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Investigating Coordination Indicators in Epidemiological Surveillance for Influenza

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ABSTRACT

Containing infectious disease requires coordination among various epidemiology organizations on a global basis. Coordination at a global level is dependent epidemiological surveillance processes that, while under the management of local epidemiology departments, require the participation of a disparate group of non-epidemiologists. In this paper, the influenza virus is isolated to examine if strong analytic process coordination is occurring in practice for this annually reoccurring disease. Confirmatory factor analysis is utilized on 2,484 cases of influenza recorded during a 15-month timeframe in the epidemiological database of a local public health department. The results confirm the presence of four, primary constructs that underlie this analytical process. The results suggest that coordination conflict is substantial even with a cyclically, reoccurring disease. The analysis demonstrates how theory and methodology can intertwine to assist in identifying process coordination and conflict in epidemiological surveillance, and support the application of this analysis approach to other analytical processes.

Keywords

Coordination, confirmatory factor analysis, covariance-based SEM, epidemiological surveillance, influenza

INTRODUCTION

When communicable disease exists at a global level exceeding contemporary death tolerance, a pandemic warning is issued. In addition to the mortalities, the resulting illnesses can cripple economies by reducing necessary levels of work and procurement. Therefore, proper detection has social and economic importance to communities and organizations, leading to the research question: *With influenza occurring annually on a worldwide basis, is the epidemiological surveillance process occurring with strong analytics process coordination? How can we identify dimensions of analytics process coordination with respect to influenza epidemiological surveillance in a public health agency?*

On April 2, 2009, an outbreak of influenza was reported in La Gloria, Mexico (CNN Health, 2009). Veracruz state officials tested those afflicted to find all but one carried a common flu virus. By May 30, 2009, the disease had moved beyond Mexico, and there were 13,217 reported cases and 27 deaths in the United States (CDC, 2009). On June 11, 2009, following a total of 27,737 reported cases of H1N1 across 74 countries and 141 deaths (see Figure 1), the World Health Organization declared H1N1 a pandemic. At that time, Mexico reported the most fatalities (106), but the US comprised 48% of the total reported cases. As of November 2009, 6770 deaths have occurred globally (WHO 2009b).

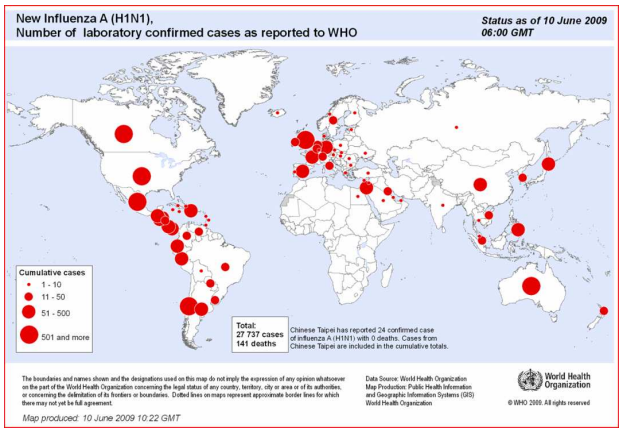

Figure 1: Global H1N1 Cases June 2009 (WHO 2009a)

The H1N1 pandemic will be the fourth pandemic in the last 100 years (HPA 2008). In 1918, the Spanish flu resulted in over 50 million reported deaths, exceeding the deaths attributed to World War I. The second pandemic, called the Asian flu, resulted in at least 1 million deaths. The Hong Kong flu was the last pandemic of the 20th century, resulting in between 1-3 million deaths (ibid). These results highlight that every pandemic or pandemic threat in the last 100 years relates to influenza. Four official pandemics (Spanish, Asian, Hong Kong, and H1N1) and three pandemic threats (Swine, Russian, and Avian) provide evidence of the insidiousness of this disease. The epidemiology of the influenza

virus is unique in two aspects: (1) the disease occurs annually with attack rates of 10-30% in all global regions, and (2) the virus is antigenic, causing its human host to produce antibodies in an effort to destroy the invading disease. (Steinhoff, 2006).

