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► To cite this version:

Robin Le Conte Des Floris, Cédric Dalmasso, Pierre Jouvelot. The impact of motivation on the quality of project management data: an emailbased communication case study. EURAM 2022 (leading Digital Transformation), School of Management and Law, Jun 2022, Winterthur, Switzerland. hal-03662794

HAL Id: hal-03662794

<https://hal-mines-paristech.archives-ouvertes.fr/hal-03662794>

Submitted on 9 May 2022

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The impact of motivation on the quality of project management data: an email-based communication case study

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Keywords

Data quality, motivation, project management

Summary

Organizations, be they companies, governmental or non-governmental bodies or even associations, manage their projects on the basis of the value of indicators that are obtained automatically or filled in by the various project stakeholders, including the project managers. In this paper, we experimentally study the effect that employees' motivation can have on the data collection process related to project management. By sending two different types of email messages to 177 project managers in a large engineering company, one using the classic corporate format, the other mentioning an academic research objective on the subject, using a somewhat more leisurely presentation style and asking only for volunteer participation, we quantitatively assess the impact of the type of stimulus (one relying on extrinsic motivation, the other, intrinsic) on the overall data collection process. Our results suggest that the type of incentive has no significant effect on the amount of data collected. However, we note a significant effect on the way in which project performance is qualified according to the type of stimulus. In particular, the evaluation of the company's maturity with regard to projects or their

success is significantly different depending on the stimulation mode. We were thus able to quantify the extent of the differences induced by the employees' motivation, extrinsic or intrinsic. The results obtained confirm the difficulty of characterizing project performance by means of self-provided indicators by highlighting the effects induced by the context of acquisition of these data.

Introduction

For organizations, whether they are companies, governmental or non-governmental bodies or even associations, to have effective information systems, a high degree of input data quality is required (R.Y. Wang et al., 1995). Indeed, it is widely accepted that the quality of the information directly or indirectly deduced from these source data significantly affects the performance and effectiveness of the decision support tools used by organizations for the informed conduct of their activities (Raghuathan, 1999). And yet, except in the case where the collection of the relevant information is totally automatic, it remains that this quality is strongly linked to the motivation of the agents responsible for updating these information systems.

We have taken advantage of an ongoing collaboration with a large company specializing in the field of engineering and IT services, subsequently called LCES, to investigate the link between the quality of certain data collected internally by the company, in this case those related to the progress of hundreds of projects managed by LCES on behalf of clients or internally, and the motivation of the managers of these projects to provide them. This choice of project data is, in fact, linked to the longer-term objective of this research, which is, among other things, to identify what should be the key characteristics of a (future) decision support information system that would enable the best possible detection, in particular as early as possible, of projects with potential risks of not reaching a state of good completion within the planned time and budget.

LCES has a sophisticated information system (IS) that enables it to monitor the progress of on-going projects in a very detailed manner. During the preliminary analysis of the project data stored within the IS, in this case various engineering project management monitoring indicators (cost, time, performance, quality), we identified what appeared to be a quality problem. The values of the indicators filled in monthly by the project managers regarding the risks and progress of each project were characterized by a very low dispersion, which seemed to be inconsistent with the values typically mentioned in the literature of project management (Johnson, 2020).

The presence of data of poor quality in an IS and the suggested ways of dealing with such an issue have been widely discussed in the literature (Batini et al., 2009). If one can, for example, try to clean up the data, albeit at the cost of a sometimes very significant reduction in its volume, a more satisfactory approach is to influence its capture. One can thus try to act on certain external factors of the data collection process, such as the managerial influence or the technological structure of acquisition, or to act on users' motivation (Molina et al., 2013).

We present here the result of an experiment that quantifies, by implementing differentiated email communication within LCES, the impact of motivation on data collection. This experiment took place from July to December 2021 and involved 177 project managers in charge of several hundred projects in progress. In accordance with the best practices of the A/B testing method used here to study the impact of a given factor (Kohavi et Longbotham, 2017), two situations were compared, identical with the exception of the factor we wish to observe, in this case the type of mail asking users to enter the data for the projects they have in charge. If a statistically significant difference is observed between the two groups, chosen at random, for a predefined criterion, the hypothesis that only the distinct factor influenced this criterion can be validated; otherwise, it will be rejected.

