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| A | 1.00 | 0.81 | 0.13 | 0.67 | 0.60 | 0.49 |
| B | 0.89 | 1.00 | 0.09 | 0.43 | 0.53 | 0.20 |
| C | -0.32 | -0.33 | 1.00 | 0.20 | -0.09 | 0.09 |
| D | 0.63 | 0.43 | -0.50 | 1.00 | 0.71 | 0.82 |
| E | 0.61 | 0.51 | -0.61 | 0.96 | 1.00 | 0.61 |
| F | 0.30 | 0.14 | -0.74 | 0.88 | 0.88 | 1.00 |

Note:
*Relationality coefficients above diagonal*
*Correlations below diagonal*

### *Step 2: Obtaining Relationality Clusters (Schemas)*

To discover the distinct schemas or "islands of meaning" (i.e., clusters that organize cognitive elements in similar fashions), Goldberg recommended the Newman algorithm, which employs modularity maximization, where the optimal number of clusters is given by the largest modularity coefficient. The Newman community detection algorithm's modularity index (using UCINet version 6.381) indicated optimal modularity for 4- to 14-cluster solutions. Because all clusters beyond the first four clusters in the 5- to 14-cluster solutions contained only single observations (initiatives), we retained the 4-cluster solution.

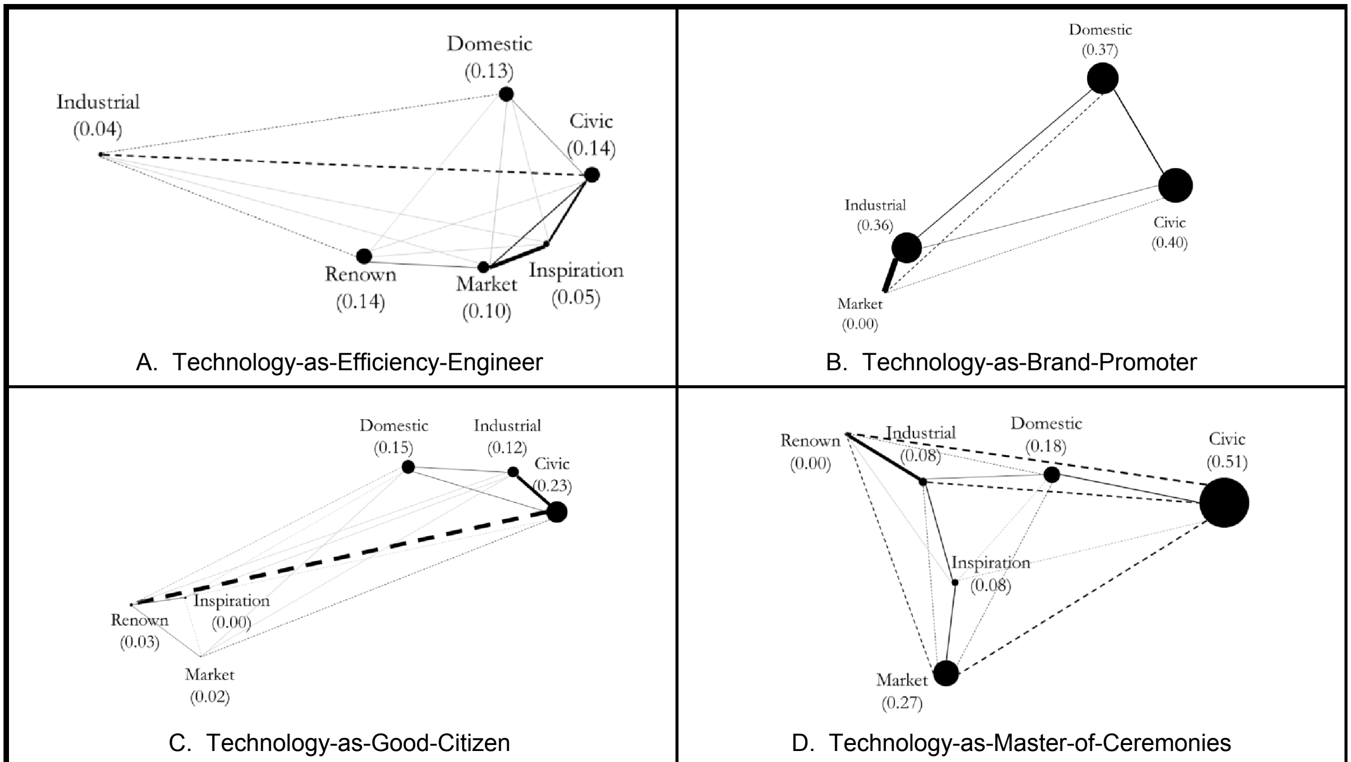
### *Step 3: Representing the Schemas Detected*

The graphical representation of schemas recommended by Goldberg depicts two characteristics of the relationships among variables in a schema. First, it depicts each variable's correlation with every other variable in the line joining pairs of nodes on a graph, where nodes represent variables (here, principles). Second, it depicts the extent to which each variable or node holds together other variables/nodes within the schema in the size of the nodes. The extent to which each variable holds together other variables is given by the weighted clustering coefficient (CC), which was computed using MS Excel as per Goldberg's footnote 22:

$$CC_i = \frac{2}{k_i(k_i - 1)} \sum_{j,k} (\tilde{w}_{ij}\tilde{w}_{jk}\tilde{w}_{ki})^{1/3}$$

where $w_{ij}$ is the correlation between nodes $i$ and $j$ (included only if positive),
$\tilde{w}_{ij} = w_{ij} / \max(w_{ij})$, and
$k_i$ is the degree of node $i$.

The resulting graphs for the four schemas are presented in Figure C2.




**Legend:** *Node size* represents CC (also depicted numerically); that is, the extent to which principle constrains pairings of other principles in justifying initiatives within a schema.
*Solid lines* represent positive correlation among principles; *dashed lines* represent negative correlations; *heavier lines* represent larger correlations; *darker lines* represent more significant correlations.

