A Conceptual Model for the Application of Business Analytics in the Horizontal Strategic Alliance

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Abstract

The formation of strategic alliances amongst organisations has grown in recent years as globalisation has opened new markets for firms to pursue. It is of ever-increasing importance that organisations have a thorough understanding of the performance of their alliance to achieve competitive advantage. However, much research on strategic alliance has focused on examining the organisations within the alliance rather than focusing on the alliance itself. Using the new discipline of business analytics, this paper proposes a hierarchical model blending the functional roles of business analytics with data standardisation and context mediation frameworks to allow business analytics to be applied to horizontal strategic alliances with the aim of producing valid, alliance-wide strategic options. A proof of concept whereby the proposed model is theoretically applied to a real-life alliance in the airline industry is given, demonstrating how the model generates insight at the alliance level at each of the model's five levels.

Keywords: Business analytics, horizontal strategic alliance, conceptual model, proof of concept, data standardisation framework, context mediation framework

1 Introduction

The advent of globalisation in recent years, combined with the commoditization of information technology (IT), has put firms under increasing competitive pressure. The rapid adoption of the Internet has provided consumers an even wider array of choices by expanding the market, while reducing barriers to entry for potential newcomers seeking to enter the market (Porter, 2001). It is in this light that non-equity strategic alliances offer firms a reprieve from these increasing pressures and the chance to regain control of the market.

Simply put, strategic alliances are voluntary arrangements between two or more firms whereby a product, technology, or service is co-developed (Gulati, 1998). Strategic alliances offer firms benefits such as reduced product development times, access to competencies they may not possess, and the ability to block competitive threats from other actors in the market (Zhang & Zhang, 2006). Non-equity strategic alliances build upon these benefits by being easy to form and easy to dissolve. However, the challenge of forging a successful non-equity strategic alliance lies in its decentralised nature - firms within the alliance are most often independent actors with disparate interests to serve. Thus, gauging the performance of many non-equity strategic alliances have mostly become a guessing game; as long as none of the firms within the alliance have raised serious issues, it is assumed the alliance is functioning, as it should. However, the advent of big data, and with it the practice of business analytics, offers the potential to solve this conundrum.

Business analytics allow firms to run analyses on data, plan scenarios, and even forecast future dynamics (Schlafke et al., 2013). Furthermore, business analytics can be used in a variety of scenarios - as an overall performance dashboard for a firm, or more appropriately for strategic alliances, as an in-depth tool to tease out trends within a specific area (Kiron et al., 2012). Thus, given the importance of strategic alliances to a firm's business strategy, it is proposed that further research is conducted into how business analytics can be applied to alliances between disparate parties to create a unified strategy that: 1) uses definitions understood by all parties, and 2) provides the most optimal solution for the alliance. However, much research on strategic alliance to date has focused on deducing the performance of the alliance from examining the performance of the organisations within the alliance rather than focusing on the alliance itself. Using the new discipline of business analytics, this paper proposes a hierarchical model blending the functional roles of business analytics with data standardisation and context mediation frameworks to allow business analytics to be applied to horizontal strategic alliances with the aim of producing valid, alliance-wide strategic options. A proof of concept whereby the proposed model is theoretically applied to a real-life alliance in the airline industry is given, demonstrating how the model generates insight at the alliance level at each of the model's five levels.

2 LITERATURE REIVEW

2.1 Strategic Alliances

The field of strategic alliances encompasses a wide variety of inter-firm relationships: the existence or lack of equity swaps between firms, the establishment of franchises with affiliates or non-affiliates, or the creation of a joint venture independent of the parent firms (Gomes et al., 2014). Strategic alliances are also normally formed with one of either two motivations in mind: cost-economisation or long-term profit optimisation (Narula & Hagedoorn, 1999). With cost economisation, firms enter into alliances with the goal to minimise their net costs, and as such, these alliances tend to be short-term and vertical (for example, customer-supplier agreements) in nature. Conversely, firms seeking to optimise their long-term profits by forming an alliance are generally willing to sacrifice short-term profit in the hope that their long-term market positions are enhanced (Narula & Hagedoorn, 1999).