The two situations are differentiated by the sending of two separate email messages soliciting the data collectors, one using the corporate language traditionally used within LCES to ask employees to fill in a form, the second doing the same, but offering an increased motivational content according to the motivation theories mobilized here and specified below. In the first case, the message builds upon the concept of extrinsic motivation and uses incentives such as obligation or performance control; in the second case, the message is based on the concept of intrinsic motivation, the action being voluntary this time and based on incentives such as the integration and internalization of the values and objectives of the goal mentioned in the message. The latter also benefits from a freer text style and motivational graphics to make it more attractive and thus further stimulate intrinsic motivation.

Two hypotheses are tested through this controlled experiment:

- the use of a motivational method influences the operational performance of data collection, characterized by response rate, speed of response and quantity of data collected (H1);
- the use of the same motivational method has an influence on the nature of the data collected, characterized by the general distribution and dispersion of the data (H2).

The experimental data collected, presented and discussed below, allow us to evaluate the influence on data collection of the motivational incentives conveyed by the content of e-mails designed specifically for this case study on several criteria.

The main results suggest that the motivational technique used here does not have a statistically significant impact on the operational performance of data collection in terms of speed, quantity and response rate (H1), but it does have a clear influence on the nature of the data collected, i.e., the shape of its distribution, its dispersion and its overall trend (H2). The managerial impact of these results is significant, as they suggest that the relevance of the data collected for project

management purposes within organizations should be questioned, while at the same time proposing avenues based on motivation theories to increase the adequation of the collected data to the realities of the project management field.

In the remainder of this paper, we discuss the state of the art related to the impact of motivation on corporate data collection and the foundations of the A/B testing methodology. We then specify our experimental protocol for data collection, with the key factor of the type of email used for this, before presenting the results, negating H1 but confirming H2. We discuss these results before concluding.

State of the art

In this section, we introduce the main references to the motivational theories and A/B testing methodology used here.

Motivation

The propensity of users in an organization to share information and the quality of that information can be positively influenced by a set of incentives aimed at motivating the system users (Friedrich et al., 2020) (Molina et al., 2013) (Richard Y. Wang et Strong, 1996). Several approaches exist for the implementation of such incentives, such as: the gamification approach, which borrows mechanisms used in the design of *hedonic* systems, which are systems used for the entertainment provided by its very use for utilitarian purposes (Koivisto et Hamari, 2019); the Self-Determination Theory approach, which uses the concept of regulation to maximize user motivation (Ryan et Deci, 2000); or UTAUT, based on user acceptance, which looks at the factors that promote acceptance and use of a system in organizations (Venkatesh et al., 2003). In order to differentiate between the two groups in A/B testing without having to resort to the development of a complete gamified system, the motivational mailer used here is based on the

Self-Determination Theory approach and the UTAUT user acceptance theory, which both offer more easily activable means of action in our context.

Self-Determination Theory (SDT) (Ryan et Deci, 2000) takes a cognitive-psychology approach to the study of human thought in terms of information processing. SDT opts for a differentiated approach to motivation in order to highlight the determining factors related to the characteristics of agents, contexts and actions. From this point of view of differentiation, two types of motivation are distinguished:

- *intrinsic* motivation, which characterizes an individual's free commitment to what an activity brings him or her in terms of pleasure, satisfaction, relaxation, etc.;
- *extrinsic* motivation, which characterizes engagement prompted by factors external to the activity itself such as rewards, social pressure or competition.

If SDT is concerned with the factors that promote intrinsic and extrinsic motivation respectively, then it is important to understand which of these two types of motivation affects data collection in an enterprise context. In our case, to understand which of these two types of motivation affects enterprise data collection, we need to ask what motivates users to participate in data collection. The Unified Theory of Acceptance and Use of Technology (UTAUT) analyses the factors that specifically affect the intention to use an information system in a company. Based on a comparison of several existing user acceptance models, it highlights three main factors determining intention to use: effort expectancy, performance expectancy and social influence (Venkatesh et al., 2003).

In the LCES company studied, participation in data collection and the use of the IS are compulsory, as they are imposed by management, and the motivation induced by such an obligation is, by definition, extrinsic. As users are extrinsically motivated, it could be beneficial, if only to enhance factors such as work participation or quality of life in the workplace, to act

on this extrinsic motivation in order to try to motivate more intrinsically the users involved in the production and input of data. SDT proposes two processes for influencing extrinsic motivation, called controlled and autonomous regulations.

