On Decision Making in Business-Driven IT Management

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Abstract— **Business-driven IT management (BDIM) is a recent research effort to drive IT management decisions from a business perspective by considering business indicators such as profit, cost, and customer experience. BDIM studies complicated decision making processes, dealing with the relationship between the IT function and the business value it generates. The present paper aims at stimulating the discussion on decision making theory and practice within the BDIM research community, in order to develop a better understanding of the theoretical background and consequently improve current tools and practices. To this end, the paper analyzes the most challenging aspects of decision making in BDIM and proposes a few discussion topics that could be of interest for future research studies.**

Business-driven IT management; decision making; decision support systems.

I. INTRODUCTION

In IT service management, the most commonly adopted IT management practice [1] [2], the IT department plays the role of technological service provider. Business-driven IT management (BDIM) is a recent research effort that aims at driving IT management decisions from a business perspective by leveraging on business measures, such as profit, cost, and customer experience [3]. As a result, in BDIM the IT department role would be better described as that of a business partner. Bringing IT out of the technology provisioning domain means that one cannot consider it as an isolated entity and, in optimizing its performance, must also consider its complex interactions with the rest of the world i.e., customers and competing IT firms.

This has a serious impact on decision making processes. In fact, in BDIM random events and processes have a very significant impact, with major consequences on the accuracy of forecasting models – an essential component of every decision support tool. In addition, BDIM decision making has to consider irrational human decision makers as well as rational and automated decision making agents. Finally, researchers and practitioners developing BDIM tools and practices need to address the problem of identifying and modeling the relationship between the IT function performance and the business value it generates.

In our experience with the design and development of BDIM decision support tools for the optimization of the IT incident management process [4] [5] [6], as well as with the analysis of transactional data from real-life IT support organizations [7], we have encountered many decision making-related challenges. We often felt the set of theoretical and practical tools at our disposal to be limited and lacking, sometimes inadequate to deal with the challenging tasks we were facing. We believe that, with a very high likelihood, other researchers and practitioners might have met the same obstacles as well.

Building on our experience, the purpose of this paper is to stimulate the discussion between researchers and practitioners on BDIM theory and practice from a decision making perspective. To this end, we begin by presenting an analysis of what we believe are the most challenging aspects of decision making in BDIM: dealing with forecasts and uncertainty, dealing with human decision making, and modeling the IT-business linkage. Then, we propose a few discussion topics that may serve as useful research directions for the BDIM community.

The rest of the paper is as follows. Section II analyzes the impact of the transition from IT service management to BDIM in decision making. Section III discusses the most challenging decision making problems that researchers and practitioners have to deal with in business-driven IT management. Section IV proposes a few recommended future research directions. Finally, Section V concludes the paper providing some final remarks.

II. IMPLICATIONS OF THE TRANSITION FROM TRADITIONAL NETWORK AND SYSTEM MANAGEMENT TO BDIM IN DECISION MAKING

When considering the business impact of IT services – and disruptions thereof – on customers, as BDIM does, decision support becomes challenging.

In traditional network and service management, the IT function performance is usually assessed through technical measures. For instance, the IT incident management process often considers latency and throughput metrics in dealing with service recovery operations.

In BDIM on the other hand, managers adopt business criteria to evaluate the IT function performance [3] [8]. More specifically, they assess the IT function capability of providing *business value* to customers. As a result, the performance evaluation of the IT function cannot only rely on IT metrics, which fail to capture the business value of provided services, as well as the impact of service disruptions, on the customers' businesses. Different business-level metrics need to be adopted instead. In practice, we have the situation depicted in Figure 1, in which the capacity of a specific IT infrastructure state to match its objective is evaluated *outside of the IT domain*.