**Figure C2. Social Media Schemas (Organizing Visions-in-Use)**

*CC*—and node size—does not represent the relative prevalence of a variable in a schema, but rather its importance in holding together other variables within the schema. In other words, *CC* speaks to properties of *triads* within a schema, rather than dyads or nodes. Thus, while the *industrial* principle was invoked in every initiative in the *Technology-as-Efficiency-Engineer* schema, because no *two* other principles were consistently paired with it, the *CC* for the *industrial* principle is close to zero. Similarly, in the *Technology-as-Brand-Promoter* schema, while *every* initiative in the cluster invoked a *market* principle, because the *market* principle did not regularly occur with any two other principles, its *CC* is zero; in contrast, because when the *domestic* and *civic* principles occurred, they did so together and in conjunction with the *industrial* principle, we note substantial *CC*s for those principles. Of the sample initiatives in Figure C1, initiatives A and B reflected the *Technology-as-Efficiency-Engineer* schema; C through F reflected the *Technology-as-Master-of-Ceremonies* schema.

# Appendix D

## Illustrations of the Business Use Cases

Table D1 illustrates each of the ten business use cases comprising the four schemas with excerpts drawn from initiatives representing the use case.

**Table D1. Illustrations of the Ten Business Use Cases**

| Business Use Cases | Initiative (Number of Texts)[†] | Principle::Codes:= Associated Keywords |
|---|---|---|
| *Technology-as-Efficiency-Engineer* | | |
| GENERIC EFFICIENCY (*industrial* principle) | **IBM's Analytics initiative** (60)<br>"Using content analytics, an organization can *take a deeper look* at data *obtained from* external sources such as ... *blogs*" (press release 10/26/2009)<br>"An IBM *analysis* of blog posts, Tweets, news sites and other social media in the United States indicates that fewer travelers expect to cancel their Memorial Day Holiday trips this year compared with last year" (press release 5/27/2011)<br>IBM views social media as a data source that contributes to efficiency by informating organizations. | ***industrial::****take a deeper look:*= analyze; *obtained from … blogs*:= ability; *analysis:*= analyze |
| | **Wellpoint's Physician Review initiative** (1)<br>"To *make information* on the cost and quality of health care *more transparent*, we ... partnered with Zagat Survey® to develop an online tool that *enables* members *to rate* their physician experiences" (annual report 2007)<br>Wellpoint views social media as enhancing efficiency by facilitating processes through which their customers garner business intelligence and patients rate health-care providers. | ***industrial::****make information … more transparent* := ability; *enables…to rate*:=ability |
| INSPIRED EFFICIENCY (*industrial* paired with *nspiration* principle) | **Verizon's Idea Exchange initiative** (2)<br>"Verizon has *launched* a new *Idea* Exchange in its online community ... that offers community members an opportunity to *suggest* product *innovations* ... and to *comment* on suggestions by members' peers ... *votes* by community members *move* top suggestions to the company's product development teams for further review." (news release 10/7/2010)<br>Verizon views social media as instrumental in engineering efficiency by facilitating an innovation process. | ***industrial::****launched* := method; *comment*:= feedback; *votes … move*:= tool;<br>***inspiration::****Idea* := discover; *suggest innovations* := innovative |
| | **Lowe's "Dr. Maya Angelou's Garden Party" initiative** (1)<br>"Here are *ways to take* elements and *tips* from Dr. Maya Angelou's Garden Party ... start *following* @DrMayaAngelou on Twitter today…" (news release 5/20/2010)<br>Lowe discusses social media as a process for diffusing innovations. | ***industrial::****ways to take*:= tool; *following*:=tool;<br>***inspiration::****tips*:= insight |

| Table D1. Illustrations of the Ten Business Use Cases (Continued) | | |
|---|---|---|
| **Business Use Cases** | **Initiative (Number of Texts)†** | **Principle::Codes:= Associated Keywords** |
| CULTURAL EFFICIENCY (*industrial* paired with *domestic* principle, optionally with *inspiration* and/or *market* principles) | **Bank of America's "Express Your Thanks" campaign** (2)<br>"…*upload* a picture via Instagram or Twitter and *tag* it with #troopthanks … the images *uploaded* to the website will be *turned* into a *patriotic* digital mosaic" (news release 9/13/2012)<br>"…*thank* our troops … on *Veterans Day*" (news release 11/12/2012)<br>Bank of America discusses social media as instrumental in engineering efficiency by facilitating observation of cultural traditions. | ***industrial::****upload…tag*:= tool;<br>***domestic::****turned patriotic*:= tradition;<br>*Veterans Day*:= tradition;<br>*thank* := manners |
| | **Walmart's "Lucky in Love Wedding Search" initiative** (1)<br>"Liz surprised Duwayne by *proposing* to him *on her blog*" (news release 6/21/2007)<br>Walmart highlights social media as the tool by which another cultural tradition could be enacted. | ***domestic::****proposing*:= tradition;<br>***industrial::****…on her blog*:= tool |
| ***Technology-as-Brand-Promoter*** | | |
| CONVEN-TIONAL PROMOTION (*industrial* paired with *market* principle) | **Procter & Gamble's "New Gillette Fusion" campaign** (1)<br>"More than 130,000 *product* samples were distributed to men using popular social networking sites, websites and blogs, and consumers were encouraged to *share* their *reviews* with others" (news release 6/8/2010)<br>P&G spotlight social media as a way of promoting a product. | ***market::****product* := product;<br>***industrial::****share … reviews*:= feedback |
| | **Target's "Black Friday Deals" initiative** (1)<br>"Guests also have the chance to *receive* a *$500 GiftCard through* Target's Twitter account…" (news release 11/21/2011)<br>Target discusses social media use to promote a seasonal sales initiative. | ***industrial::****receive… through*:= tool;<br>***market::****$500 GiftCard* := prize |
| CULTURAL PROMOTION *(industrial* paired with *market* principle, optionally with *civic* and/or *domestic* principles) | **Dell's "The Perfect Gift" initiative** (1)<br>"For the first time ever, *holiday gifters* can *purchase* and *send* personalized Dell e*Gift* Cards *through* Facebook Connect" (news release 11/22/2011)<br>Dell presents social media as instrumental in promoting the Dell product line through a cultural tradition. | ***domestic::****holiday* := tradition; *gifters* := gift;<br>***market::****purchase* := buy;<br>***industrial::****send ... through*:= tool |
| | **Pepsi's "Start With Substance" initiative** (1)<br>"As our *culture* evolves, so do the habits of *consumers*. They are *connecting online* via social networks, *sharing* pictures and stories on Facebook® and *following* events and news via their friends on Twitter.® To *compete* in this space, we are … building a community of digitally savvy associates who are using social media to *connect* with one another and *draw* us and our *brands* into the *cultural* conversation.<br>"Our *brands* are building connections with digital influencers to further our *cultural relevance*. Early in 2009, Quaker launched the Start with Substance campaign, where Americans who ate a *nutritious*, *affordable* breakfast of Quaker Oatmeal could also 'fuel it forward' to *less fortunate families*. For every *purchase* of Quaker hot cereal recorded at the Start with Substance Facebook page, Quaker *donated* one bowl of wholesome oatmeal … to the organization Share Our Strength." (annual report 2009)<br>Pepsi references culture in promoting their products via social media. | ***domestic::****culture*:= tradition; *cultural*:= tradition;<br>*families*:= family;<br>*donate*:=help;<br>***market::****consumers*:= buy;<br>*compete* := competition;<br>*brands*:= product;<br>*affordable:* =value;<br>*purchase*:=buy;<br>***industrial::****connecting online*:= tool; *sharing*:= tool;<br>*following*:= tool; *draw*:= ability;<br>***civic::****connect*:= solidarity;<br>*nutritious*:=collective good;<br>*less fortunate*:= solidarity |