Epidemiological surveillance has never been more important than it is today. For the first time in forty years, a pandemic currently exists relating to the H1N1 virus. Since epidemiological surveillance relies on coordination and cooperation among disparate groups (epidemiologists, nurses, doctors, hospitals, schools, nursing homes, day care, mental health institutions, etc.), it is imperative to understand how coordination is occurring at the analytical level of the process.

This research applies an analytics methodology tested previously in multiple settings, including epidemiology to the epidemiological surveillance process of a major public health agency. The methodology utilizes confirmatory factor analysis (CFA) from covariance-based structural equation modeling (SEM) to identify dimensions of coordination associated with an analytics process. The results indicate that while influenza is one of the most common communicable diseases, the process of epidemiological surveillance cannot be guaranteed to run in a highly coordinated manner even when the disease is frequently occurring. These results contribute to the literature by demonstrating that analytics coordination can be measured on naturally occurring data using covariance-based analysis and highlight the need for improvements in the epidemiological surveillance process.

ANALYTICS PROCESS

Analytics has emerged as an important activity for organizations, particularly critical for product managers, sales managers, marketers, researchers, engineers and scientists. Analytics goes beyond historical business intelligence (BI) as defined in industry[1]. Historically, "BI is not architected to iterate on new scenarios or for immediate response to unanticipated questions because it is set up to automate the distribution of standardized reports that monitor pre-determined key performance metrics and planning assumptions" (Gnatovich 2006). Historical BI uses aggregate data staged in an OLAP cube to support drill-down investigation. Analytics process users "deal daily in unanticipated outcomes and unknown results and it is their job to mitigate risk and capitalize on opportunities" (ibid). Business Intelligence has typically been viewed as a report-generating activity (task-level), while analytics acts as the focal aspect of some process where action in response to the analytics activity is expected. Table 1 outlines the different orientations between historical BI and analytics processes. While most of the analytics attention has been directed toward traditional business analytics users, analytics also occurs within healthcare processes, such as epidemiological surveillance.

	Typical users	Data Orientation	Work Orientation
Business Intelligence (historical)	Line management, line operations	Aggregated (roll up) data OLAP cubes	Standard reports Pre-determined metrics Task-level assessment
Analytics Process	Product Managers, Sales Managers, Marketers, Researchers, Engineers, Scientists, Epidemiologists, Doctors	Direct, often real-time data	Anomaly resolution Unpredictable results Process-level actionable outcomes

Table 1. Differing orientations between historical Business Intelligence and Analytics processes

EPIDEMIOLOGICAL SURVEILLANCE

Epidemiological surveillance requires significant amounts of coordination among a highly disparate group of stakeholders. Public health agencies serve as the focal point, but data collection is the critical process activity and data must be recorded from any health provider (epidemiologists, nurses, doctors, hospitals, schools, nursing homes, day care, mental health institutions, etc.) who encounters a patient with a suspected infectious disease. Reddy, Dourish, and Pratt (2001) note the heterogeneous nature of medical care when a single patient is the focus, and this nature becomes increasingly disparate when public health, not a single patient, is the focus. While the epidemiologists concern themselves at the public (or organizational

[1] Business Intelligence has "no well-accepted definition" (Watson 2009, p. 491) with its roots traced to a term coined by practitioner, Howard Dresner, in 1989 (ibid), who later became a Gartner Group analyst. BI, as utilized here, is intended to capture the early industry-influenced BI practice, and is not intended as an academic definition, as "BI is always changing" (ibid, p. 499).

level of analysis), the other providers are most concerned with the individual level of analysis and work in real-time to cure or alleviate suffering from their afflicted patient. With more deadly diseases, such as Ebola or anthrax, public health epidemiologists have a similar real-time pressure to identify and announce a deadly outbreak. However, with cyclically reoccurring and less deadly disease, such as influenza, the accumulation of time and occurrences moderate the analytic time pressure.

The public health agency works with other stakeholders and data is recorded in a communicable disease database. In spite of regulations requiring health providers to report data, what they report is seemingly inconsistent. Some data may be always reported, but more often some data identified as important by the public health agency is ignored or reported sporadically. A notable observation on epidemiological surveillance is that, like other analytics processes, the recorded database serves as its critical artifact.