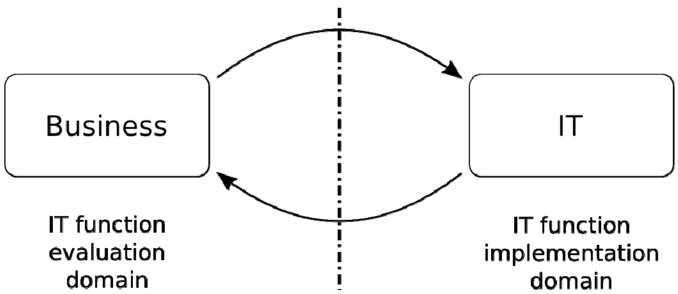

Figure 1. The Business and IT domains.

To measure (or estimate) the business value generated by the IT function, one has to consider interactions with potential, new, and abandoning customers, as depicted in Figure 2. In fact, customers influence each other's expectations with regards to interoperability, feature set, price, quality – and consequently the perceived business value – of the subscribed IT services. In addition, one often needs to consider interactions with competitor IT firms that, by defining both reference feature sets, prices, and QoS and by influencing customers' expectations, have an impact on the business value of IT services. BDIM business value generation (and disruption) metrics are also supposed to capture the effect of these interactions.

The impact of the above mentioned interactions with other customers and competitors is much more relevant in BDIM than in traditional network and systems management. Unfortunately, the interactions between the business and IT domains, while strong, are very subtle and difficult to identify and model.

The peculiar characteristics of the BDIM scenario have an important impact on decision making. In our experience, we realized that BDIM decision making needs to deal with an environment where random events and processes have a much more significant impact, that it needs to consider irrational human decision makers instead of (or as well as) rational agents, and that has to address the problem of identifying and modeling the relationship between the IT function performance and the business value it generates. The next section discusses in details these problems.

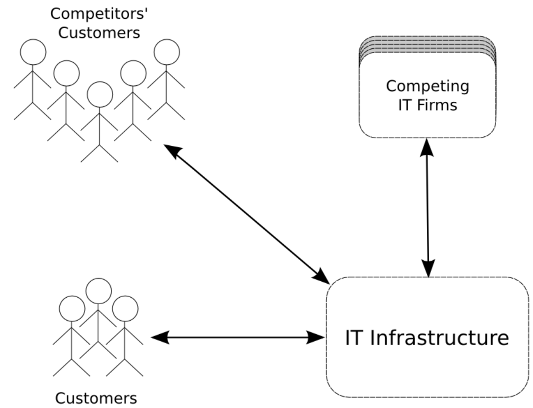

Figure 2. Influences between the IT infrastructure and the outside world.

III. Decision Making Problems in BDIM

There are many problems in decision making in BDIM, but in our experience the most important and challenging ones seem to be dealing with forecasts and uncertainty, dealing with human decision making, and modeling the IT-business linkage.

A. Forecasts and Uncertainty

One subtle but very significant change with respect to the traditional network and system management case, where objectives are expressed in terms of target values for IT performance metrics, is that BDIM deals with business objectives, which in turn (often) heavily rely on *forecasts* of future performance, e.g., monthly or quarterly results.

The adoption of forecast-based measures as a primary tool to evaluate the IT function performance specifically characterizes the BDIM practice. The complexity of the application scenario, where unpredictable interactions between human agents take place, means that one cannot assume to deal with the *mild nature of randomness* that characterizes mechanical systems in physics and engineering, where reasonably accurate forecasts are possible [9].

In complex scenarios such as BDIM, *wild randomness* should instead be considered [10]. In this case, one cannot rule out the chance of highly unlikely or totally unexpected events. This significantly complicates forecasting, limiting the applicability of regression tools such as those commonly employed in econometrics [11] and raising serious doubts about whether the realization of accurate forecasting models is even possible [12] [13].

The challenges presented by the wild nature of randomness to BDIM decision making go beyond the development of forecasting models. In fact, notice that operating in a regime of wild randomness one might even question the effective applicability of utility-based rational decision making models, such as those based on Von Neumann-Morgenstern utility functions. In fact, utility functions assign a "utility value" to every possible outcome, but in wild randomness regime *one effectively cannot know all possible outcomes*.