- *Controlled* regulation is related to obtaining a reward, avoiding punishment or decreasing social pressure to avoid anxiety or satisfy the ego, for example.
- *Autonomous* regulation, linked to the integration of objectives and the internalization of underlying general values, goes further and should make it even possible to reach a stage of extrinsic motivation close to intrinsic motivation, which is usually considered stronger and more productive.

These concepts of regulation are used here to differentiate the groups in A/B testing, referring indeed to controlled regulation, for the group that will receive the *corporate* mail, and autonomous regulation, for the target group of the *motivational* mail.

A/B Testing

So-called *controlled experiments* such as A/B testing are the best scientific way to establish a causal relationship between a change in a situation and its effect, in our case, on user behavior. The simplest way to set up a controlled experiment is to randomly select users and assign them to one of two groups:

- the *control* group, often a version of the existing situation, and
- the *treatment* group, often assigned to a new version, which is evaluated.

Metrics such as execution performance, user behavior and survey results are collected. *Overall Evaluation Criteria* (OEC) are also defined to compare the two groups (Kohavi et al., 2009). If the experiment has been properly designed and executed, the only difference between the two variants should be the change in the treatment variant, and therefore any observed change in OECs should follow from this, establishing a causal link.

In the rest of this paper, we will use the following classical notions, recalled here for completeness:

- *Overall Evaluation Criterium (OEC)*, a quantitative measure of the objective of the experiment;
- *Variant*, one of the different user experiences tested, here the control or the treatment;
- *Null hypothesis (H_0)*, which means that there is no difference in the OEC between the control and treatment variants or, if there is, that it is due to random variations;
- *Alternative hypothesis (H_1)*, which refers to a difference in the OEC between the control and treatment variants (H_1 is said to be *accepted* when H_0 is *rejected* with a sufficient level of confidence, usually 5%);
- *Confidence level*, which corresponds to the probability that the true value of a measured indicator of the population tested is actually within a fixed confidence interval.

The confidence level is usually set at 95%, i.e., there is a 5% chance that one would conclude that there is a significant difference for the population under study when in fact there is none. All else being equal, decreasing this level decreases the discriminatory power of the experiment.

Protocol

The A/B testing methodology used and the OECs studied are detailed below.

Methodology

The A/B testing of the impact of motivation on project data collection was carried out according to the methodology and conditions specified by Kohavi *et al.* in *Controlled experiments on the web: survey and practical guide* (Kohavi et al., 2009). Validated by numerous controlled experiments at Amazon, Microsoft and NASA, this method is well suited to the large enterprise environment that LCES represents.

The first phase of the experiment consisted of asking all 177 LCES project managers and directors to label all the 880 projects they manage or have managed via an interface specially designed for this purpose (figure omitted for confidentiality reasons) in the management tool usually used by the company. To collect the project data, the interface asks the user, for each project, to answer 3 closed-choice questions (see the figure below, where black boxes are used for confidentiality reasons). The first question concerns the success of the project, defined in terms of Quality, Cost, Delivery and Performance (QCDP), on a Likert scale of 1 to 6. The second one addresses the quality of the customer relationship, also on a Likert scale of 1 to 6, voluntarily leaving the managers free to interpret the exact meaning of this notion, which is difficult to specify, in particular for projects currently in progress. The last question concerns the perceived maturity of the company with regard to the project, on a Likert scale of 1 to 10, 1 corresponding to high maturity, and 10, low maturity. Andersen & Jessen (Andersen et Jessen, 2003) define “*‘mature’ as being ripe or having reached the state of full natural or maximum development. Maturity is the quality or state of being mature. If we apply the concept of maturity to an organisation, it might refer to a state where the organisation is in a perfect condition to achieve its objectives. Project maturity would then mean that the organisation is perfectly conditioned to deal with its projects.*”

The choice of even Likert scales avoids neutral answers and forces managers to take sides. The text of the questions is given in the figure below.

Smart_{PS}

OTP *
[Redacted]

Project
[Redacted]

How would you rate the success of the project (QCDP)?