Edgington, Raghu, and Vinze (2005, 2010, forthcoming) hypothesized that data recorded in analytics processes was likely to occur from intentional discretion rather than from random error. Intentional discretion notes participating stakeholders use their own judgment and perspective when recording data. A number of settings have been tested including epidemiology (Edgington et al. forthcoming) to support the identification of four primary constructs which influence the process. These constructs are identified as Observe, Discover, Produce, and Context[2]. The first three highlight the influence of specific case-level analysis and the fourth addresses the need to record data that allows the process itself to be evaluated. Each organization will record data specific to their organizational needs. The relation of the specific types of data recorded to each other not only allows for identification of these constructs, but also serves to provide insights as to actual process coordination. Since individuals in organizations may have different priorities, motivations, and understandings about a particular process, it is reasonable to anticipate that process coordination in actual execution may have some limitations.

In a previous study (ibid), the epidemiology director had expressed significant dissatisfaction with their surveillance process covering all communicable disease possibilities. Overall, their process was working, yet the director noted continual difficulty to obtain necessary data from other stakeholders. These comments corresponded with our results that identified various deviations from our theoretical research model. While finding support for process execution, we also found support for coordination conflict. However, the question arose: Is coordination conflict attributable to the process itself or the result of separate, coordinated processes being used for different diseases. The rationale for the latter option is that at least for regularly occurring disease, it is reasonable to consider that high levels of process coordination would exist.

There is insufficient research currently on processes whose primary purpose is analytics, and less on the measurement of coordination actually occurring in these processes. The focus of this paper's research addresses if analytics process coordination is occurring when controlling for the disease. Influenza is interesting in that it is one of the most reliability occurring communicable diseases, occurring annually on a worldwide basis. Our results support evidence of significant analytics process coordination problems even with a disease that is predictable, and globally reoccurring.

RESEARCH MODEL

The research model of Figure 2 serves as the hypothesis set for this research. This model was tested and supported in various studies (Edgington et al. 2005; Edgington 2006; Edgington et al. 2010) as a generalized MTMM (multi-trait, multi-method) model, and in various contextual settings, such as software bug analysis, manufacturing semiconductor failure analysis, help desk, and general epidemiological surveillance. As noted by SEM/CFA research (Chin 1998; McDonald and Ho 2002), the predicted model in covariance-based SEM should not be considered as individual hypotheses, but as one unified hypothesis. This analysis technique is based on the covariance that exists (or not) among all declared variables. In Figure 2, the model predicts that four primary constructs will be identified as directly influencing the recording of various types of data (data elements). These data elements will be named in accordance to the contextual relevance of the setting, but their instantiation patterns (i.e., instances of recorded data) will cluster to identify how they align with these constructs. Previous research (Edgington et al. 2005, Edgington 2006, Edgington et al. 2010) has produced highly reliable Cronbach's alpha > .9) models. Previous research (ibid) has provided support that the extent to which the identified model deviates from the predicted, theoretical model, the greater the dissatisfaction previously described by the stakeholders.

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[2] Dewey (1933) in defining four factors of learning included Invention as the fourth (introducing the concepts of Observe, Discover, and Produce). Senge (1992, 1999) and Senge et al. (2005) acknowledged Dewey's construct noting Invention the ability to 'invent new actions' (p. 86). Context subsumes this concept to include both the new actions or solutions, but also a characterization of the need, problem, or disease (as in the case of epidemiology). Neither Dewey nor Senge's models have been empirically tested, particularly using quantitative methods.