In our experience with the SYMIAN decision support tool [6] and the analysis of real-life IT support organizations [7], we found that the many interactions with other support groups significantly amplify the impact of small variations in the current working condition of a support group. Unfortunately, this is potentially a major source of randomness, as the amplification phenomena also apply to random-induced changes in the state of most system components in IT support organizations.

B. *Human Decision Making*

Another major challenge in BDIM decision making – which occurs much more rarely in traditional network and system management – involves the inclusion of human decision makers in the loop. Decisions to realign the IT function according to business objectives may result in a major effort, such as re-staffing (the restructuring of the IT function personnel by increasing, transferring, or cutting staff), re-training, new equipment purchasing, and the implementation of different management policies. The process of implementing the actual corrective measures can potentially be very expensive and time-consuming, so decisions should be carefully considered before putting them in practice. As a result, decision of this importance cannot be left to automated tools, but must be taken (or at least acknowledged) by business managers.

To make things more complicated, people are not always rational decision makers. Relatively recent social science disciplines, such as cognitive psychology and behavioral economics, pioneered by Nobel laureate Daniel Kahneman's research on heuristics and biases, have clearly demonstrated that human decision making criteria are rarely rational [14] [15]. Factors such as loss aversion, status quo bias, anchoring, and expectations on the outcomes play a major role in human decision making [16] [17]. Research has also demonstrated that excess information may turn out to be useless, or even harmful, for human decision makers – a highly counterintuitive result indeed [18].

In addition, learning aspects cannot be ignored when dealing with human decision making in complex scenarios. Human decision makers' skills significantly improve as they observe the outcomes of their decisions. This is especially true in case of multiple, possible conflicting objectives.

Taking into account the peculiarities of human decision makers in the design and implementation of BDIM tools and techniques might contribute to improve their effectiveness. In particular, there is the opportunity to design tools that present only essential information to decision makers, identifying and focusing on the most important variables in decision making while discarding other information, and to provide captivating, efficient, and immediately understandable visualization. In addition, whenever an automated decision making component simulating business managers' decisions is adopted in BDIM tools, it should try to mimic human decision making as accurately as possible.

Notice that the integration of human-like decision making components in BDIM tools represents a challenge but also an interesting opportunity. In fact, research in behavioral economics has demonstrated that humans have two systems of reasoning: an intuitive one (also known as *blink*, after the title of Malcolm Gladwell's popular scientific divulgation book), which is fast and low-cost, and a rational one, which is slow and extremely expensive to use. Being able to reproduce human-like intuitive decision making could be a very powerful tool to deal with complex decisions.

In our research on critical incident management, we encountered the need to integrate a component simulating human decision making in the HANNIBAL decision support tool [5]. Unfortunately, we found very difficult to think of a way to automate human decision making. Rational decision making frameworks, e.g., based on Von Neumann-Morgenstern utility functions [19], seem inadequate to properly describe human decision makers. Machine learning-based techniques and tools that analyze human decision making criteria and distill them in rules or regression functions seem to represent a more interesting and promising approach.

C. *Modeling the IT-Business Linkage*

Modeling the IT-business linkage, i.e., the relationship between the IT function performance and the business value it generates, is one of the most studied – and challenging – problems in BDIM.

Figure 3 depicts the characteristic BDIM double closed loop feedback scheme, highlighting the interactions between the IT function performance, the BDIM control procedures, and the business processes and strategies. The figure shows both the *inner loop* between IT function and the BDIM control component and an *outer loop* that also includes the lines of business.

From the decision making perspective, we can identify two essential processes: the *forward process*, measuring how well the IT function is aligned with the business objectives defined by the business management, and the *backward process*, detecting which changes in configuration (restaffing, reorganization, adoption of different management policies, etc.) of the IT function are required in order to achieve the perfect alignment. Both the forward and the backward processes are of critical importance for decision making in BDIM.

