Proposition of a Unified Theory on Resistance to Data – Empirical Studies and Experimentations to Reduce Barriers to Data Usage in Decision Support Systems

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Benito Giunta[1,2,3], Corentin Burnay[1,2,3]

[1]*University of Namur, 61 rue de Bruxelles, Namur, 5000, Belgium*
[2]*PReCISE Research Center*
[3]*Namur Digital Institute (NaDI)*

Abstract

Data is ubiquitous and constitutes a significant source of competitive advantages for private and public organizations that manage to turn it into proper support for decision-makers. This holds true as long as two postulates are verified; "using data boosts quality of decision output" and "people are willing to use data". While support for the first one is significant, we find surprisingly too few pieces of evidence for the second one. The second postulate being unverified can however have some serious implications. If people do not want to use data but are actually constrained to do so for instance, they will face anxieties, poor understanding and reduced decision outcomes. If resistant people decide not to use data, they take the risk of missing important business opportunities. The alternative scenario, on which we focus in this project, is to understand this resistance and mitigate it to make resistant people more comfortable with data. There is currently no theory that offers a complete view on the resistance of people to data. Therefore, this project intends to propose a unified Resistance to Data Theory (RDT) with three main contributions: (1) RDT formation where we will design the theory by identifying existing factors that influence this resistance from the literature and uncovering new ones with qualitative studies, (2) RDT validation where we will validate the theory and (3) RDT exploitation where new approaches to Decision Support Systems will be identified to decrease resistance to data. Together, these three contributions provide a comprehensive view on a new fundamental issue (resistance to provided data) with a potentially significant switch in the perception of how data is used within an organization, and how data should be introduced to decision-makers to exploit its full potential more systematically.

Keywords

Resistance, Resistance to Data, Data Barriers, Data-Driven Decision-Making, Decision Support Systems

1. Context and Motivation

Modern companies produce tremendous amounts of data and consume information as a way to produce knowledge, and ultimately wisdom. This data consumption in turn is expected to grant - through the use of Decision-Support Systems (DSS) - business managers with the abilities to monitor, analyze and track their business activities and decisions. These activities, and the

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benito.giunta@unamur.be (B. Giunta); corentin.burnay@unamur.be (C. Burnay)
0000-0003-3707-6650 (B. Giunta); 0000-0002-0325-1732 (C. Burnay)
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support to them, are often recognized as a key success factor for the management strategy and a source of competitive advantages [1, 2]. With data becoming ubiquitous in our society, many companies are *digitizing* almost everything and spending huge amounts of resources to use this data under various forms, e.g.: through business intelligence, data analytics, machine learning, etc. All these investments start from the two postulates that "using data helps improve decision output" and that "people naturally always seek to use data". These postulates can be formalized as follow: (1) *people should use data* and (2) *people want to use data*. While support for the first hypothesis is significant, the second one is nearly dogmatic.

Support for the first condition is quite clear in the literature. The importance of decision-making has always been, and still is, at the forefront of organizational concerns and management research [3, 4]. With the rise of data and its ubiquitous presence in our society, we now talk about Data-Driven Decision Making (DDDM). The way decision-making is conducted has been revolutionized bringing new analytical tools for companies to differentiate themselves by taking better decisions than the competition [1]. When uncertainty is prevailing, strategic decision-makers need to master – and to trust – as much as possible the only thing that is certain; their current and actual business situation, which can be reflected by the data [5]. Having a great understanding, through data, of the current business situation then creates a strong competitive position by providing decision-makers with the necessary knowledge to make that *right* decision [1]. Robust data management undeniably leads to competitive advantages since it allows to clear up ambiguities in strategic decisions with more intelligible pieces of information. Insightful management and mastery of information make an organization reach faster business value. Information is the trigger to strategic actions [1].

The satisfaction of the second condition is less obvious to achieve. In practice, many decision-makers oppose some resistance to the use of data, regardless of its form, especially when it is shared by someone else, i.e. not their own data. The very idea of using data provided by a tier generates some sort of cautiousness. Some people do naturally use available data without any restriction, but in many instances people are also willing to capitalize more on their intuition and past experiences [6], their knowledge of the problem, collaborations with other colleagues, and not as much as usually assumed on the data made available by others via a DSS. Besides, we found no proper validation in the scientific literature confirming that condition (2) holds true in a real-world setting. Now what are the possible consequences of condition (2) not being true? There are three possible scenarios. In the first scenario, data resistance is not recognized as being something real, leading data resistant people constrained to use data – as it is almost inevitable from a business perspective. This would likely result in decision-makers using data but lacking trust, feeling anxieties [7] and with a poor understanding of the tool they are using, thereby presenting a higher risk of leading to poor quality decisions outcomes and decision-maker frustration. In the second scenario, data resistant people would be free to not use data during their decision-making processes, thereby violating condition (1) and resulting in inefficient decision-making.