Christoffersen (2013) identified five dominant areas by which the performance of strategic alliances are measured: subjective measures, stability, accounting measures, cumulative abnormal return, and external evaluation. By in large, a majority of prior research around gauging and improving the performance of strategic alliances have centred on the use of subjective measures (Christoffersen, 2013; Gomes et al., 2014). Proponents of this approach argue that subjective measures allow the performance of the alliance to be measured not only in terms of finite outcomes (such as amount of profit), but also in terms of ongoing issues and feelings towards the state of the alliance (Arino, 2003). However, subjective measures are, by their very nature, subject to the questions being asked, and thus can vary based on the source being used or the measurements being proposed (Christoffersen et al., 2014; Podsakoff & Organ, 1986).

On the other hand, the use of accounting measures in gauging strategic alliance performance has seen relatively scant use (Gomes et al., 2014; Christoffersen et al., 2014). Some prior works have criticised accounting measures as being unable to take into account non-financial aspects of alliance performance (Gong et al., 2005). However, accounting measures are generally recognised as being able to be more confidently interpreted than other measures, such as the subjective measures mentioned above (Beamish & Lupton, 2009). Furthermore, in using accounting measures, data sets from current and prior transactions are used: data that, when used appropriately, can be evaluated using business analytics allowing for a detailed, more accurate view of past events, and highlighting of trends that can be taken advantage of for the future.

2.2 The Role of Business Analytics

The promise that business analytics offers is great: companies can innovate faster and better to achieve competitive advantage and improve performance (Hopkins et al., 2010). Business analytics also helps to anticipate and manage strategic risks better (Kiron et al., 2012). And by focusing on the use of business analytics on the biggest drivers of performance for organisations, Barton and Court (2012) suggest that more relevant prediction and optimisation models can be built, thereby helping organisations to sustain competitive advantage.

However, many organisations today seem to a lack a sufficient understanding of what "business analytics" mean, thus leading to often mistaken and inappropriate applications of the discipline. As defined by Schniederjans et al.'s work (2015), "business analytics" not only seeks to generate insights from data, but uses these insights to create finite measures by which business performance can improve. Stubbs (2011) further builds on this definition by requiring that any successful implementation of business analytics must clearly provide results relevant, implementable, and measurable to the business. Interestingly, there is less agreement on how to classify techniques used within business analytics - some subscribe to the three-classification standard set forth by INFORMS (the Institute of Operations Research and Management Sciences), while others, such as Gartner, use a more detailed four-classification standard (Bertram, 2014). As the model given later in this paper will use the four-classification standard, a brief overview of the classifications are given below:

- Descriptive Analytics: It involves the identification of possible trends by examining past and current data (Evans, 2013, p. 30). The most commonly used type of analytics, techniques used within descriptive analytics tend to categorise, characterise, or classify data into useful information via the use of charts and reports to help analyse and understand business performance. Simply put, insight gained from descriptive analytics can help answer the "what happened?" types of questions - for example, "What was the revenue for fiscal year 2015?" or "What variants of products are selling the most units?"
- Diagnostic Analytics: Often grouped with predictive analytics in three-classification standards, diagnostic analytics seeks to answer the question "Why did this happen?" through examining past and current data to find patterns or relationships (Evans, 2013, p. 30). While diagnostic analytics can also use visualisation techniques to display insights generated from data, it focuses on explaining the root causes of an observed phenomena whereas descriptive analytics simply show the existing situation.
- Predictive Analytics: In predictive analytics, statistical and data mining techniques (such as ANOVA) are used to predict potential future scenarios based on analyses of past and current data trends (Banerjee et al., 2013). However, while predictive analytics can generate future scenarios, thereby answering the question "What will happen next if current trends continue?", predictive analytics on its own cannot recommend a certain course of action over another.
- Prescriptive Analytics: Prescriptive analytics can be a powerful tool for organisations unsure of how to proceed, or faced with a myriad of potential options - i.e., the question "What do we do?" paralyses organisational decision-making (Evans, 2013, p. 31). When used in conjunction with the mathematical/statistical techniques of predictive analytics, prescriptive analytics help organisations allocate resources optimally to take advantage of predicted trends to maximise a certain objective, such as profit maximisation or cost minimisation (Schniederjans et al., 2015).