**Table D1. Illustrations of the Ten Business Use Cases (Continued)**

| Business Use Cases | Initiative (Number of Texts)† | Principle::Codes:= Associated Keywords |
|---|---|---|
| ***Technology-as-Good-Citizen*** | | |
| SOCIAL RESPON-SIBILITY (*civic* paired with *industrial* principle, optionally with *domestic* principle) | **Pfizer's "GetOld" initiative** (2)<br>"At the center of the initiative is a first-of-its-kind online community, GetOld.com , where people can *get and share* information, *add to the dialogue* and *contribute* to the growing body of knowledge about this important topic. This critical information will help inform the *unmet needs related to aging* and what role the company and its partners can play to *help people* live longer and better lives." (news release 6/18/2012)<br>Pfizer invoked the *civic*, *domestic*, and *industrial* principles, using social media to build knowledge regarding issues related to aging. | ***industrial::****get and share*:= tool; *add to the dialogue*:=ability; *contribute*:=ability; ***civic::****unmet needs related to aging*:= collective good; ***domestic::****help people*: = help |
| | **AT&T's "It Can Wait" initiative** (12)<br>"AT&T's 'It Can Wait' campaign launched in March 2010, and to date, more than 21,600 consumers have taken the pledge *not to text and drive* on AT&T's Facebook page, in addition to more than 16,700 AT&T employees *through* its internal social media channel" (news release 12/27/2010)<br>AT&T discusses using social media to disseminate information and educate the public on the dangers of texting while driving. | ***civic::****pledge not to text and drive*:= collective action; ***industrial::****through*:=tool |
| ***Technology-as-Master-of-Ceremonies*** | | |
| GENERIC DISTINCTION (*renown* paired with *industrial* principle) | **Kraft's "Triple Double Oreo" initiative** (1)<br>"OREO *fans* were *buzzing through*out social media about this new take on the *iconic* cookie" (news release 8/17/2011)<br>Kraft discusses using social media as a vehicle for spotlighting the popularity of their product. | ***renown::****fans*:=popular; *buzzing*:= recognition; *iconic*:=reputed; ***industrial::****buzzing through*:=tool |
| | **General Electric's Blissdom '11** (1)<br>"To introduce the new 'Overnight Ready' feature, GE …welcomed some of the most *influential* women in our culture - mommy *blog*gers" (news release 2/7/2011)<br>GE suggests that social media can be a tool to gain influence. | ***renown::****influential*:= attention; ***industrial::****blog*:= tool |
| MATERIAL DISTINCTION (*renown* principle, optionally with *industrial*, *inspiration*, and/or *market* principles) | **Boeing's "Opportunity of a Lifetime"** (1)<br>"…Dr. Jeremy Hampton, an aviation enthusiast and amateur photographer who is also an emergency medicine specialist at Kansas City's Truman Medical Center and assistant professor at the University of Missouri - Kansas City School of Pharmacy, will be Boeing's guest at the debut of the *newest* 747 passenger plane, the 747-8 Intercontinental... Dr. Hampton *came to* Boeing's *attention* when he *posted* his photos on The Boeing Store's Facebook page.... 'We are trying to find a few *unique* opportunities during each year for some of the more than 73,000 fans we have on our Facebook page to engage with Boeing,' said Director of Brand Management & Advertising"<br>Boeing discusses social media as enabling them to pay attention to their fans. | ***renown::****attention*:= attention; ***industrial***::*came to…attention*:=enable; *posted*:=tool; ***inspiration::*** *newest:=innovative; unique*:= unique; |
| | **Ford's "Fiesta Movement" initiative** (28)<br>"The Ford Fiesta also is *gaining attention* on Facebook and Twitter, with more than 300 *fans* on the Fiesta Movement Facebook fan page and more than 600 *followers* on the @FordFiesta Twitter account … 100 young trendsetters will test drive and … then *relate* their experiences *through* a variety of social media sites … Consumers … use social media daily and offer a prime *opportunity* for Ford to tap into a group that hasn't yet established *brand* loyalty" (news release 4/7/2009)<br>Ford discusses promoting both its product and its popularity via social media. | ***renown::****gaining attention*:=attention; *fans*:=popular; *followers*:= popular; ***industrial::****relate … through*:= tool; ***market::****opportunity*:= opportunism; *brand*:= product |