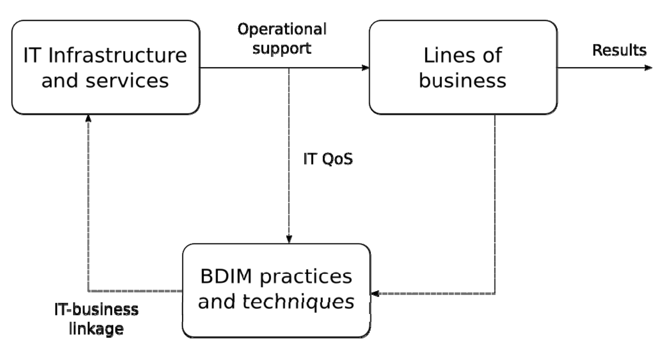

Figure 3. BDIM Closed Loop.

The forward process is probably the most defining aspect of BDIM. For this reason, so far it has arguably received much more attention in the research literature than any other aspect of BDIM. Since IT metrics alone fail to capture the whole impact of IT services (and their disruptions) on the customers' businesses, the forward process also leverages on business-level metrics or *Key Performance Indicators (KPIs)*, based in turn on Service Level Agreement (SLA) violations and penalties. While this "pipelined" process, as depicted in Figure 4, appears rather simple in theory, in practice the accurate estimation of the business value generated by IT services is an incredibly difficult task. In addition, there are non-negligible concerns about the SLAs capability to accurately capture the impact of IT services on the customer businesses [20].

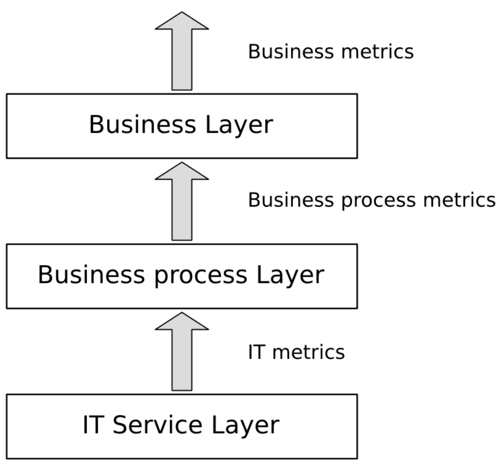

Figure 4. The forward process "pipeline".

Despite having received less attemption from the research community so far, the backward process is also an essential element of BDIM decision making, at least as important as the forward process. In fact, the backward process produces a set of changes to apply to the IT function configuration in order to minimize its disalignment with respect to the business objectives set by the management, as well as cost and time estimates for their implementation. More specifically, the backward process analyzes the output of the forward process, i.e., the current IT function business value creation, calculates the displacement with respect to the target business objectives, and proposes the IT function configuration changes. Given the significant levels of complexity that typically characterize IT functions, this is an incredibly challenging task.

To complicate the picture further, both the forward and the backward processes have to deal with the assessment of *intangibles*, i.e., "hidden" business value generating or disrupting processes. The impact of most intangibles, such as customer-perceived QoS, is particularly tricky to identify, estimate, and model.

Our experience with the SYMIAN [6] and HANNIBAL [5] decision support tools showed that accurately modeling both the forward and the backward process is an essential, albeit dishearteningly challenging, step in the design and implementation of BDIM tools. We believe that applied research in BDIM decision making would immensely benefit from any theoretical development in the analysis of the forward and backward processes.

IV. DISCUSSION TOPICS

After the analysis of the most challenging aspects that researchers and practitioners have to deal with in BDIM decision making, we now present a list of interesting discussion topics that we would like to be addressed in the near future. We hope that these topics will stimulate the BDIM community to push forward both theoretical and applied research in decision making.

A. *Avoiding general, quantitative, a priori, and excessively complicated models*

In a complex scenario such as BDIM, it is very difficult to think of models that can accurately represent the reality, especially if they are developed (and exploited) with the ambition to have generic applicability or to produce reliable quantitative evaluations.

The difficult-to-capture and ever-changing nature of the interactions among the parties involved in typical BDIM scenarios make the effort to develop general and/or quantitative models almost hopeless. Instead of frameworks that accurately represent reality, we suggest that BDIM models instead be considered mostly as reasoning tools, developed on a case-by-case basis. It is also convenient to keep in mind the relative nature of models' outcomes, and evaluate them only in comparison with the outcomes provided by other models.