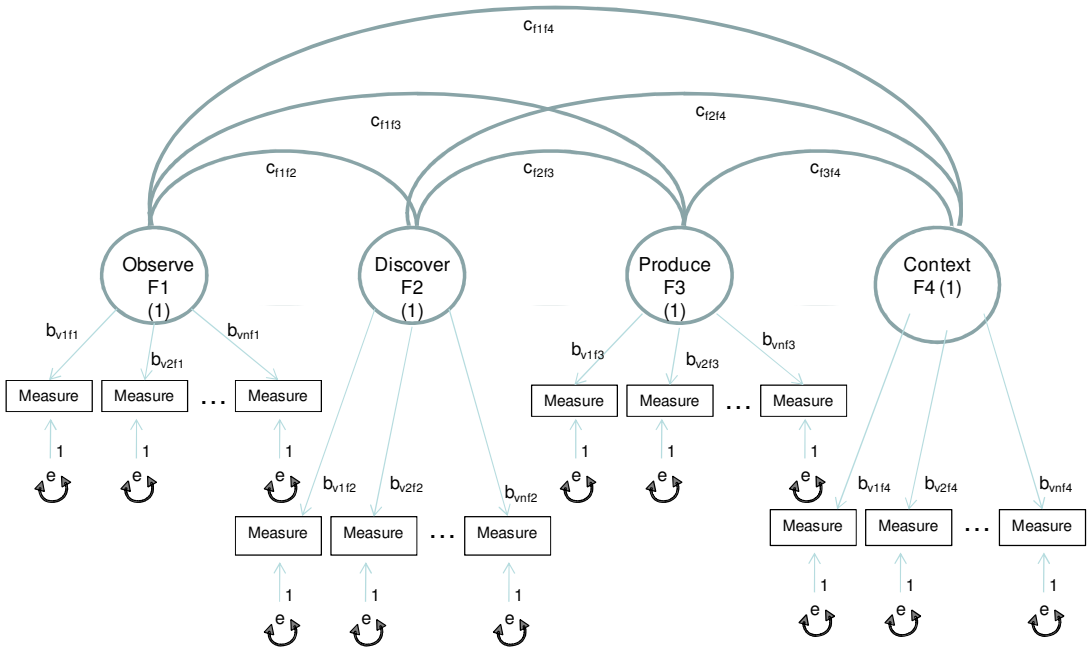

Figure 2: Research (CFA) Model

METHODOLOGY

Data and Measurement

I take a novel approach to data collection, using naturally occurring, empirical data, i.e., the data occurs from its actual use in practice. It is not generated hypothetically as in simulation. It does not come from speculation or perception of actual participants. It is the data that actually was recorded in the direct operation of the surveillance process. Typically, CFA analysis is applied to survey data; while such data are considered empirical when the participants come from practice, they are the result of perception or speculation, rather than from actual naturally-occurring process execution. The unit of analysis is the case (reported incident) and 2,484 cases were collected over a 15-month period. Thirty-five data elements served as indicators for the CFA analysis. As described in (Edgington et al. 2010), the collection and recording of data is more central to an analytics process such as this than is any specific workflow; therefore, the data can act as a surrogate for this analytics process.

During this time period, epidemiologists would record data provided by other process stakeholders (doctors, nurses, and other medical specialists) incrementally as the surveillance process was executed for each incident, transforming the record from not only an instance of explicit knowledge on this case, but as a proxy for the process (remembering that analytics is the critical focus of the surveillance process). The process ends with each case at the point when the epidemiology director can declare whether the incident is an outbreak (initial instance), an epidemic (disease exceeds the level of tolerance for the community), and what additional actions are needed when the level of tolerance is exceeded for the disease.

Confirmatory Factor Analysis (CFA) from covariance-based SEM leverages the methodology. This approach adopts the text mining technique of isolating term counts and regularization (Weiss, Indurkhya, Zhang, and Damerau 2005), but introduces the concept of covariance present in naturally-occurring analytics processes. The term frequency for each data element (attribute-level metadata or column in a spreadsheet) is noted retaining the case as the unit of analysis.

The approach is to perform CFA on the set of cases to identify how closely the actual data supports the hypothesized model. I record the presence or absence of data for each data element (corresponding to the observed measures in the CFA Model) and then analyze the coded data using CFA. The methodology assesses the strength of occurrence (variance) and the strength of association (covariance) among the declared observations (attributes or columns) to identify the underlying constructs (SEM-identified factors) that influence the epidemiological surveillance process. Hu, Bentler, and Kaner (1999) cutoff criteria for fit and reliability assessment are utilized.