3 Methodology

As this paper attempts to combine two disparate fields that have yet to be observed in academic literature in a single study, two separate searches for relevant publications were conducted – one for strategic alliances, and another for business analytics. For the field of strategic alliances, a search for relevant academic literature was conducted using the EBSCOhost search engine with the keywords "strategic alliances", "non-equity strategic alliances", and for the proof of concept, airlines strategic alliances". In reviewing the field of strategic alliances and examining phenomena observed in the field, peer-reviewed journals, books, and conference publications were prioritised and non-scholarly articles were removed. However, for the proof of concept, an academic case study by Zhang and Zhang (2006) on strategic alliances within the aviation industry was used as the basis, as the author of the paper possess industry background in the aviation industry, and literature and data involving alliances are easily accessible in said industry. Numerous industrial, organisational, and news media resources around strategic alliances in the aviation industry were added to the case study to create a more complete case with updates to the industry over the last decade included where applicable. For the field of business analytics, a search for relevant academic literature was conducted also using the EBSCOhost search engine with the keywords “business analytics”, “descriptive analytics”, “predictive analytics”, “prescriptive analytics”, and “big data”. While academic, peer-reviewed journals, books, and conferences were prioritised, choice publications from industry, such as the four-classification business analytics standard by Gartner, were also included where relevant (Bertram, 2014). Finally, industry publications involving the aviation industry were used in the proof of concept, where applicable, to provide context to the reader around industry conventions, practices, and terminology.

4 Proposed Model

A review of strategic alliance literature found there to be potential for business analytics to address the seeming lack of objective measures to determine and improve the strategic performance of strategic alliances. To this end, this paper proposes a five-level, hierarchical organisational model supported by a data exchange framework that allows alliances to reconcile data from different organisations into one data source so that meaningful insight is generated and relevant strategic options for the alliance are identified. In constructing the organisational model, the “business analytics roles framework” from Schniederjans et al. (2015) is blended with the data standardisation framework given by Kravets and Zimmermann (2012). Additionally, a couple of assumptions are made regarding the environment in which the model is to be operating in. First, this model assumes that the alliance is a “horizontal alliance”, i.e., the organisations in the alliance all operate in the same field rather than in complementary fields. This model also assumes data coming from different organisations are not significantly different from a statistics point-of-view, and can thus be combined into one data set without any data integrity issues. This is because in horizontal alliances, products are sold under an alliance brand should have coherent unifying traits, for example, a first-class airplane seat sold under the airline alliance brand SkyTeam should have traits that make it easily identifiable across SkyTeam's member airlines as a first-class seat. If products sold under an alliance brand having significant differences, there would be a high likelihood that the product being sold is not unified, and therefore calls into question the validity of the alliance's product strategy and consequently the alliance itself. Finally, it is important to note that the model being proposed will focus on providing the most optimal solution for the alliance - not the most optimal solution for each of the parties involved.

In this section, the five levels of the proposed model (metrical, situational, aggregate, alliance, and executive) are covered in mostly ascending order, from most operational to most managerial. A subsection is also devoted to how the model is operationally supported by a data exchange framework called COIN.

4.1 Metrical Level

The metrical level is unique in the model in that it does not directly contribute to generating insight or assisting in analysis - its role is to set the standards by which the alliance will operate. In the metrical level exist two types of roles: the Organisation Liaisons, who exist at each organisation that participates in the alliance (and thus have the same role replicated across the alliance), and the Monitoring Analyst, who acts on behalf of the entire alliance (and not on behalf of a particular organisation) and is unique within alliance. The Monitoring Analyst is responsible for critically analysing the various business processes and strategies of the organisations within the alliance, and identifying from the processes and strategies common analytics that can be used across the alliance. Once identified, the Monitoring Analyst will then establish what each common metric means, and enforce guidelines around how these metrics can be measured so that each organisation's efforts are measured appropriately, which in turn allows for valuable insight to be gained from the metrics. As such, the individual who successfully fills the role of the Monitoring Analyst will normally have a strong background in business analytics and some prior management experience. On the other hand, the role of the Organisation Liaison is typically filled by a low-level manager or a programme manager within each organisation who possesses vast knowledge about the many domains within their company, or if not, is well connected to individuals within their organisation that possess the requisite knowledge. As the business domain expert of their respective organisations, Organisation Liaisons provide input to the Monitoring Analyst around specific business processes and strategies at their company so that metrics can be appropriately identified and when established, enforced within their organisation. Where needed, the Organisation Liaison also serves as the point of contact to help others across alliance interpret and understand the meaning of the raw data extracted from his or her organisation.