On a scale of 1 (Very well known) to 10 (New), do you consider this to be a type of project usually manage by [Redacted]?

On this project, how do you rate the relationship between [Redacted] and the customer?

[Redacted]

Close

The test population was randomly divided into two groups: a control group of 86 members and a treatment group of 91 members. The treatment group received initial and follow-up email messages designed according to the principles of autonomous regulation (see Annexes 3 and 4), while the control group received initial and follow-up email messages designed according to the principles of controlled regulation (see Annexes 1 and 2).

- The control group is thus under controlled regulation, and therefore motivated by the mere mandatory nature of the request coming from the top management for this data collection.
- The treatment group, which will also be referred to as the *motivational group*, is autonomously regulated. The compulsory nature of the data collection is not mentioned, the presentation is made a bit more attractive and the managers are made aware that their action will be (judged as) useful and effective for themselves and others, even beyond the limited scope of the LCES company. The reason for this data collection and the explanation of why it will be useful are detailed in the content of the email, which is therefore longer than that of the control group and more illustrated.

The expected differential action of this email-based communication on the two groups stems from the fact that, first of all, the primary reason an individual internalizes an activity in which he or she participates on the basis of initially external justifications is the feeling that it is

perceived as effective and useful by others around him or her (Ryan et Deci, 2000). Furthermore, providing an individual with the means to understand the meaning of his or her activity potentially allows him or her to merge it with his or her own goals and values, and thus to foster the integration and internalization of his or her motivation (Kuhl et Fuhrmann, 1998).

To ensure that the timing of the mailings did not influence the results, the two groups of project managers were again split in two, and the mailings were carried out in two stages, 1 and 2, which will follow the same process but with a launch date two months apart.

OEC

To statistically analyze possible differences between the two groups of the experiment (control and motivational ones), OECs are defined to measure, respectively, the operational performance of the data collection and the nature of the data collected.

The operational performance of data collection is measured by 3 OECs:

- the average user response time (in days);
- the rate of participation in the collection process;
- the number of projects labelled, characterized by their number and proportion.

To measure the nature of the data collected, two EOCs are used.

- The first indicator is based on the [Mann–Whitney U test](#)¹, which evaluates the difference between the empirical distributions of two samples of data, corresponding to the control group and the motivational group, respectively.
- The second is tailor-made, based on our business knowledge of the data. It responds to an observation, made during a previous study by LCES, of a very high rate of projects labelled as having no managerial or technical problems and having excellent results.

¹ <https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.mannwhitneyu.html>

This tailor-made indicator therefore aims to quantify the (apparent) tendency of project leaders to over-rate projects. It is the cumulative frequency of the last two Likert-scale items (answers 5 and 6), and the difference between the two groups is tested using a classical Z-test, in this case the one implemented in [statsmodels](#)².

As the projects were labelled on three indicators (success, customer relations and maturity), the analysis of the nature of the data collected will therefore be carried out respectively for each of these indicators. As there is no notion of positive or negative value for the maturity indicator, the last OEC will not be used on this indicator.

Results

We present the results of our differentiated e-mail experiment and their statistical analysis for aspects related to the operational performance of the data collection process and the nature of the collected data.

Efficiency of data collection

We present results related to response time, participation and quantities obtained.

Response time

Users in the control group took an average of 5.01 days to respond, and users in the motivational group, 3.91 days. After correcting for outliers (response time greater than 1 month), the average is 3.48 days for the control group, and 1.66 for the treatment group.

The difference in mean response time without correction between the control and motivational versions is not statistically significant. The alternative hypothesis (to the null hypothesis) is largely rejected with a p-value of 0.612 for the difference in means. However, after removing the outliers (response time greater than 1 month), the p-value becomes 0.096, and the alternative

² https://www.statsmodels.org/v0.11.1/generated/statsmodels.stats.proportion.proportions_ztest.html

hypothesis can therefore be accepted with a confidence level of 10%, or rejected with a confidence level of 5% or less.

A difference is therefore observed between the two groups, just significant after correction for outliers, but not significant without correction.

Participation rate

Over the two stages of mailing, 46.5% of the control group responded to the request to label projects and labelled at least one of the projects they manage, while 40.7% of the motivational group responded.

The test gives a p-value of 0.432; the null hypothesis cannot be rejected, and the difference in response rate between the two groups is therefore not significant.