I incorporate the model orientation of covariance-based SEM of EQS. This orientation produces equivalent results as does LISREL, but utilizes the approach to SEM introduced by Bentler (1968, 1975, 1983a/b) and Bentler and Weeks (1979, 1980). This approach, as noted in the citation on his 2007 Distinguished Scientific Award from the American Psychological Association, simplified the application of SEM allowing a broader audience to participate in its usage. He and his students in collaboration advanced statistics and procedures including "model fit indices, multivariate methods for model testing and development… methods to assess power to detect differences between alternative models…[and] methods to handle data that did not fit the assumed multivariate normal distribution" (Wandersman 2007). This advanced SEM orientation moves both model declaration and reporting to be stated either graphically, aligned to the research model orientation (see Figure 2), or statistically as a unified set of linear equations (see Figure 3). Such an orientation can broaden the audience for SEM analyses.

A full explanation of the EQS adoption of the Bentler and Weeks model is beyond the scope of this paper; briefly, instead of the thirteen matrices utilized in LISREL, the EQS model focuses on two types of variables, dependent and independent, and the relationships between them. All dependent variables must be explicitly declared. Data elements (or measurable observations) are modeled as variables, V1, V2, V3, and so on. Factors are intended to serve as proxies for theoretical constructs and are labeled as F1, F2, etc. Data elements represented as dependent variables consist of one or more factors and residual error, labeled as E1, E2, etc. with the numeric corresponding to the numeric value assigned to the data element label. The model is primarily represented as a set of linear equations of form, Vx = Fy + Ex, where x = the numeric labeling for the data element(s) and y = the numeric labeling for the factor term(s). With higher-order or formative models, factors become the dependent variable and a disturbance term, Dy, models the error term. The original modeling of SEM focused on reflective models (data elements as the dependent variable); however, current formative modeling can also be supported (but is not addressed in this paper). Variances and covariances are either fixed (to a specific value) or allowed to be freely estimated in the model, such as F1 = 1 (factor variance) or F1, F2 = * (covariance allowed to be estimated between the two, specified factors). Figure 3 shows the results reported from EQS for the confirmatory model in this study. The R-squared value represents the portion of variance in the actual data captured by that linear portion of the model. While the model focuses on a set of linear regressions, they act not independently, but as a unified set of equations modeling a complex phenomenon. Byrne (2006, pp. 18-53) provides more details of the Bentler-Weeks model and its implementation in EQS. This level of modeling allows one to define the measurement model, the focus of CFA and this study.

Results

To identify dimensions of process coordination within the epidemiological surveillance process, isolating the influenza disease, 2,484 cases of reported influenza taken from a contiguous 15-month period were analyzed utilizing EQS6.1 (build 94), applying maximum likelihood estimation. The hypothesized four primary factors were identified. Reliability was excellent as measured by Cronbach's alpha (.977) and Reliability Coefficient Rho (.986). Fit indices indicate that the data supports the hypothesized model very well. Fit is excellent as measured by NNFI (.965), NFI (.961), CFI (.976), and SRMR (.069). RMSEA (.078) is in the acceptable range. The standardized regression model can be seen in Figure 3 which includes factor loadings (influence of the factor upon the observed data elements), R-squared (assessments of how well each equation in the standardized solution is confirmed by the data), and factor correlations.

The size of factor correlations can be interpreted with respect to discriminant validity. Brown (2006) indicates that when factor correlations exceed .8, the highly correlated factors should be combined and the adjusted model retested to see if it provides a superior model. Only F1 (Observe) and F3 (Produce) exceed .8 in our results. The adjusted model not only is not superior, but does not meet cutoff criteria for fit and reliability indices. These results support evidence of discriminant validity in these results. Convergent validity is a topic addressed within the Discussion section.

Sixty-three percent of the measures have cross loadings (i.e., a measure loading on more than one factor); 64.7% of those measures cross-loading on multiple factors reveal Heywood cases. Error covariances (31) and residual error in excess of .5 (25.9%) indicate substantial external influence, but not strong enough to explicitly identify an additional factor. No correlation was found between Discover and Context factors or between Produce and Context factors. This is a deviation from our theoretical model which would expect correlation as an outcome of the process influence itself.