4.2 Situational Level

The first step in generating insight from data within the alliance rests within the Situational level. Like the Organisational Liaison within the Metrical level, the Situational level consists of one role replicated across the alliance - the Implementation Specialist. Located in each organisation, Implementation Specialists are normally senior Data Analysts within their respective organisations' Data Management team, possessing considerable skill in extracting raw data from one or more data sources, and ideally some experience in enterprise architecture. Working under the guidance of the Organisation Liaison at his or her organisation, the Implementation Specialist extracts those data that make up the metrics defined by the Monitoring Analyst where available. The data extracted by the Implementation Specialist will tend to produce metrics falling under the “Descriptive Analytics" classification - metrics such as averages (i.e., mean), most frequently occurring instances (i.e., mode), and tendencies (i.e., median). In cases where data used in measuring the metric isn't available, the Implementation Specialist will attempt to create a substitute from other data, or inform the Organisation Liaison about the difficulties in obtaining the data for the metric. Once the appropriate data is identified, extracted, and gathered, the Implementation Specialist inputs the data, with its original organisational context, into COIN.

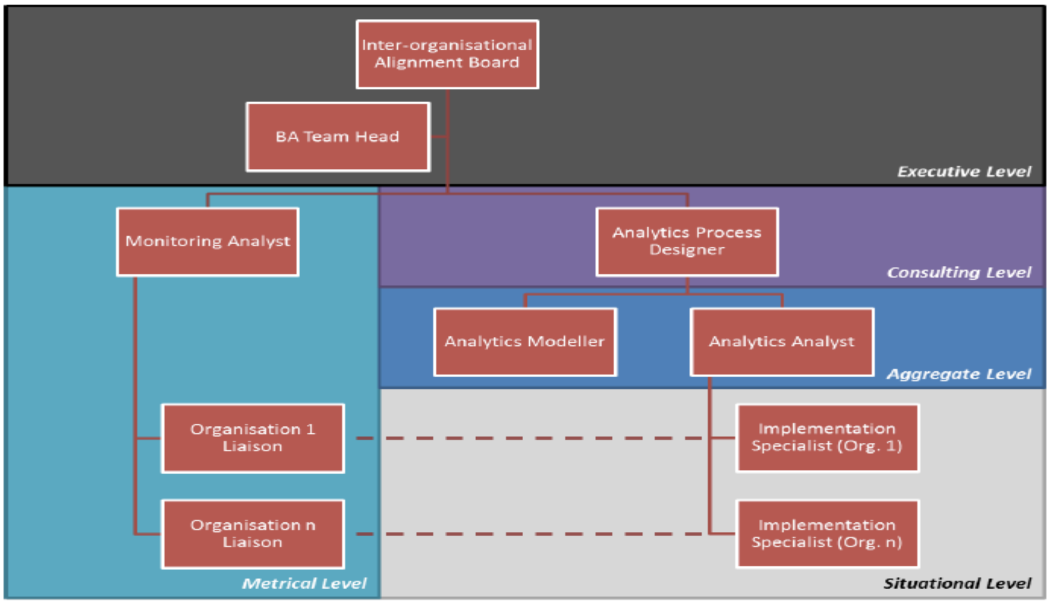

Figure 2: An overview of the proposed model

4.3 COIN - The Operational Linkage Across the Alliance

The model relies on a framework called “COIN", short for “COntext INterchange". First proposed by Madnick and Zhu (2006), the COIN framework allows data residing in different sources to be viewed through a single lens via a “context mediation service" (for example, which can be a program running on a server), as though the data came from one source. In terms of the model being proposed, this means that the use of COIN allows data from each organisation within the alliance, residing in its original organisational context (for example, “miles" for distance at a US-based company), to be viewed from an overall alliance context (for example, “kilometres" for distance at the Spanish-based alliance it subscribes to). Through this, the data submitted to COIN is reconciled to alliance standards. The use of the COIN framework within the model offers several advantages over a central database managed by the alliance itself or one of its organisational members. COIN's decentralised design, whereby the data in question remains owned solely by the organisation and is simply translated into a different context, facilitates the nature of non-equity strategic alliances; organisations minimise occurrences where they take positions that make it more difficult to disband and control their own actions. The building and maintaining of a central database to be run by the alliance or one of its organisations presents not only issues around data being duplicated across the alliance, but also issues around data storage and access. Organisations forwarding data to another database, whether managed by the alliance itself or another organisation on behalf of the alliance, become vulnerable as they lose some control over potentially competitively sensitive data. Moreover, in cases where alliances span international borders, strict and sometimes contradictory requirements that governments place on storage of data generated in their own countries can cause the alliance and its organisations to come under unnecessary legal pressure that may detract from any benefits gained by participating in the alliance (Gustke, 2013). COIN circumvents many of these concerns as it simply acts as a medium by which data is transferred and reconciled; the organisation that owns the data being requested via COIN is in control of the data throughout all steps of the process. Furthermore, though in its original application COIN was proposed to be used for strictly SQL-based databases, recent developments in Big Data (such as the use of SQL front-end emulators for Hadoop) have the potential to allow for COIN to be used on the sort of massive data sets often used in cross-alliance operations (Yegulalp, 2014).