Researchers and practitioners may also find it hard to build useful a priori models. Our experience shows that it is essential to continuously evaluate models, and possibly refine them, by considering feedback from (their application to) the real world, as depicted by Figure 5.

Finally, in our experience we have noticed that a particular importance should be dedicated to the tradeoffs of model complexity. While some applications might indeed require very complicated models, we believe that in most cases keeping models from becoming excessively complicated is very important. In fact, complicated models are difficult to work with.

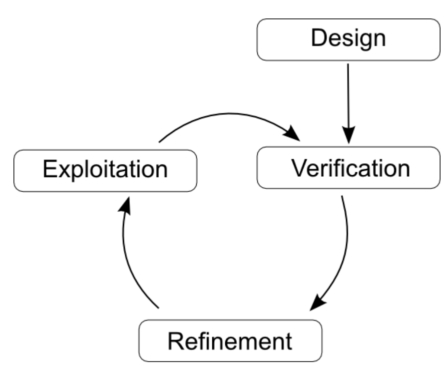

Figure 5. The Exploitation-Verification-Refinement model continuonus development loop.

In addition, *sophisticated models are detrimental as they provide the illusion of control*. Practitioners tend to believe that models are accurate just because they are sophisticated. This assumption, which is not necessarily true, might potentially be very harmful. In BDIM decision making, it is of utmost importance not to rely on any unverified assumption and to keep a critical thinking and problem solving approach.

In our opinion, the effort in building complicated a priori models would be better spent in model verification. There is no point of building a complex and precise model of reality if it's not accurate.

Unfortunately, it is difficult to think of rigorous, automated, and broad-applicability criteria to choose the appropriate level of model complexity. Decisions on model complexity tradeoffs will likely need to be driven by application-specific objectives and constraints.

B. Involve customers in the decision making process

Another important guideline is to involve the customers' feedback in the decision making processes.

Customers' feedback is essential to accurately measure the business value provided by IT services. IT metrics and SLAs (as well as their violations) are clearly inadequate as instruments to measure the business value created by IT services (and lost with service disruptions) [20]. It is also very difficult to think of a way to measure intangibles by leveraging only on business and IT metrics.

As a result, it is indispensable to look for customers' feedback in order to evaluate business value creation and generation, and to set business objectives accordingly.

In addition, the involvement of customers in the decision making process can actually generate business value.

C. Good enough is just good enough

The complexity of the BDIM scenario calls for continuous validation of working conditions, verification of business objectives, and for the consequent IT function realignment.

In this continuous optimization process, it is absolutely essential to avoid costly and potentially harmful overspecializations. By over-optimizing the IT function according to the current business objectives, there is the risk to achieve an excessive fit to the current environment and hinder future adaptations to different conditions. This is a typical phenomenon in evolutionary environments, where individuals that are especially fit to the current conditions are wiped out by natural selection as they are less capable to adapt to new conditions.

In BDIM applications, when the customer set (or the customers' expectation) changes the business objectives to optimize for might change accordingly, and costly efforts to perfectly align the IT function with respect to previous business objectives might turn obsolete, detrimental, and a waste of resources.

Since business objectives can change unexpectedly, it is unreasonable to set a difficult to reach target for optimization. It makes sense to optimize up to a certain point and check frequently whether there is the need for further optimizations.

D. Investigate the human component in decision making

Acquisition of decision skills is not easy, as it requires learning through a trial-and-error process where the quality of each decision, i.e., the satisfaction with its outcomes, should be evaluated shortly after the decision making process [21].

Unfortunately, BDIM systems are not easy to experiment with. In order to evaluate the quality of BDIM decision making, it would be necessary to evaluate the performance changes – in terms of the alignment with the business objectives – brought by the changes the IT function configuration that the decision maker requested. This is a very challenging task, as it requires considering a large set of possible operations, such as re-staffing (the restructuring of the support organization by increasing or cutting staffing levels, or the transfer of operators around support groups, possibly on retraining), and the implementation of different policies for incident assignment and prioritization. In addition, the process of implementing the actual corrective measures is very expensive and time-consuming, so alternative IT function configuration should be carefully considered before putting them in practice.