STANDARDIZED SOLUTION:					R-SQUARED
DATE DIAG=V4 =	1.449*F1	- 1.083*F3		+ .586 E4	.656
DATE CLOS=V5 =	.083*F1	+ .918*F3		+ .158 E5	.975
EST AGE =V8 =	1.064*F1	- .267*F2		+ .443 E8	.804
AGE GROUP=V9 =	1.406*F1	- .828*F3		+ .528 E9	.721
GENDER =V10 =	1.026*F1	- .164*F2		+ .397 E10	.843
CITY =V12 =	1.219*F1	- .473*F3		+ .501 E12	.749
ZIPCODE =V15 =	1.356*F1	+ .145*F2	- .922*F3	+ .520 E15	.729
SERO =V16 =	.879*F3			+ .476 E16	.773
SEROTYPE=V17 = -	.130*F2	+ 1.019*F3		+ .341 E17	.884
LAB NOTE =V18 =	.107*F2	+ .853*F3		+ .379 E18	.856
SPECIMEN=V19 =	.199*F1	+ .451*F2		+ .794 E19	.369
DATE COLL=V20 =	.965*F3			+ .262 E20	.932
DATE FINL=V21 =	.850*F1			+ .527 E21	.722
PHYS NO =V23 =	.487*F2	+ .657*F4		+ .575 E23	.670
PCP PHONE=V24 =	.769*F2	+ .601*F4		+ .218 E24	.953
FACIL RPG=V25 =	.653*F1	+ .370*F2	- .297*F4	+ .453 E25	.795
FACSTR N =V26 =	.998*F2			+ .067 E26	.995
FAC DIR =V27 =	.997*F2			+ .075 E27	.994
FACST NM =V28 =	1.000*F2			+ .000 E28	1.000
FAC SUFFX=V29 =	.968*F2			+ .252 E29	.937
PCP CITY =V30 =	.787*F2	+ .524*F4		+ .326 E30	.894
PCP STATE=V31 =	1.001*F1	- .106*F3		+ .405 E31	.836
PCP ZIP =V32 =	.889*F1	+ .597*F2	- .580*F3	+ .278 E32	.922
UPDATE BY=V35 =	.970*F3			+ .241 E35	.942
ICD9 =V38 =	.895*F4			+ .446 E38	.801
LAB NAME =V41 = -	.331*F2	+ 1.092*F3		+ .404 E41	.837
LAB DATE =V42 =	.967*F3			+ .254 E42	.935

CORRELATIONS AMONG INDEPENDENT VARIABLES

	F1	F2	F3	F4
F1 Observe	1.00			
F2 Discover	.702	1.00		
F3 Produce	.834	.645	1.00	
F4 Context	.506	.000	.000	1.00

Figure 3: Standard Regression Results and Factor Correlations

DISCUSSION AND SUMMARY

This study contributes to research in applying covariance-based quantitative analysis to the epidemiological surveillance process with regard to its influenza analysis focus. The analytics process is characterized in terms of the underlying factors supported as identified by the actual data elements actually used and the structures resulting from their use. Within this extended, virtual organization, analytics coordination is confirmed with a well-identified model, supporting the primary constructs of Observe, Discover, Produce, and Context. At a base level, these results confirm evidence of an analytics process, but a deeper investigation suggests that the coordination does give evidence of significant conflict.

Using empirical and naturally-occurring data from unobtrusive measures, the results indicate that while the data supports a repeatable process, significant coordination conflict is occurring. Remembering that the data occurs as a result of the organization's on-going process, it suggests that the disparate stakeholders do not share common motivations when participating in this process. Evidence for this assessment comes from the instances of numerous cross-loadings (not characteristic of identified CFA models), numerous error correlations, and high levels of residual error. Note that statistically, these are indicators of convergent validity, but in this application of analyzing the surveillance process using naturally occurring data and a very large sample to mitigate variance due to error, they suggest not limitations of the theoretical model, but of coordination conflict of the surveillance process in practice. In light of the global impact of influenza and the potential for pandemic spread, it is important for global coordination to occur and for sources of conflict to be identified and resolved.

Such coordination remains at substantial risk when local epidemiological surveillance evidences significant analytics process conflict.

The application of CFA to measuring coordination presents itself as a harmonious intertwining of theory and method. The issues of discriminant and convergent validity that are addressed in CFA can provide substantive revelation to practice as indicators of process coordination conflict when applied to large sample sizes, such as exist in the epidemiological surveillance process.

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