4.4 Aggregate Level

When COIN has received all the data (used to create the metrics set by the Monitoring Analyst) from each organisation's Implementation Specialist, a unified data set with alliance-level context is created. This then begins the second step in generating insight from data across the alliance, designated in this model as the Aggregate level. In the Aggregate level exists two roles that are unique within the alliance (i.e., only one individual fills each role): the Analytics Analyst, who performs tasks involving diagnostic analytics, and the Analytics Modeller, whose tasks involve predictive analytics techniques. Using the unified data set created and maintained by COIN, the Analytics Analyst uses diagnostic analytics techniques to attempt to find correlations between metrics and identify antecedents to observed behaviour (i.e., answering the question "Why did the observed behaviour occur?"). Where correlations are not found, the Analytics Analyst works with the Implementation Specialists to identify the underlying assumptions behind the data provided from each organisation to ensure metrics were appropriately generated. Assuming metrics were appropriately generated, the Analytics Analyst then provides feedback to the Monitoring Analyst, who then identifies new common analytic metrics. As such, the individual who performs the role of the Analytics Analyst must possess a strong statistical background with strong problem solving skills, along with great communication skills. In contrast, the Analytics Modeller uses the same unified data set created and maintained by COIN to develop various forecasting models in order to identify emerging trends based on certain assumptions (i.e., answering the question "What will happen next?"). The Analytics Modeller works closely with the Analytics Analyst to ensure forecasting models centre on correlations found within the data set from COIN so that useful insight is generated. An expert in using predictive analytics techniques, the individual who performs the role of the Analytics Modeller possesses extensive experience in statistics and various types of analytical modelling, along with some experience in business processes. Thus, by combining the findings from both roles at the Aggregate level, the antecedents and subsequent behaviour of the alliance can be viewed from a single lens.

4.5 Alliance Level

In the third and final step, designated as the Alliance level, the insights from the Situational level and Aggregate level are combined to identify and determine the best courses of action for the alliance. Making this happens at the Alliance level is the unique role of the Analytics Process Designer. As the final step in generating insight for the alliance, the Analytics Process Designer consults both the Analytics Analyst and the Analytics Modeller in order to understand the context behind the data set provided by COIN, and the direction the alliance is currently heading in. Additionally, the Analytics Process Designer works closely with those in the Executive level to ensure that the programs and simulations produced through prescriptive analytics techniques satisfy as many of the objectives those in the Executive level have for the alliance. With inputs from both levels in mind, the Analytics Process Designer then creates the programs and simulations necessary to generate optimal outcomes for the alliance. Thus, the individual who fills the role of the Analytics Process Designer must have a very strong background in operations research and statistics, along with strong communication skills. With the necessary insight to determine the optimal course for the alliance generated, the Analytics Process Designer interprets the insight into simple options written in business language for the Executive level to review.

4.6 Executive Level

The last layer of the model, lying at the top of proposed framework, is the Executive level. Like the Metrical level, the Executive level does not involve generating insight; instead, the level focuses on using the insight generated to determine the best course of action. The executive level is comprised of two roles that are jointly responsible for setting the course of the alliance - the Inter-organisational Alignment Board and the Business Analytics (BA) Team Head. As the ultimate source of power in the model, the Inter-organisational Alignment Board acts on decisions that have a wide scope across the alliance and sets strategically important directions for the alliance based off the insight generated in the Alliance level. Thus, the Inter-organisational Alignment Board will usually consist of executives from each organisation within the alliance, with the chief executive of the alliance itself acting as the chair. Helping enforce the direction set by the Inter-organisational Alignment Board is the BA Team Head, who is tasked with two main responsibilities. With the first responsibility, the BA Team Head serves as an advisor to the Inter-organisational Alignment Board. Where the possible solutions produced by the Analytics Process Designer in the Alliance level cannot meet all the goals of the alliance, the BA Team Head uses his or her judgement around the alliance's stated objectives to advise the Interorganisational Alignment Board on the trade-offs necessary. The second responsibility sees the BA Team Head acting as the day-to-day head of the model and providing leadership to the other roles in the model, along with mentoring where needed. As such, the role of the BA Team Head is typically given to an individual with an extensive background in management and management consulting, along with a strong background in business analytics.