**Table D1. Illustrations of the Ten Business Use Cases (Continued)**

| Business Use Cases | Initiative (Number of Texts)† | Principle::Codes:= Associated Keywords |
|---|---|---|
| CULTURAL DISTINCTION (*civic* and/or *domestic* paired with *industrial* and/or *renown* principles) | **Kroger's "Stuff the School Bus"** (1)<br>"Texans running back Arian Foster and Kroger…, both *leaders* in their respective industries, are *teaming* up to roll out programs targeted to local *families*, *schools* and *communities*... *To stay in the loop* about upcoming *contests*, *community* programs and special events involving Foster, *follow* Kroger on Facebook and Twitter." (news release 8/9/2012)<br>Kroger uses a cultural icon, Arian Foster, to promote the cause of helping students begin school with the necessary supplies. | ***domestic::****families*:= family; ***civic::****schools*:=educate; *communities*:= community; ***industrial::****To stay in the loop … follow*:=tool; ***renown::****leaders*:=fame; |
| | **Johnson & Johnson's "BABY CARES"** (1)<br>"A way to ensure *every baby has a healthy and happy start* in life,... the JOHNSON'S® BABY CARES campaign kicks off by leveraging the support of *actress* and new mom Hilary Duff to assemble 'Care Kits' that will be *distributed* to *families in times of natural disasters*. Consumers are encouraged to *support* the *charitable* platform *by visiting* the JOHNSON'S® BABY CARES tab on the JOHNSON'S® Baby Facebook page." (news release 4/12/2012)<br>J&J discusses using social media to alleviate community problems. | ***civic::****every baby has a healthy and happy start*:= collective good; *distributed …in times of natural disasters*:=solidarity; *charitable*:=collective good; ***renown::****actress*:= fame; ***industrial::****support… by visiting*:=enable; ***domestic::****families*:=family |
| CAUSE-RELATED MARKETING (*civic* and/or *domestic* principles paired with *market* principle, optionally with *industrial* and/or *renown*) | **Walgreens's "Walk with Walgreens"** (3)<br>"Walgreens ( www.walgreens.com/walk ) is an online community and digital platform that *enables* members to log the steps they take and get rewards, in the form of weekly *coupons*, redeemable at Walgreens stores nationwide. Participants can also *learn* about the *health benefits* of walking, set walking goals, find local *community* walks and share content and information with *family* and *friends* through the site." (news release 4/6/2011)<br>"With more than 4 billion steps logged by Walk with Walgreens participants in the program's first year, Walgreens tonight teamed up with Donald Trump and The *Celebrity* Apprentice® to promote more healthy steps in 2012." (news release 4/2/2012)<br>Walgreens discusses promoting habits beneficial to the public by offering monetary savings. | ***industrial::****enables*:= ability; ***market::****coupons*:=deal; ***civic::****learn*:=educate; *health benefits*:=collective good; *community*:= community; *friends*:=community ***domestic::****family*:=family; ***renown::****Celebrity*:=fame |
| | **Best Buy's "@15 Exchange" initiative** (16)<br>"By participating in activities on www.at15.org , such as *creating* a profile…inviting a friend to @15 or *writing* a *blog post* on a key issue, *teens* can *earn* Change Exchange points. Each quarter, *teens*' points will be converted into real *donation* dollars up to $250,000, and participants will be invited to *donate* their dollars to one of four *nonprofit* partner organizations focused on *social change*." (news release 2/2/2009)<br>"…the @15 Web site, along with its social networking pages and YouTube channel, will *feature messages* from *teens* engaged in Best Buy programs, *celebrities* and musicians and Members of Congress" (news release 7/2/2009)<br>Best Buy discusses invoking the public's acquisitiveness for the collective good. | ***industrial::****writing a blog post*:=tool; *feature messages*:=tool; ***domestic::****teens*:= generations; *donation*:=help; *donate*:=help; *nonprofit:*= benevolence; ***market::****earn*:= pay; ***civic::****social change:*= collective action; ***renown::****celebrities*:=fame |

†Italics in quotes highlight codes associated with keywords signaling principles.

# Appendix E

## What Is Meant By Diffusion?

There are two perspectives on what "diffusion" means. The original perspective focuses on adoption (Rogers 2010). Some researchers have argued this *diffusion-as-adoption* perspective is incomplete in the context of organizational innovations because it ignores post-adoptive use. For example, Fichman (1992, pp. 196-197) noted: "While much of classical diffusion theory is still applicable to adoption of innovations by organizations…the organizational adoption of an innovation is not typically a binary event, but rather, one stage in a process that unfolds over time." Zhu and Kraemer (2005, p. 62) observed that "we need to view ebusiness diffusion as a multistage process that starts at adoption and extends to usage." In this view, adoption and use are two essential steps in diffusion of organizational innovations. Table E1 summarizes MIS research based on this alternate *diffusion-as-use* perspective.

For the benefit of readers who strongly subscribe to the *diffusion-as-adoption* perspective, we attempt to quantify the initiatives in our dataset representing a *diffusion-as-adoption* perspective versus a *diffusion-as-use* perspective. To do so, we draw upon Cool et al.'s (1997, p. 552) approach of treating "each adopting unit as a social system where diffusion of the innovation occurs." The key indicator of the extent to which the phenomenon underlying our study is *diffusion-as-adoption* versus *diffusion-as-use* lies in *the extent to which distinct groups of social actors were involved with each initiative* in our study. If social actors were associated with multiple initiatives, we would characterize their first use as adoption of the technology and subsequent use as use (Cooper and Zmud 1990). If more-or-less distinct sets of actors were associated with the initiatives, we would characterize each use as adoption. We develop these estimates by examining the networks of social actors surrounding a few initiatives in our sample.

**Table E1. Summary of MIS Research based on Diffusion-as-Use Perspective**

| Authors (Year) | Diffusion Construct: Conceptualization | Diffusion Construct: Operationalization |
|---|---|---|
| Zmud (1982) | Initiation, adoption, implementation | *Initiation*: extent of each practice currently being applied<br>*Adoption*: proportion of recognized practices in use beyond an experimentation stage<br>*Implementation*: average extent to which adopted practices were used |
| Zmud (1984) | Use | Extent to which each practice was used within organization |
| Cooper and Zmud (1990) | Adoption, infusion | *Adoption*: whether MRP was adopted<br>*Infusion*: extent to which MRP is used to its fullest potential |
| Nilakanta and Scamell (1990) | Initiation, adoption, implementation | *Initiation*: # of DB design methods recognized by the designer<br>*Adoption*: the proportion of recognized DB design methods in use beyond an experimentation stage<br>*Implementation*: average extent to which adopted methods were being used |
| Premkumar et al. (1994) | Adaptation, infusion | *Adaptation*: extent of initial use of EDI<br>*Internal diffusion (infusion)*: extent of integration of EDI into organizational activities<br>*External diffusion (infusion)*: extent of external EDI partners and EDI transaction documents |
| Purvis et al. (2001) | Assimilation | Percentage of projects that had used the CASE technology for at least 25% of the information systems tasks within those projects. |
| Zhu and Kraemer (2005) | Use | Extent of e-business use |
| Zhu, Dong et al. (2006) | Use | Extent of e-business use |
| Zhu, Kraemer, and Xu al. (2006) | Assimilation (initiation, adoption, routinization) | *Initiation*: how the potential benefits of e-business were rated before the firm began using e-business.<br>*Adoption*: whether the firm had used the Internet for each of the seven value chain activities (aggregated measure)<br>*Routinization*: extent of organizational usage of e-business to support value chain activities |