Amount of labelled data per person

Users in the control and motivational groups labelled an average of 5.6 projects per person. The null hypothesis is obviously not rejected, with a p-value of 0.978.

In addition, the percentage of projects labelled out of the total number of projects allocated to each person was also tested. The users in the control group labelled on average 62% of their projects, while the users in the motivational group labelled on average 65% of their projects. This difference is not statistically significant, and the null hypothesis is not rejected, with a p-value of 0.744.

Nature of the data collected

The projects were labelled according to three indicators: success, customer relations and maturity. The analysis of the nature of the data collected will therefore be carried out respectively for each of these indicators with the OECs provided for this purpose and defined

above. As a reminder, the first criterion is the difference between the empirical distributions of the two samples, and the second is the tendency to evaluate projects positively.

The differences between the two groups are tested with the Mann-Whitney test for the distribution of the data and with a proportional test on the normal distribution for the positive evaluation indicator (grouping the characteristics *Quite successful* and *Very successful*).

Project success

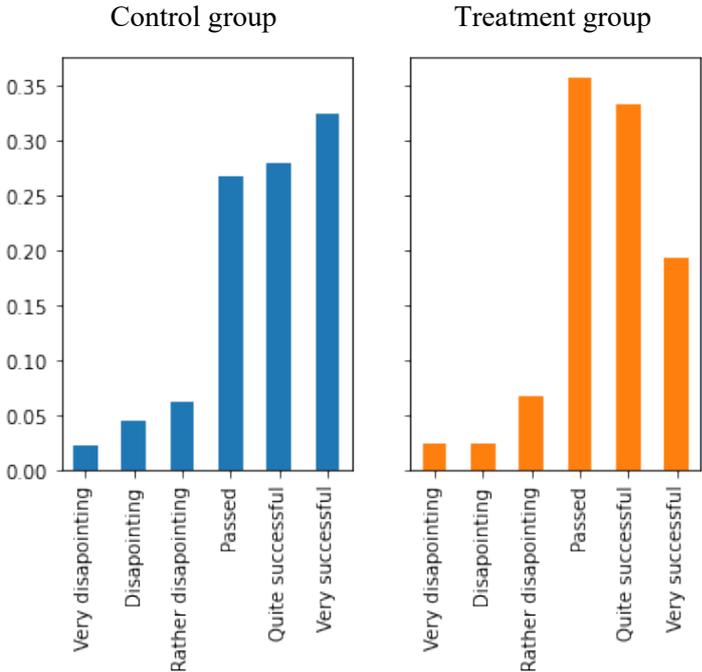


Figure 1: Empirical distributions of project success (control, left; treatment, right).

A difference is observed in the distribution of data between the two groups (Figure 1) with a tendency to respond more positively for the control group than for the treatment group. The positive trend indicator is 60.4% for the control group and 52.7% for the treatment group. This difference is confirmed by the Mann-Whitney test with a p-value of 0.015, for which the null hypothesis is therefore largely rejected at the 5% confidence level.

The proportion test also confirms this observation with a p-value of 0.051; this time, the null hypothesis is therefore rejected at the confidence level of 10% and not rejected, narrowly, at the confidence level of 5%.

Users in the control group therefore tend to respond more positively and in a less diverse manner than the treatment group.

Customer relations

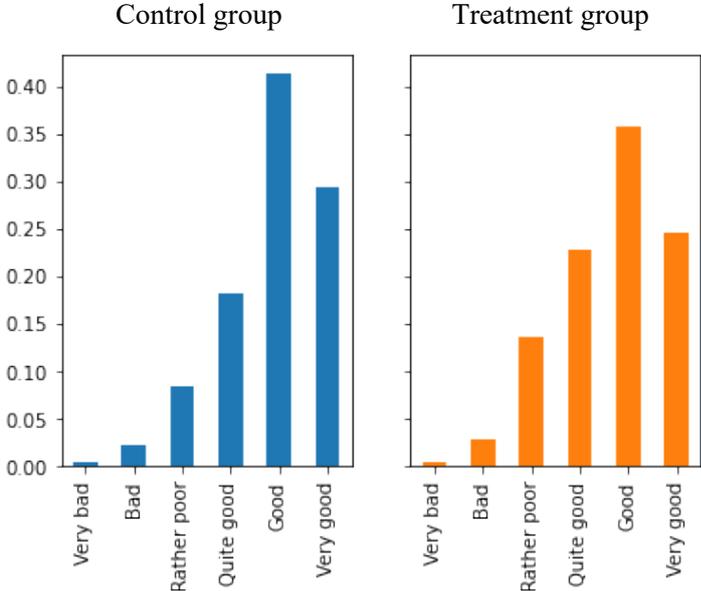


Figure 2: Empirical distributions of indicators of the quality of the relationship with the customer (control, left; treatment, right).