4.7 Summarising the Proposed Model

A model blending business analytics-related roles with data standardisation frameworks, adapted to the job roles structure of strategic alliances, was proposed and detailed in this section to assist alliances in generating objective measures towards identifying and improving strategic performance. To this end, the proposed model can be summarised into five distinct levels covering different responsibilities. In the first level, the Metrical level, standards for metrics by which the business analytics team within the alliance will operate under are set by the Monitoring Analyst, with input from his or her deputies, the Organisational Liaisons. Next, the Implementation Specialists at the Situational level (i.e., the second level) identify data within their respective organisations that constitute the metrics established in the Metrical level, and extract the data for submittal to COIN. The data submitted to COIN then undergoes context appropriate translation, so that data that originally came from different data sources with different contexts are represented as one data set with one unified context, defined by the Metrical level. Upon the one data set being created, the Analytics Analyst at the Aggregate level (i.e., the third level) runs diagnostic analytics procedures to determine if correlations or patterns exist between metrics in order to find antecedents to observed behaviour in the unified data set. Additionally, the Analytics Modeller (also within the Aggregate level) runs predictive analytics procedures upon the same data set to determine future trends for the alliance given its current direction. In the fourth level, the Alliance level, the Analytics Process Designer combines the insights from the Analytics Analyst and Analytics Modeller, along with running prescriptive analytics programs and simulations on the unified data set, to identify and determine the best courses of action for the alliance. Taking the insights gained from the prior levels, the Executive level is then tasked with making a decision as to the course of the alliance, with the BA Team Head running day-to-day activities and the Inter-organisational Alignment Board making judgement calls on strategically important decisions.

5 Proof of Concept

To demonstrate the use of the proposed model above in potential real-world applications, a case study by Zhang and Zhang (2006) on multi-party alliances within the airline industry, modified to include more technical information and to reflect more recent developments within the industry, is used as an example. The international airline industry is a unique industry where political barriers, rapidly changing economic conditions, and technological advances compound to make companies (i.e., airlines) predisposed to forming non-equity strategic alliances, thus providing a great environment in which to study the model (He & Balmer, 2006). It is in this environment that the aforementioned case study examines four airline alliances - Oneworld, SkyTeam, Star Alliance, and the now-defunct Wings - on their competitive positioning (Pearce & Doernhoefer, 2011). Each of the three currently-existing alliances are composed of international, full-service airlines that operate long-haul commercial flights throughout the North Atlantic, European, and Asian markets, where alliances, and by extension the members composing the alliance, seek to gain competitive advantage over non-allied airlines operating in the same market (Zhang & Zhang, 2006).

In the interest of keeping the proof of concept simple, the proof of concept will focus on the “trans-Atlantic market" (i.e., airline itineraries where the origin is either in North America or Europe, and the destination is within the other continent) from the point-of-view of the Oneworld alliance. (However, this concept can be readily observed in other airline markets from the point-of-view of the other alliances.) The proof of concept will start by introducing four main organisations within the organisation that operate in the trans-Atlantic market, and identifies “CASK” as an alliance-wide metric that is defined and determined at the Metrical level by the Monitoring Analyst and Organisation Liaisons. Then, , the Implementation Specialists at each of the four airlines extract data around CASK and RASK, and have the results translated into a single alliance (i.e., Oneworld) context via COIN. Additionally, the Analytics Analyst and Analytics Modeller respectively run diagnostic and predictive analytics techniques on the data set from COIN to find the reasons behind why revenues in Central Europe are dropping, and what future Central European traffic patterns look like. Finally, the Analytics Process Designer combines the insights found from the Analytics Analyst and Analytics Modeller to find the optimal routing for Oneworld airlines to restore revenue levels while taking advantage of traffic patterns, and provides the BA Team Head and Inter-organisational Alignment Board the results. Taking these results into consideration, the BA Team Head advises the Inter-organisational Alignment Board on how the solution was found, and works to determine the best way to implement the optimal solution using the organisational resources within the alliance.

5.1 Creating Unified Data Definitions

Competition in the trans-Atlantic market is fierce: all three currently existing airline alliances operate routes in the market, and capacity (i.e., the supply in the number of seats available for passengers to buy) has steadily grown over the past decade (Bilotkach & Huschelrath, 2015). Furthermore, the airline alliances have gradually come to dominate the capacity being offered in this market - in 2013 alone, 75% of passengers travelling within the trans-Atlantic market flew on flights that were operated as part of an airline alliance. With both Europe and North America slowly recovering from economic crises in the past decade, growth in passenger traffic in both continents have also accelerated, thus providing a golden opportunity for alliances to increase market share and put pressure on other competitors.