Prior to examining actors associated with initiatives, we note two things. First, recall that our unit of analysis is the social media initiative. To develop our observations, our sampling frame was the top 50 Fortune firms in 2011. However, the social actors involved with the various initiatives and constituting the community of actors producing and appropriating the social media organizing vision were members of firms from the sampling frame as well as actors external to those firms. Recognizing all actors associated with initiatives sampled—not only those internal to the firms in the sampling frame—provides a more comprehensive picture of diffusion of social media across the community. Thereafter, we are able to analyze the entire set of actors identified or restrict analysis to community members internal to the sampled firms. In either case, we can view an initiative as the nexus of a network of social actors. Second, note that diffusion theory allows for some overlap across the networks of actors associated with different initiatives. Ideas about an innovation diffuse as an actor associated with one initiative (a bridge) spawns another initiative with an actor network relatively distinct from that associated with the earlier initiative (Strang and Soule 1998). Thus, as technology diffuses, we would necessarily anticipate some overlap among the networks of social actors around the initiatives. A single tie across groups of social actors represents a minimum condition for diffusion of the underlying innovation. However, the presence of multiple ties across such groups enhances diffusion (Centola 2010). We offer a stylized representation of such diffusion-as-adoption in Figure E1. (All network visuals are constructed with NodeXL [Smith et al. 2010]).

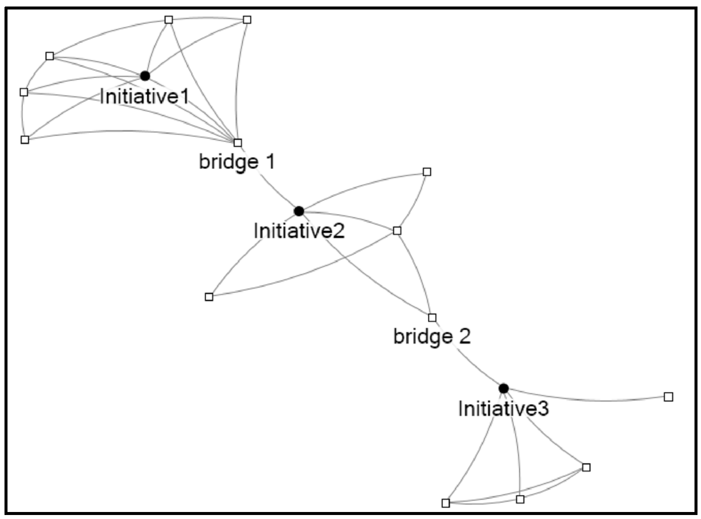
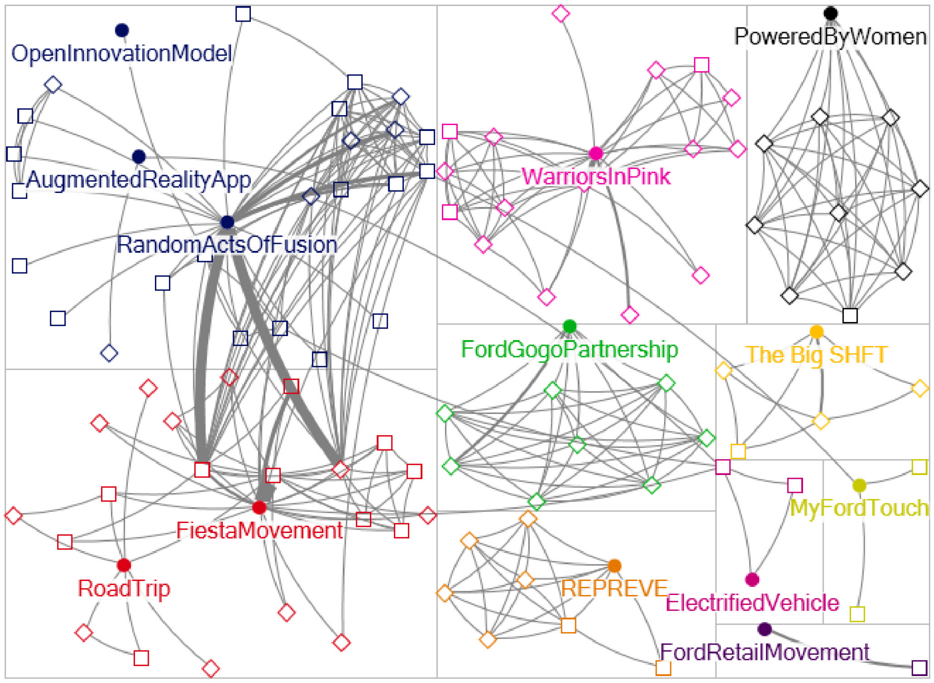



**Figure E1. Stylized Representation of *Diffusion-as-Adoption* Networks for Initiatives**

The question of whether initiatives in our study represent *diffusion-as-adoption* or *diffusion-as-use* then may be resolved by comparing our data to this stylized network. Specifically, what we wish to see is weakly linked (bridged) clusters of densely interconnected actors grouped around initiatives, with as many clusters as initiatives (Centola 2010). To what extent does our data resemble groups of actors clustered around initiatives as depicted in Figure E2?

To address this question, we drew a random sample of 15 (of 59) social media initiatives launched by the Ford Motor Company. Sampling from a single firm rather than from across all firms in our dataset increased the likelihood of observing ties across initiatives. For each of the 15 initiatives, we searched ABInform and LexisNexis for newspaper and magazine articles on the initiatives. From these articles and Ford's news releases (in our data set) describing the initiatives, we identified actors involved with launching the initiatives. These actors included executives, managers, and designers from Ford; consulting and market research agencies (e.g., Undercurrent and Ipsos); advertising agencies (e.g., TeamDetroit); entertainment companies (e.g., FOX and MTV); and beneficiaries of Ford's philanthropy (e.g., Susan G. Komen). We coded actors as associated with an initiative and with each other when mentioned together in an article or press release. We summarize these initiatives in Table E2.