The same phenomenon is observed in the case of the customer relationship (Figure 2), even more so, with a tendency, therefore, to respond more positively in the control group than in the treatment group. The positive trend indicator is 70.7% for the control group and 60.3% for the treatment group.

The statistical significance of this difference is again confirmed by the Mann-Whitney test, with a p-value of 0.019, for which the null hypothesis is therefore largely rejected at the 5%

confidence level. Furthermore, the proportion test gives a p-value of 0.012; this time, the null hypothesis is therefore rejected with a confidence level of 5%.

Users in the control group therefore tend to respond more positively and in a less diverse manner than the treatment group.

Maturity

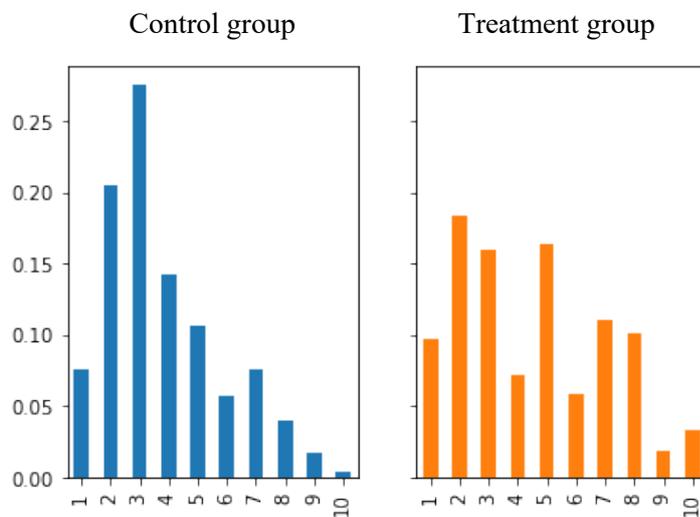


Figure 3: Empirical distributions of maturity indicators (control, left; treatment, right)

Figure 3 shows a radically different dispersion of maturity data between the two groups. The control group shows a response pattern concentrated around its mode while the treatment group has a much more uniform distribution. The Mann-Whitney test confirms this observation with a p-value of 0.011; the null hypothesis is therefore largely rejected.

Users in the control group therefore tended to respond in a less diverse manner than the treatment group, with a higher concentration with high levels of maturity, signaling that the company is well prepared to deal with those projects.

Discussion

The analysis of the indicators measuring the operational performance of data collection shows almost unanimously that there is no significant difference in participation rate, speed of collection and quantity of data collected between the control and treatment groups. This result is surprising, as the literature in this area (Friedrich et al., 2020) indicates that the use of control methods to encourage information sharing increases the quantity of information collected, at the expense of quality. However, our results suggest that the use of control methods does not influence the amount of data collected. In general, what these results suggest us is that the uses of control methods and motivational methods do not influence the operational performance of the collection. Further experimentation with larger sample sizes, another company or even a company in another business field may help to resolve the apparent contradiction between our field study and the state of the art.

With regard to the nature of the data collected, there is an observed and statistically significant difference: the users in the control group respond in a more concentrated manner, with a tendency to give answers that highlight their projects, i.e., to provide the most positive answers. Conversely, the users in the motivational group responded in a more diversified manner and were less likely to highlight their projects. This difference obviously raises questions about the relevance of the data collected and its use downstream for the decision-making processes impacting actual project management.