The third scenario is the one we propose to develop in this project. It implies to further elaborate on the reasons why a decision-maker could violate condition (2). If we prove data resistance exists and come up with a theory which formalizes the factors that influence resistance to provided data, then it would be possible to design DSS (and more generally any information system) in a smarter way, that would reduce data barriers making reluctant people more comfortable with the use of data. Scenario 3 relies on the understanding, control and reduction of resistance and raises a number of questions central in this proposal and in the context of DDDM; what is resistance to data? Under which form does it exist? When does it occur? What are the factors influencing such resistance, linked to the individual, the organization or the data itself? How can we manage these factors to reduce reluctance to data? Answers to these different questions form the ambition of this project.

The scope of this project is relevant with the Research Challenges in Information Science (RCIS) conference. The core concept of RCIS is the information systems which necessarily gather, process and manage data. To ensure valuable information systems, we need to ensure its users do not face any barriers to use them.

The remainder of this paper is structured as follows: section 2 State of Art reviews the current state of the literature regarding resistance, section 3 Research Project presents the contributions of the current proposal, section 4 Research Methodology outlines the methodology that is to be followed.

2. State of Art

Resistance is not something new in the literature. The concept primarily came out, in the psychological field, from Freud [8]. Resistance has strongly been studied and many definitions have been proposed. It has then been introduced in the management field under the form of Resistance to Change [9] and has been studied together with; the affective processes [10], the personality traits [11], the group belonging [12], etc. These studies claim that no milestone can be reached in a company's strategy change if Resistance to Change is not considered [13].

When resistance is coupled with data in the literature, four types of resistance seem to be outlined. The first one is a *technology-based resistance* [14]. The rise of big data brings new possibilities but comes with technological challenges that can produce resistance. The variety, the velocity and the volume of data require a technological revolution [15]. Another example is provided with [16] which emphasized how technological choices of a DSS can provoke transparency and understanding issues. The second is an *individual-based resistance* where the roots of the resistance lie in the user perception. In the context of citizen data, the rise of data-based companies and smart-cities highlighted the discomfort people may feel when external actors use their data [15]. The lack of knowledge on what is effectively processed to their data inhibits the willingness to use the systems [15]. Other factors are uncovered by [7] whose findings claimed that the data present in "everyday life" activities is a source of anxiety, pressure and uncertainty. In the same direction, [17] investigated the interaction between Resistance and "IT adoption", "intention to use" and "perceived usefulness" of users in the case of mobile data. The authors concluded by calling for a general theoretical model arguing that other factors may certainly exist and additional research efforts are required to uncover them. The third resistance is *organization-based.* Data has constrained companies to review their business model [18], culture or policies. For instance, designing great data governance sends positive signals to users and can reduce their resistance. In [19], authors found that managers do not always use decisions when resulting from data science processes if they do not perceive the quality and reliability of the data. One way to communicate on this aspect, is to settle and share about the company's data governance and data strategy [19]. The last type is the resistance based on the *data characteristics themselves.* Some factors, directly linked to data itself, have already been discussed, like the quality or the level of reliability [20]. Other factors may exist and some are uncovered by [21]. The authors identify a number of barriers to data usage – e.g.: opaqueness, lack of practice, etc – but also a number of enablers – e.g.: support, willingness to participate, etc – by focusing on the specific case of DDDM in High School and the subsequent district policy consequences.

All in all, significant gaps are noticed in the current literature: there is a need for a theory that integrates all the components that may influence resistance to data - those from the literature, but also others which may have never been uncovered to this day - with a proper empirical validation and a more general view, i.e. not tied to a specific context or technology, but to data in general. Particular approaches, like the technology-based resistance, only focus on a limited number of factors missing the ones from other approaches and their interrelation. In this project, one of the objectives (see section 3 Research Project) is to provide a unified view that would identify and organize, under the same theoretical model, the different types of tensions that may occur when talking about resistance to data. This theory would be built on theoretical foundations of Resistance and would come with empirical validations uncovering and evaluating new factors relevant to DDDM.

3. Research Project

The contribution of the project is three-fold; (1) Resistance to Data Theory (RDT) formation, (2) RDT validation, (3) RDT exploitation.

RDT formation – While the strategic issues inherent to data cannot be disregarded, there is a lack of theorization on the tensions that provided data can trigger for employees. First, Resistance will be prospected via a combination of a literature review – to gather existing factors, called drivers, to resistance to data – and primary data coming from qualitative studies – to uncover new drivers. Both will contribute to a unified view on these drivers. This contribution thus forms a Unified Theory of Resistance to Provided Data – called RDT for the sake of simplicity. This stage aims to clarify the ins and outs of resistance to data and to further motivate the relevance of the research questions of this project. It will emphasize the implications with previous postulates, the drivers and the typology of resistance; are all the four types of resistance dimensions relevant for data, and if yes how do they interact?

RDT validation – The second stage is the validation of the findings of contribution (1) to come up with a validated RDT. This stage aims to dive deeper in the roots of resistance. Each driver within each category of resistance will be empirically tested. The intensity of each driver will be measured to understand its prevalence in the theory. The direction of each driver will also be determined. Indeed, among these drivers, all the barriers will be formally grasped – the ones that may increase Resistance – but also the boosters that may decrease Resistance in favor of data. All in all, it will lead to a valid RDT formalizing the tensions raised by data that are not considered from a technical perspective; some technically feasible solutions are not viable if these tensions are not taken into account [10].