News releases and articles for two of the initiatives provided no information about actors associated with them and were excluded from the analysis. Of the 40 Ford actors identified across the remaining 13 initiatives, 32 (80%) participated in only a single initiative. Of the 54 non-Ford actors participating in the initiatives, two (TeamDetroit and FOX Entertainment) participated in more than a single initiative (two each). In all, 89 percent of the actors (84 of the 94) identified across the 13 initiatives were unique to one initiative.




**Legend:** ● Initiative ☐ Ford actor ◇ External actor
Line thickness: number of texts mentioning actor/actor-initiative pairs (tie strength)
Node colors and boxes: distinct clusters of actor/actor-initiative pairs

**Figure E2. Actor Networks Around the Sample of Ford Initiatives**

**Table E2. Summary Characteristics of Sample of Ford Social Media Initiatives**

| Initiative | Start Date | News Releases | Articles | Actors | |
|---|---|---|---|---|---|
| | | | | Total | Unique to Initiative |
| Fiesta Movement | 2/20/2009 | 28 | 9 | 20 | 12 |
| You Speak Green | 9/9/2009 | 2 | 0 | NA | NA |
| Road Trip | 10/8/2009 | 3 | 4 | 7 | 5 |
| Open Innovation Model | 4/13/2010 | 1 | 0 | 1 | 0 |
| Ford Retail Movement | 6/24/2010 | 1 | 2 | 1 | 1 |
| MyFord Touch | 9/9/2010 | 1 | 4 | 3 | 2 |
| Warriors in Pink | 10/6/2010 | 2 | 13 | 16 | 16 |
| Ford-Gogo Partnership | 2/2/2011 | 1 | 2 | 8 | 8 |
| Electrified Vehicle | 2/23/2011 | 1 | 0 | 2 | 1 |
| Pickup Comparison | 9/28/2011 | 1 | 0 | NA | NA |
| Augmented Reality App | 12/13/2011 | 1 | 1 | 2 | 1 |
| Random Acts of Fusion | 4/2/2012 | 11 | 10 | 25 | 18 |
| The Big SHFT | 4/18/2012 | 1 | 2 | 4 | 4 |
| REPREVE | 5/3/2012 | 1 | 2 | 7 | 7 |
| Powered By Women | 6/6/2012 | 1 | 0 | 9 | 9 |
| *Total actors* | | | | 94 | |
| *Actors appearing in single initiative* | | | | | 84 (89%) |

To determine the extent to which independent networks of actors were associated with each initiative, we cluster analyzed the overall network of actors associated with the 13 initiatives. Clustering algorithms partition a network by maximizing the ratio of ties within clusters to the ties across clusters. Three different clustering algorithms identified between 13 clusters, suggesting independent sets of actors across the 13 initiatives, and 10 clusters, suggesting shared actors for some initiatives as depicted in Figure E2.[1] Therefore, a conservative estimate of the number of initiatives comprising relatively unique sets of actors (in other words, initiatives reflecting first-time use or *diffusion-as-adoption*) is 77 percent (i.e., 10 out of 13), with 23 percent of initiatives in this sample representing *diffusion-as-use*. Examining the network constituted solely by Ford actors revealed similar results: the most conservative clustering algorithm suggested 10 of the 12 initiatives (83%) represent *diffusion-as-adoption* and two represent *diffusion-as-use*.

We summarize estimated proportions of initiatives in our data representing *diffusion-as-adoption* versus *diffusion-as-use* in Table E3. Based on the four criteria, we estimate 77 percent to 89 percent of initiatives represented *diffusion-as-adoption* and 11 percent to 23 percent represented *diffusion-as-use*. Therefore, researchers subscribing to the stricter *diffusion-as-adoption* perspective may be assured that the majority of our data represent *diffusion-as-adoption*.

**Table E3. Summary of Estimated Percentages of Diffusion-as-Adoption/Use**

| Criterion | Estimated Percentage of Initiatives Representing | |
|---|---|---|
| | **Diffusion-as-Adoption** | **Diffusion-as-Use** |
| Unique actors | 89% | 11% |
| Unique internal actors | 80% | 20% |
| Clusters-to-initiative ratio (all actors) | 77% | 23% |
| Clusters-to-initiative ratio (internal actors) | 83% | 17% |

[1]Further details regarding this analysis are available from the authors.

# Appendix F

## Theoretical Elaboration of Diffusion Antecedents

Glaser and Strauss (1980) recommended comparing simple and partial correlations to discover the structure of multivariate relationships that constitute a causal model (i.e., mediator and suppressor[2] effects) (Cheung and Lau 2008). First, we compared simple and partial correlations to confirm the *curvilinear* relationships of coherence, continuity, and clarity with diffusion observed in the scatterplot matrices. Table 5 in the article provides evidence of nonlinear effects: while none of the simple correlations between each of the three facets and diffusion was significant in any of the four quarterly periods, every partial correlation was significant when both the linear and squared terms were included simultaneously. Second, we wished to determine whether each facet *mediated* effects of other facets. A mediator is "the generative mechanism through which the focal independent variable is able to influence the dependent variable of interest" (Baron and Kenny 1986, p. 1173). Statistically, two facets related to each other and with diffusion (baseline correlations) and the relationship between one facet and diffusion diminishing considerably in the presence of the other (partial correlations) would be indicative of mediation. We consider possible mediators in Table F1.