Indeed, the origin of the experiment presented here and its associated research questions were related to a problem with the quality of LCES project data observed by the authors of this paper. What had attracted attention was the very high rate of projects labelled as having no managerial or technical problems and excellent results. This observed distribution is in contradiction with the distribution usually observed in the rest of the world (Johnson, 2020). This observation and

the results presented here highlight the issue of the so-called "contextual" quality of the data, i.e., the fact that the data must be taken into account and analyzed in the context of the task performed (Strong et al., 1997). More specifically, the characteristic that may have been lacking in our initial analysis of the project data was precisely the "relevance" of the data, as introduced by (Strong et al., 1997). By mobilizing this notion of contextual data quality, we can posit that the professional or even psychological environment in which users enter data into the IS each month is responsible, at least in part, for the low relevance of the data collected.

The results of our comparative experiment seem to confirm the impact of the notion of context in data collection, and a number of hypotheses can be formulated as to the causes of this difference between the control and motivational groups. Being more aware of the value of data collection, users in the motivational group may be more motivated to respond in a thoughtful manner. Furthermore, as they are not subject to any form of control, their responses are unlikely to be influenced by implicit, or explicit, management expectations.

Conversely, the users in the control group, who were solicited in a controlled manner, with a clear indication of the mandatory nature of the data collection, may have responded in a biased manner, out of apprehension that these data are likely to be observed by management. To further understand this observed difference, interviewing these individuals on a case-by-case basis about their motivation for labelling the data and gathering their views on what might explain these differences could add weight to and enrich these results. Of course, this extension of the research presented here will have to be analyzed from the perspective of the context in which these interviews will take place.

Conclusion

We experimentally investigated the impact of motivation on the quality of project management data collected from project managers in a large engineering company, called LCES. Our

experimental results suggest that, of the two hypotheses, (H1), postulating that the use of a motivational method has an influence on the operational performance of data collection, and (H2), that the latter has an influence on the nature of the data collected, only the second is statistically valid. Thus, the data present within the information system to characterize and pilot LCES projects appear not to have the objectivity that one might have wished for in order to make it the impartial ally of data-driven project management. We were also able to quantify the order of magnitude of the differences observed, which may make it possible to question the current choice of scales of indicators collected by LCES from its project managers.

The managerial impact of the results reported here is, if confirmed by studies on a larger scale and in other sectors of activity, major, as it resonates throughout the downstream chain of decisions and analyses carried out within the framework of project management, both in terms of resources allocated for each project and in terms of financial or HR impacts for the company and its employees. This raises fundamentally two new key questions: (1) what is the best way to collect project management data, in particular on a recurring basis, which admittedly seems difficult with the motivational approach used here, but which could be made possibly effective via an approach based on gamification (Hamari et al., 2014)? and (2) what is the best way to apprehend those data according to the context of their acquisition, in the support of managerial decisions taken on the basis of these data? Both are matters for future work.

Acknowledgements

Thanks to Mathilde Bouget for support and help.

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ANNEXES

Annex 1: First control mail³

Bonjour à toutes et à tous,

Pour donner suite à la présentation faite en comité de direction sur le projet d'intelligence artificielle, destiné à mieux gérer et anticiper les performances des projets, nous avons obtenu le GO des directeurs techniques pour vous solliciter. Nous vous remercions par avance de bien vouloir répondre à un questionnaire pour les projets (en cours et terminés) qui concernent votre périmètre.

Cliquez simplement sur le lien ci-après, vous y trouverez toutes les informations nécessaires.

Lien cliquable

Merci de bien vouloir répondre aux questions portant uniquement sur les projets pour lesquels vous avez une proximité suffisante.

Merci de votre participation.

³ Good morning to all of you. As a follow-up to the presentation made to the Management Committee on the Artificial Intelligence project, designed to better manage and anticipate project performance, we have obtained the GO of the technical directors to ask for your opinion. We thank you in advance for answering a questionnaire for the projects (ongoing and completed) that concern your perimeter. Just click on the link below and you will find all the information you need. *Clickable link* Please answer the questions only for those projects for which you have sufficient proximity. Thank you for your participation.

Annex 2: Second control mail⁴

Bonjour à toutes et à tous,

Vous n'avez pas encore répondu à l'enquête de **caractérisation des projets LCES**.

Pour Rappel, nous avons obtenu le GO des directeurs techniques pour vous solliciter pour faire avancer le projet d'intelligence artificielle, destiné à mieux gérer et anticiper les performances des projets.