RDT exploitation – Starting from a validated RDT, the next stage consists in identifying new approaches to tackle data resistance factors, and hence to better handle the two postulates of section 1 Context and Motivation. Our perspective here is that it should be possible to design system Requirements, taking into account RDT drivers, to propose new designs of DDDM systems that would reduce the significance of the data barriers. Each candidate solution will be tested during an experimentation. To do so, a subset of RDT drivers will be selected and requirements of a system will be adapted to control these drivers and to reduce data barriers. The solution will be designed, tested and analyzed with companies, in a real-world context and in situations where the data barriers mentioned all along this project are observed and unresolved. The objective of the RDT exploitation is three-fold: (i) to evaluate the actual relevance of the candidate solution(s) with regards to the RDT, (ii) to assess the extent to which the candidate solution(s) overcome(s) the data barriers and (iii) to get feedback from the non-technical users for which the solutions are designed.

One interesting experiment that has already been identified is about Complex Performance Indicators (CPI) design. In any kind of reporting system, the user faces a number of visuals depicting the current state of its business' situation. These visuals build on indicators – e.g.: turnover, revenue growth or profit margin — but also on CPI — e.g.: the employees' well-being or the customers' satisfaction. The former is simply produced by aggregating one data column while the latter is a composition of many individual indicators/data that are combined following a more complex mathematical model. The use of CPI in DDDM is almost systematic, yet the complexity of CPI often creates fear, lack of trust and opaqueness decreasing the willingness of the user to adopt them. CPI therefore offer a nice case-study — that necessitates the postulates presented earlier — for one experiment. More particularly, with the case of CPI, a number of data barriers have already been discovered (opaqueness, lack of trust and ownership, technical complexity, etc). Thanks to the rise of No Code/Low Code development (NC/LC), we elicited a number of requirements that would decrease these barriers. NC/LC is a method to let non-IT people produce their own IT solutions, by means of graphical interfaces utilizing drag and drop mechanisms. This approach partially or totally reduces manual coding, allowing non-initiated users to develop applications and still leveraging powerful technologies without facing technical concerns [22, 23]. The NC/LC represents a great opportunity to break technical barriers tied to data usage in general. By empowering non-technical users, we grant them with greater understanding and flexibility regarding what they want to do with the system. They are not constrained to use a system as a black box but they can shape it, without technical prerequisite, to produce information they actually understand, trust and want. With the NC/LC approach, non-technical users will use visual artifacts to implement CPI (similarly to [22]) instead of using programming languages dedicated to IT-experts only. Concretely, they will have to draw a graphical model that defines, in a more natural language, what they want to implement. The model will then be automatically translated into code lines that effectively implement the desired software, in this case the CPI visualizations. These requirements are expected to decrease the data barriers tied to CPI and would be tested in real conditions to assess their effectiveness.

Of course, all the data barriers have not been uncovered yet. While some requirements of this approach are already known, the solution is not at all fully designed. The process will be similar for new data barriers; identification of the barriers with contribution (1) and (2), new requirements design (to decrease the barriers) and testing with contribution (3). The already identification of some candidate solutions reinforces the ability to find answers to this research problem. However, the project is not tied to that specific solution and it is expected to elicit several other requirements and/or experimentations by that time.

4. Research Methodology

The research project will mainly be conducted in a waterfall perspective since findings of each contribution trigger in a causal-effect the foundation of the next contribution. However, some feedback loops are expected with contribution (3).

Contribution (1) – First, a literature review will be conducted to (i) assess the current state of research, (ii) capitalize on fundamental Resistance basics, (iii) identify existing and recognized RDT drivers. Second, qualitative studies will take place with (i) top-managers (organization-based resistance), (ii) frontline managers and decision-makers (technology- and data characteristics-based resistance), (iii) non-technical end-users (individual-based resistance), all from any type of companies to uncover new RDT drivers. The studies will be held in a semi-structured way to guide the discussion based on what has already been discovered but also to give the possibility to the participants to express themselves on the specifics of their particular situation.

Contribution (2) – the foundations of RDT and its drivers will be validated. A quantitative study will be held, targeting the same roles (managers, decision-makers, non-technical users) at a greater scale. The objectives are to (i) confirm/discard the drivers, (ii) assess their strength and direction in the RDT. Since the concept of Resistance is a multidimensional construct with an underlying system of relations among factors, we plan to base the data treatment on Structural Equation Modeling, mainly leveraging Measurement Theory, Regression and Factors Analysis.

Contribution (3) – Based on previous contributions, new approaches will be identified, designed and implemented. Some real-world case-studies which face the two postulates will be identified. Such a task will not be a problem since every type of company is using data. The new approach will then be (i) initialized, (ii) feedback mechanisms will be settled with the different type of actors, (iii) refinement of the approach based on the feedback will be considered, (iv) to conclude with the assessment of the approach what regards the challenges of RDT.

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