Given this situation, the Oneworld management team (i.e., the body analogous to the Interorganisational Alignment Board role for this case study) may seek to identify routes in the Oneworld trans-Atlantic network that have high operating costs or low revenues in order to find alternate routes or solutions that allow Oneworld's airlines to fly routes between Europe and North America at a higher profit. To this end, there are four main players in Oneworld's trans-Atlantic market: British Airways (BAW), Iberia (IBE), and Finnair (FIN) on the European side, and American Airlines (AAL) on the North American side. Each of these carriers possess different databases with different data definitions - for example, AAL uses IBM's Cognos suite for data with metrics denominated in miles and US Dollars, while BAW uses SAS with metrics denominated in kilometres and pound sterling (Commercial Analytics, 2012).

One common metric used in the airline industry to measure cost is “CASK", or Cost per Available Seat Kilometre (“CASM" or Cost per Available Seat Mile is used for carriers based in countries that use the Imperial measurement system) (Basic Measurements in the Airline Business, 2007). Yet CASK has two major shortcomings which make it difficult to be used, in and of itself, as a fair metric that can be used to compare different airlines. The first shortcoming is that CASK is made up of fixed and variable costs, thus inherently favouring airlines that fly longer routes over shorter ones, as fixed costs (such as depreciation) can be amortised over longer distances. The second shortcoming is that it does not take into account the type of “seat” being made available - a much more valuable business-class seat at the front of the plane is treated the same way as a middle seat in economy located in front of the lavatory. Thus, airlines like BAW that proportionally offer more first- and business-class seat will have a higher CASK than a mostly economy-class airline like FIN without taking into account the extra revenue a first- or business-class seat brings. Moreover, what an airline may count as “cost" may differ based on the accounting practices of the organisation and country it is based in.

This is where the Metrical Level comes into play. The Organisation Liaison for each organisation (in this case, BAW, IBE, FIN and AAL) will consult with the relevant people in their organisations to define what is meant by “cost” in their organisation, and how it is measured. They will identify the different seat classifications used within their airline and on the trans-Atlantic routes in question. Once these areas have been identified, the Organisation Liaisons then discuss their findings with the

Monitoring Analyst, who will then use their expertise in business analytics to determine what data is necessary, define what is meant by “cost”, and propose workaround metrics for areas where a member airline doesn't store a particular metric. The Monitoring Analyst will also use his or her judgement in determining how seats across the alliance are classified for the sake of properly analysing CASK.

5.2 Finding the Optimal Solution

With unified data definitions in place, and discrepancies in antecedents and subsequent scenarios accounted for by a single diagnostic analytics approach and a single predictive analytics approach, finding an optimal solution for the alliance using prescriptive analytics becomes much less daunting. A non-equity alliance, by its very nature, features many unique constraints per company, yet the strategy forward must include all parties. For example, costs vary by airline due to factors, such as differing target consumers (for example, BAW focusing on the premium business traveller vs. AAL focusing on cost-conscious travellers) and home country regulations, yet all must find a way to reduce costs to allow fares to be cheaper (or margins to be larger) as an alliance than other alliances and even independent airlines. As such, if prescriptive analytics is run on an organisational level, piecing together the optimal solutions of each organisation may result in a solution that is contradictory, or difficult to discern amidst a cacophony of different metrics and assumptions. This is where the groundwork laid by the lower levels in the proposed model allows for an optimal solution to be found more easily.