This raises the opportunity to invest in Interactive Learning Environments (ILEs), that can help by both providing a tool for managers to improve their decision skills. In this context, a particularly interesting approach is *what-if scenario analysis*, a technique that enables the behavioral analysis of complex real-life systems under alternative working conditions. More specifically, what-if scenario analysis is based on the definition of an accurate model of the system under evaluation and on its exploitation to reenact of the system behavior with modified parameters. This kind of tools enable their users to play out what-if scenarios, allowing them to assess the outcomes, i.e., performance improvements or drops, without having to go through the expensive and time-consuming process of implementing actual organizational, structural and behavioral changes.

Our experience with what-if scenario analysis tools demonstrates that this technique produces very effective results in learning how the IT function works, and that it could be effectively applied to decision making as well.

More specifically, BDIM-specific ILEs should allow to build an accurate model of the IT function, and reproduce the IT function behavior through computer simulation techniques. ILEs should then provide extensive performance evaluation functions that can enable user to check the outcomes of their decisions, exploiting advanced Human Computer Interface (HCI) systems. These tools should also guide users all along the decision making process, providing functions for configuration rollback and ad hoc visualization of outcomes.

ILEs could also represent a terrific opportunity to learn how business managers decide. This could be a first step towards the development of human-like decision making components and their integration in BDIM tools.

E. *Improved forecasting models*

Another interesting question to address is how much we can rely on model-based forecasts. By their very nature, models are abstractions of reality that only capture what they were developed to do. Anything outside of the model is, by definition, not considered. While this is a problem in any application domain, the complexity of BDIM scenarios calls for paying a particular attention to the model limitations in their adoption.

In fact, most models are built on strong assumptions. While (at least for well-developed models) most of the times these assumptions hold and can be safely ignored, sometimes in BDIM systems the working conditions may change so abruptly that the models are not applicable anymore.

These considerations are especially important when models are used for forecasting. As mentioned above, BDIM models leverage on forecasts to assess the performance of the IT function – in its current configuration or in a different one – both in the context of the forward and the backward processes. As a result, accurate forecasts are absolutely essential for BDIM tools.

In addition to accuracy concerns, there are also questions about which kind of forecasting to adopt. Given the complexity of the BDIM scenario, forecasts that simply produce point estimates are likely to be of very limited use. In this context, it would be much better to rely on forecasts that instead provide interval estimates of the desired metrics, including the degree of confidence in the estimate. However, those kind of forecasting models are very difficult to develop and to work with.

A promising, although somewhat radical and perhaps not broadly applicable, approach would be to ditch quantitative forecasting methods altogether and instead focus on forecasting the likelihood that a certain event, e.g., a given metric exceeding a threshold value, will happen or not. While this kind of forecasts produced a limited informative content, they seem to be a rather robust approach.

Notice that, so far, mainly two forecasting models have been proposed in BDIM literature: econometrics [22] and what-if scenario analysis-based forecasts [6], both belonging to the point estimate category.

V. Conclusions

Decision making in BDIM represents an extremely difficult problem, where the most challenging aspects lies in the fundamentally interdisciplinary nature of BDIM. In fact, in the development of BDIM decision making tools and practices, researchers and practitioners must deal with problems that belong to many different fields, such as engineering, computer science, economics, and cognitive psychology. Dealing with such a series of disheartening challenges requires both a thorough theoretical understanding of the playing ground and an empirical, bottom-up, case-based approach, and out-of-the-box critical thinking.

We believe that there is the need to develop a better understanding of both theoretical and practical issues involved in BDIM decision making. The questions that researchers and practitioners will need to address, such as "What are the fundamental limits of decision making in the BDIM domain?", "How does complexity fit in the BDIM scenario?", and "Can we use results from research on decision making in other disciplines and apply them to BDIM?", are compelling and challenging. We would very much like to see them addressed in the near future.

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