**Table F1. Exploring Facets as Mediators†**

| Vision Facets | Diffusion in Subsequent | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1st Quarter | | 2nd Quarter | | 3rd Quarter | | 4th Quarter | |
| | Baseline *r* | Partial *r* | Baseline *r* | Partial *r* | Baseline *r* | Partial *r* | Baseline *r* | Partial *r* |
| ***Step 1: Concurrent Effects of Coherence² and Continuity²*** | | | | | | | | |
| Coherence | 0.2963* | 0.2296+ | 0.4000* | 0.3417* | 0.4080* | 0.3575* | 0.3384* | 0.2950* |
| Coherence² | -0.3132* | -0.2132+ | -0.3900* | -0.3176* | -0.3973* | -0.3231* | -0.3545* | -0.2804* |
| Continuity | 0.4206* | 0.3735* | 0.3611* | 0.2962* | 0.3406* | 0.2786* | 0.3068* | 0.2410+ |
| Continuity² | -0.4313* | -0.3808* | -0.3485* | -0.2847* | -0.3375* | -0.2827* | -0.3254* | -0.2598* |
| ***Step 2: Concurrent Effects of Coherence² and Clarity²*** | | | | | | | | |
| Coherence | 0.2963* | 0.1214 | 0.4000* | 0.3016* | 0.4080* | 0.2482* | 0.3384* | 0.2214+ |
| Coherence² | -0.3132* | -0.0352 | -0.3900* | -0.2052 | -0.3973* | -0.0980 | -0.3545* | -0.1518 |
| Clarity | 0.4321* | 0.4114* | 0.2365* | 0.1938 | 0.3575* | 0.3893* | 0.2365* | 0.2635* |
| Clarity² | -0.4423* | -0.4112* | -0.2449* | -0.2020 | -0.3689* | -0.4032* | -0.2449* | -0.2662* |
| ***Step 3: Concurrent Effects of Coherence² and Diversity*** | | | | | | | | |
| Coherence | 0.2963* | -0.0655 | 0.4000* | 0.1222 | 0.4080* | 0.0947 | 0.3384* | 0.0360 |
| Coherence² | -0.3132* | 0.1551 | -0.3900* | -0.0188 | -0.3973* | 0.0174 | -0.3545* | 0.0402 |
| Diversity | 0.4212* | 0.4526* | 0.3202* | 0.3169* | 0.3438* | 0.3623* | 0.3926* | 0.3460* |
| ***Step 4: Concurrent Effects of Continuity² and Clarity²*** | | | | | | | | |
| Continuity | 0.4206* | 0.3356* | 0.3611* | 0.2927* | 0.3406* | 0.2417+ | 0.3068* | 0.2262+ |
| Continuity² | -0.4313* | -0.3355* | -0.3485* | -0.2564* | -0.3375* | -0.2127 | -0.3254* | -0.2323+ |
| Clarity | 0.4321* | 0.3589* | 0.2365* | 0.1513 | 0.3575* | 0.2927* | 0.2365* | 0.2571+ |
| Clarity² | -0.4423* | -0.3531* | -0.2449* | -0.1623 | -0.3689* | -0.3035* | -0.2449* | -0.2568+ |
| ***Step 5: Concurrent Effects of Continuity² and Diversity*** | | | | | | | | |
| Continuity | 0.4206* | 0.2467* | 0.3611* | 0.1937 | 0.3406* | 0.1707 | 0.3068* | 0.1327 |
| Continuity² | -0.4313* | -0.2212+ | -0.3485* | -0.1483 | -0.3375* | -0.1339 | -0.3254* | -0.1161 |
| Diversity | 0.4212* | 0.2561* | 0.3202* | 0.2444+ | 0.3438* | 0.2555* | 0.3926* | 0.2680* |

[2]Suppressors are variables which, when accounted for, reveal the true relationship between the predictor and criterion variables (Tzelgov and Henik 1991).

**Table F1. Exploring Facets as Mediators (Continued)†**

| Vision Facets | Diffusion in Subsequent 1st Quarter | | 2nd Quarter | | 3rd Quarter | | 4th Quarter | |
|---|---|---|---|---|---|---|---|---|
| | Baseline *r* | Partial *r* | Baseline *r* | Partial *r* | Baseline *r* | Partial *r* | Baseline *r* | Partial *r* |
| ***Step 6: Concurrent Effects of Coherence², Continuity², and Clarity²*** | | | | | | | | |
| Coherence | 0.2963* | 0.0997 | 0.4000* | 0.2704* | 0.4080* | 0.2241+ | 0.3384* | 0.2138 |
| Coherence² | -0.3132* | -0.0125 | -0.3900* | -0.1842 | -0.3973* | -0.0797 | -0.3545* | -0.1427 |
| Continuity | 0.4206* | 0.3186* | 0.3611* | 0.2588* | 0.3406* | 0.2051 | 0.3068* | 0.1927 |
| Continuity² | -0.4313* | -0.3321* | -0.3485* | -0.2390+ | -0.3375* | -0.1991 | -0.3254* | -0.2158 |
| Clarity | 0.4321* | 0.3677* | 0.2365* | 0.1338 | 0.3575* | 0.3492* | 0.2365* | 0.2259+ |
| Clarity² | -0.4423* | -0.3584* | -0.2449* | -0.1438 | -0.3689* | -0.3618* | -0.2449* | -0.2192 |
| ***Step 7: Concurrent Effects of Coherence², Continuity², and Diversity*** | | | | | | | | |
| Coherence | 0.2963* | -0.0270 | 0.4000* | 0.1348 | 0.4080* | 0.1086 | 0.3384* | 0.0590 |
| Coherence² | -0.3132* | 0.1028 | -0.3900* | -0.0528 | -0.3973* | -0.0103 | -0.3545* | 0.0132 |
| Continuity | 0.4206* | 0.1564 | 0.3611* | 0.1397 | 0.3406* | 0.0947 | 0.3068* | 0.0668 |
| Continuity² | -0.4313* | -0.1520 | -0.3485* | -0.1207 | -0.3375* | -0.0882 | -0.3254* | -0.0735 |
| Diversity | 0.4212* | 0.3047* | 0.3202* | 0.2018 | 0.3438* | 0.2545+ | 0.3926* | 0.2426+ |
| ***Step 8: Concurrent Effects of Continuity², Coherence², Clarity², and Diversity*** | | | | | | | | |
| Coherence | 0.2963* | -0.1147 | 0.4000* | 0.1043 | 0.4080* | 0.0288 | 0.3384* | 0.0151 |
| Coherence² | -0.3132* | 0.2060 | -0.3900* | -0.0076 | -0.3973* | 0.1092 | -0.3545* | 0.0672 |
| Continuity | 0.4206* | 0.1115 | 0.3611* | 0.1225 | 0.3406* | 0.0470 | 0.3068* | 0.0340 |
| Continuity² | -0.4313* | -0.1201 | -0.3485* | -0.1006 | -0.3375* | -0.0369 | -0.3254* | -0.0488 |
| Clarity | 0.4321* | 0.3631* | 0.2365* | 0.1204 | 0.3575* | 0.3428* | 0.2365* | 0.2156 |
| Clarity² | -0.4423* | -0.3475* | -0.2449* | -0.1271 | -0.3689* | -0.3519* | -0.2449* | -0.2051 |
| Diversity | 0.4212* | 0.3075* | 0.3202* | 0.1859 | 0.3438* | 0.2340+ | 0.3926* | 0.2373+ |

†Baseline *r* is simple *r* for diversity and partial *r* for coherence, continuity, and clarity; +p < 0.10; *p < 0.05

Because we wished to situate the two new facets within a theoretical model of the two previously identified facets and diffusion, we first considered coherence and continuity. In Step 1 in Table F1, we notice that partial correlations for both coherence and continuity diminish in the presence of the other, but in most cases remain significant. We therefore cannot conclude either coherence or continuity mediates the effect of the other on diffusion.