Prescriptive analytics are made up of three main components: the goal (for example, “increase market share”, “reduce cost”), constraints (for example, plane/fleet size, regulations), and variables (for example, passengers). Under the model, the goal is set in the Metrical Level, where the Inter-organisational Alignment Board (or BA Team Head) set out objectives for the alliance to accomplish, to which the Monitoring Analyst defines metrics to measure progress towards achieving the objective. Constraints are also defined in the Metrical Level, and further expounded in the Situational Level, where each airline's capabilities and limitations are identified. Variables are found in the Aggregate Level, where through the use of diagnostic analytics factors that have a correlation with performance are identified, and through predictive analytics, are examined for their effect on performance. With all three components in mind, the Analytics Process Designer, in the Alliance Level, creates a prescriptive analytics model (such as using a Linear Optimisation scheme) to attempt to find the best solution for the alliance. The Oneworld alliance may find that traffic in Central Europe is forecast to increase, but currently are ill-positioned to capitalise on the increase due to high CASK resulting from routing traffic through IBE's home airport of Madrid. The Analytics Process Designer may find through examining trans-Atlantic operations data and running it through a prescriptive analytics model, Oneworld can keep overall travel times mostly the same and significantly decrease CASK on routes between North America and Central Europe if Oneworld resources (i.e., in this case AAL's, BAW's, FIN's and IBE's planes) are reconfigured to route passengers through FIN's lower-cost home airport of Helsinki onto their Central European destinations. In this manner, Oneworld - and by extension its member airlines - can turn the trans-Atlantic routes between North America and Central Europe into a cash cow with high margins, or afford to cut ticket prices while maintaining existing margins, by reconfiguring alliance-wide resources, putting significant pressure on other alliances and non-Oneworld airlines to respond to the competitive threat posed against a route network with a lower cost base.

Given the identification of an optimal solution by the Analytics Process Designer, the Interorganisational Alignment Board (i.e., executives at Oneworld, AAL, BAW, FIN, and IBE) must now make an informed decision around how to pursue the solution given. The BA Team Head explains to the Inter-organisational Alignment Board how the metrics behind the model were developed, what they mean, and as a management consultant, recommends a couple of ways around how each Oneworld airline can deploy their resources so as to realise the optimal solution found, should the Inter-organisational Alignment Board choose to pursue the solution. Thus, the BA Team Head plays a critical role in deploying the solution - the proposed model provides a prescribed optimal solution, but the BA Team Head must combine his or her knowledge of business analytics with knowledge of management to put in place the solution taking into consideration non-quantifiable constraints. To put this within more real terms using the optimal solution given above, Oneworld may choose to route more passengers through FIN's Helsinki hub by having all itineraries with a destination in the Czech Republic handled only by FIN. However, such an action may meet political resistance from IBE, who may have a strong attachment to its route between Madrid and Prague. Thus, the BA Team Head will help advise the Inter-organisational Alignment Board on trade-offs to ensure the optimal solution is still set in place with special considerations given due thought.

6 Conclusion

With the current trends of globalisation, technology adoption, and free-trade agreements between countries showing no sign of abating in the world economy, organisations are increasingly cast into an unfavourable position of high inter-market rivalry and strong customer power. To relieve these pressures, the formation of strategic alliances, whereby organisations can share resources and competencies to develop products or push other players out of the market, have rapidly gained pace. Yet, measuring the alliance's performance has thus far remained mostly a guessing game - organisations present their own view on how the alliance is working for them, but a comprehensive, alliance-wide view of how the alliance is performing, along with ways to improve the alliance, remains lacking. The discipline of business analytics has been solving a similar problem for individual organisations: i.e., business analytics takes data from within the organisation to identify areas needing improvement, and produces strategic options that allow the organisation to better respond to competitive threats and take advantage of organisational strengths. Logically, it would thus make sense to apply business analytics to strategic alliances. However, given the nature of strategic alliances, where organisations remain functionally separate, the problem of how to reconcile data from different organisations has thus far made the application of business analytics to strategic alliances infeasible.

This paper fills this gap by proposing a model that 1) uses definitions understood by all parties, and 2) provides the most optimal solution for the alliance. To this end, functional roles within a business analytics team, a data standardisation framework and organisational structure, and a data exchange framework were all blended to create a five-level hierarchical organisational model supported by a data context mediation service. In the model, metrics to be used by the alliance were identified from organisational contexts and data in the first level, and were then generated in the second level. After reconciling the metrics to a pre-defined alliance standard, various types of business analytics were performed on the metrics in the third and fourth level, leading to insight that allowed alliance executives at the fifth level to make an informed decision on whether to pursue a certain strategic option produced by the model given future trends and antecedents to observed behaviour. A proof of concept using the airline industry was then given to show how the model would produce strategic options for an alliance in a real-world context. Yet, though the proof of concept used the specific example of the Oneworld alliance's operations in the trans-Atlantic market, the model is likely to be able to be used in a wide range of applications and across a wide range of industries. In the proof of concept cited in the paper, an example of a horizontal, non-equity alliance (i.e., the Oneworld alliance) was utilised; however, the model could feasibly work in any business arrangement (regardless of whether it is a “strategic alliance") where functionally separate units within the same industry work with a common goal in mind, supported by a central organisation.

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