Nous vous remercions par avance de bien vouloir répondre à un questionnaire pour les projets (en cours et terminés) qui concernent votre périmètre.

Cliquez simplement sur le lien ci-après, vous y trouverez toutes les informations nécessaires.

Lien cliquable

Merci de bien vouloir répondre aux questions portant uniquement sur les projets pour lesquels vous avez une proximité suffisante.

Merci de votre participation.

⁴ Good morning to all of you. You have not yet responded to the **LCES project characterization** survey. As a reminder, we have obtained the GO from the technical directors to ask you to move forward with the Artificial Intelligence project, designed to better manage and anticipate project performance. We would be grateful if you could fill in a questionnaire for the projects (ongoing and completed) that concern your perimeter. Just click on the link below and you will find all the information you need. *Clickable link* Please answer the questions only for those projects for which you have sufficient proximity. Thank you for your participation.

Annex 3: First motivational mail^{5,6}



En juin 2020, LCES a initié une collaboration avec [REDACTED] dont l'objectif est de produire un outil d'aide à la décision fondé sur l'Intelligence Artificielle.

L'IA peut constituer un outil essentiel de management et d'accompagnement de projets au sein des entreprises.

Il s'agit pour LCES de mettre au point un système de gestion des données plus fluide, plus proche de la réalité du terrain et plus efficace. Les résultats de ce travail sont déjà très encourageants et nous avons besoin d'aller plus loin dans le process, d'être plus précis et pointus dans la collecte des données.

Pour cela nous avons aujourd'hui besoin de vos compétences, de votre regard et de votre expertise pour que nos outils soient plus robustes scientifiquement, plus proches de vos attentes et de celles de l'entreprise.

Cliquez simplement sur le lien ci-après, vous y trouverez toutes les informations nécessaires.

Lien cliquable

⁵ In June 2020, LCES initiated a collaboration with the (*Anonymized*) with the objective of producing a decision support tool based on Artificial Intelligence. AI can be an essential tool for managing and supporting projects within companies. LCES's aim is to develop a data management system that is more fluid, closer to the reality on the ground and more efficient. The results of this work are already very encouraging and we need to go further in the process, to be more precise and sharper in the collection of data. To do this, we now need your skills, your vision and your expertise to make our tools more scientifically robust, closer to your expectations and those of the company. Just click on the link below and you will find all the information you need. *Clickable link* Please answer the questions only for those projects for which you have sufficient proximity. Thank you for your participation.

⁶ Image: SLPHOTOGRAPHY/GETTY IMAGES/ISTOCKPHOTO <https://lexpansion.lexpress.fr/actualite-economique/robots-66-millions-d-emplois-menaces_1999993.html>

Merci de bien vouloir répondre aux questions portant uniquement sur les projets pour lesquels vous avez une proximité suffisante.

Merci de votre participation.

Annex 4: Second motivational mail⁷



⁷ (Figure: We are not very far from reaching our goal of labeling 50% of the projects, i.e., 440 projects) We are taking the liberty of sending you this reminder e-mail, as we have noticed that you have not yet responded to the **LCES project characterization** survey. The goal of this operation is to advance the understanding of the potential of AI and decision support tools in the context of project management. We need to have a sufficiently large sample size to be statistically significant and, to do this, we have set ourselves the **target of labeling 50% of the projects in the database**, i.e., 440 projects (out of a total of 880). Thanks to all the people who have already participated in this operation, **we are not far from this goal and we need one last effort from you**. As a reminder, this operation is part of a collaboration between LCES and the (*Anonymized*), the objective of which is to produce a decision support tool based on Artificial Intelligence. LCES's aim is to develop a data management system that is more fluid, closer to the reality on the ground and more efficient. The results of this work are already very encouraging, and we need to go further in the process, to be more precise and sharper in the collection of data. **Just click on the link below** and you will find all the information you need. *Clickable link* Please answer the questions only for those projects for which you have sufficient proximity. Thank you for your participation.

nous avons besoin d'aller plus loin dans le process, d'être plus précis et pointus dans la collecte des données.

Cliquez simplement sur le lien ci-après; vous y trouverez toutes les informations nécessaires.

Lien cliquable

Merci de bien vouloir répondre aux questions portant uniquement sur les projets pour lesquels vous avez une proximité suffisante.

Merci de votre participation.