Next, we systematically investigated changes to the incumbent diffusion path model by introducing each of the two new facets with each of the incumbent facets separately and then together. In Step 2, we notice that the partial correlations for coherence diminish when accounting for clarity. This, together with the significant simple correlation between coherence and clarity ($r = 0.69$, $p < 0.001$), suggests that clarity might mediate the effects of coherence on diffusion. In Step 3, we notice that partial correlations of the linear and the squared coherence terms with diffusion across all quarters diminish when accounting for diversity. This suggests that diversity mediates the effects of coherence on diffusion.

In Step 4, when accounting for both sets of terms for continuity and clarity, we find all partial correlations with diffusion in the first and fourth subsequent quarters remain significant; the partial correlations for clarity with diffusion in the second quarter were insignificant; the partial correlation for the squared continuity term with diffusion in the third quarter was insignificant. In this step, we lack clear evidence of mediation of continuity by clarity or vice versa. In Step 5, the partial correlations of both continuity terms with diffusion in the first quarter diminished, but remained significant after accounting for diversity; the partial correlations between the continuity terms and diffusion in the next three quarters was insignificant after accounting for diversity. This suggests diversity mediates the effects of continuity on diffusion.

In Step 6, once again we note that after accounting for clarity, the partial correlations between coherence and diffusion frequently diminish to insignificance, again suggestive of clarity mediating effects of coherence on diffusion. In Step 7, we observe all partial correlations for both coherence and continuity to diminish to insignificance in the presence of diversity. Together with the correlation between coherence and diversity ($r = -0.63$, $p < 0.001$) and continuity and diversity ($r = -0.38$, $p < 0.01$), this suggests that diversity mediates effects of both coherence and continuity on diffusion. Finally, in Step 8, we note the partial correlations for clarity and diversity generally remain significant in each other's presence and in the presence of the remaining facets for two of the four quarterly periods, suggesting these two facets do not mediate each other's effects on diffusion.

Because we observed diversity to mediate the effects of continuity on diffusion, we needed to confirm the curvilinear form of the association between continuity and diversity observed in Figures 4 and 5. In Table F2, we note that while the simple correlations between diversity and the linear and squared continuity terms were significant, the partial correlations were substantially higher. Further, the partial correlation between diversity and the linear continuity term changed from negative to positive. We therefore are able to confirm the curvilinear form of the association between continuity and diversity. Similarly, because we observed diversity to mediate the effects of coherence on diffusion, we needed to confirm the curvilinear association between coherence and diversity observed in Figures 4 and 5. In Table F2, we note that while the simple correlations between diversity and the linear and squared coherence terms were significant, the partial correlations were somewhat higher. Further, the partial correlation between diversity and the linear continuity term changed from negative to positive. Therefore, we are able to confirm the curvilinear form of the association between coherence and diversity.

**Table F2. Confirming the Nonlinear Effects of Continuity and Coherence on Diversity**

| | Continuity | | Coherence | |
|---|---|---|---|---|
| **Term** | **Simple *r*** | **Partial *r*** | **Simple *r*** | **Partial *r*** |
| Linear | -0.2135+ | 0.5806* | -0.6289* | 0.6509* |
| Squared | -0.3284* | -0.6167* | -0.7594* | -0.7723* |

+p < 0.10; *p < 0.05

From Steps 3 and 4 of Table F1, we observe that diversity mediated associations of both the linear and squared coherence terms with diffusion in all quarters. In contrast, from Steps 2 and 6 of Table F1, we observe that clarity appears to mediate only the squared coherence term, but not the linear term. Further investigation of the mediation by clarity in Table F3, revealed the individual clarity terms to be insignificantly associated with diffusion when partialing coherence and coherence². Further, both coherence terms continued to be significantly associated with diffusion in all periods in the presence of either clarity or clarity², but not both. Therefore, we conclude that clarity does mediate the effects of coherence on diffusion *in toto*.

**Table F3. Exploring Mediation by Clarity†**

| | Diffusion in Subsequent | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 1st Quarter | | 2nd Quarter | | 3rd Quarter | | 4th Quarter | |
| **Vision Facets** | **Baseline *r*** | **Partial *r*** | **Baseline *r*** | **Partial *r*** | **Baseline *r*** | **Partial *r*** | **Baseline *r*** | **Partial *r*** |
| *Step 1: Coherence and Coherence² with Clarity* | | | | | | | | |
| Coherence | 0.2963* | 0.2977* | 0.4000* | 0.3962* | 0.4080* | 0.4023* | 0.3384* | 0.3373* |
| Coherence² | -0.3132* | -0.3073* | -0.3900* | -0.3610* | -0.3973* | -0.3583* | -0.3545* | -0.3377* |
| Clarity | -0.0748 | 0.0312 | -0.0563 | -0.0453 | -0.0821 | -0.0855 | -0.1020 | -0.0010 |
| *Step 2: Concurrent Effects of Coherence² and Clarity²* | | | | | | | | |
| Coherence | 0.2963* | 0.2903* | 0.4000* | 0.3888* | 0.4080* | 0.3911* | 0.3384* | 0.3305* |
| Coherence² | -0.3132* | -0.2799* | -0.3900* | -0.3382* | -0.3973* | -0.3241* | -0.3545* | -0.3146* |
| Clarity² | -0.1286 | -0.0280 | -0.0863 | -0.0737 | -0.1272 | -0.1422 | -0.1432 | -0.0398 |

†Baseline *r* is simple *r* for linear variables; for nonlinear variables, baseline r is the partial *r*; +p < 0.10; *p < 0.05

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