Outperforming managers in setting strategic targets by using a novel Computer-Aided Management (CAM) approach

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Abstract
The minimal availability of scientific literature suggests that managers hardly consider internal organizational consequences as organizational Alignment, implementation effort, and Capacity to change when setting strategic targets. This study bridges this gap in the literature by employing a self-developed algorithm that assists managers by focusing on consequences that would make the target's implementation nearly impossible. In our study: too little organizational alignment, setting too ambitious targets, and insufficient capacity to change. We first quantified how 3,300 managers in 500+ organizations set targets by themselves in terms of these three consequences. We defined this group as Classical Management (CM). Then, in the second batch of 1,000 managers in 90 organizations, we provided our algorithm that quantified their targets' internal consequences. We defined this group as Computer-Aided Management (CAM). Our finding is that comparing two target-setting approaches (CM versus CAM) indicated that the latter chose targets with a "consequence score" six times better than the former. Our recommendation: in an organizational transformation, ask as many employees and managers as possible and let an algorithm upgrade their input to refine the decision-making process.

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Introduction

The application of artificial intelligence for strategic management purposes seems to be near, at least from a conceptual perspective ("Robo-advisors," according to Davenport et al., 2018). Yet, the minimal availability of scientific literature seems to indicate that managers in practice hardly consider the internal organizational consequences of strategic target-setting like organizational Alignment about the target, the Effort to implement the target, and whether the organization has adequate Capacity to change. Let alone; they apply artificial intelligence to support strategic decision making in such a way. In this paper, we focus on how artificial intelligence can help to address these three consequences that otherwise would make a strategic target's implementation very challenging, not to say nearly impossible. We work according to Bayesian probability: will a large sample of organizations be a bellwether for any next organization. In other words, we use a benchmark to come to specific probabilities. Bayesian probability theory provides a mathematical framework for inference or reasoning using probability. Many scientific researchers successfully employed the Bayesian probability theory (Olshausen, 2004).

Organizational Alignment

Research concerning horizontal Alignment is considerably lacking, and studies available at the time were focused merely on two areas. In their literature review, Kathuria et al. (2007) found a significant imbalance between vertical and horizontal Alignment in organizations. Their forecast and suggestion pointed to the increasing importance of horizontal Alignment in firms, and therefore multi-point research should continue to grow in this direction. Alagaraja and Shuck (2015) explored the link between organizational Alignment and employee engagement and further emphasized the connection between the two and their facilitating influence on individual performance. Self et al. (2015) emphasizes knowledge management at the employee level within the scope of organizational Alignment. Effective knowledge management bolsters strategic thinking and contributes to practices that positively affect organizational Alignment. In response to the inference that strategic Alignment improves organizational performance, Ilmudeen et al. (2019) used IT and business sectors data. They found this relationship remained accurate overall but varied by sector orientation. For instance, quality-oriented strategic Alignment showed a positive relationship to all performance measures, while marketing-oriented strategic Alignment showed "an insignificant relationship with operational excellence." Therefore, the study suggests that dimensional strategies are better than whole or single strategies and allow management to focus on individual alignment scopes.

As horizontal organizational management becomes more common, we'd like to further explore goal clarity and team performance. Van der Hoek et al. (2018) demonstrate that goal clarity positively affects team performance but is not facilitated by teamwork, promoting further research in this area. In a study of 71 teams in five different banks, Hu and Liden (2011) concluded that goal and process clarity on the team level contribute positively to team performance. This positive relationship is even stronger with the use of servant leadership. In a study covering nearly 1700 employees in 45 different geographic areas, Hassan (2013) concluded that higher levels of role clarity contribute to increased employee satisfaction rates and, in turn, lower turnover rates.

The Effort to implement and Capacity to change

Through an analysis of "stretch goals" – goals that seem impossible to reach – Sitkin et al. (2011) sought to assess which organizations would benefit the most from pursuing stretch goals and concluded that "stretch goals are, paradoxically, most seductive for organizations that can least afford the risks associated with them." Along with the typical challenges such as technological and structural, Palthe (2014) stresses the importance of whether people want to change or have to change when addressing effective organizational change processes. Using regression analysis and correlation tests, Ramezan et al. (2013) confirmed the significant positive relationship between organizational change capacity and organizational performance. In their study on organizational change capacity, Kircovali and Cemberci (2020) show that it consists of three dimensions: context, process, and learning. Contrary to other previous studies in the field, Kircovali and Cemberci emphasize that individual evaluation of each dimension is essential rather than using a mean value in assessments. This study developed a new approach to set strategic targets that takes internal organizational consequences as organizational Alignment, Effort to implement, and Capacity to change (Van de Poll, 2018) into account. Towards this aim, we designed a new methodology to model aspects of strategic decision-making into a generically applicable calculation rule. This new technique involves strategic decision-making by using large numbers of employees.

A Guttman-Poll scale (van de Poll, 2018), an upgraded version of the widely employed Guttmann scale, was employed to quantify the consequences objectively. The developed model is based on the input from large numbers of employees to support an organization's upper management, where the employees become the 'eyes and ears' of upper management. The algorithm helped improve the quality of targets set by the managers considerably. The details of the model are omitted in this paper to conserve space. Readers should refer to Van de Poll (2018) for more information.

Methodology

Procedure and participants

We deemed a comparison of the *content* of the strategic targets out of scope. Such an analysis would make it very difficult to compare organizations on a scale: after all, every strategic situation is different. We also decided not to consider the topics about which there would be internal (mis-) alignment, for which topics there would be overstretched goals, and for which topics there would be too little Capacity to change. We decided we would entirely focus on the *level* – rather than the content – of (1.) organizational Alignment, (2.) the Effort to implement, and (3.) the Capacity to change. We could not look up how well an organization was doing about these three consequences in the corporate data warehouse: we had to ask people. We first designed an extensive survey based on the Guttman scale (Stauffer et al., 1950) to quantify these consequences objectively but then upgraded for employee polling (Guttman-Poll). We researched how 3,362 managers in 441 organizations set targets by themselves. This first group set targets without the help of our algorithm. We defined this group as "Classical Management (CM)." We obtained 12,253,476 answers from 112,548 employees. Then, we researched another 1,041 managers in 91 different organizations. Here, we had 42,826 employees, providing 3,710,476 answers. This second group set targets with the help of our algorithm. We defined this group as "Computer-Aided Management (CAM)." The employee polls were executed to gather the respondents' input first for the CM-organizations, and then the CAM-organizations and took place from 2015 to 2021.

We added to each of the CAM-polls a maturity model with five maturity levels showing how to improve on the questions in the questionnaire sequentially. Additionally, the algorithm calculated the organizational consequences in terms of Alignment, Effort, and Capacity of setting each of the five maturity levels as the improvement target. Then, we compared the consequences of the targets set by the CM group's managers with those of the CAM group managers. Asking as many employees as were available in these organizations, this wisdom of the crowd offered the second group much more data on which to base their decisions. Aggregated views from large numbers of individuals have proven to outperform financial market models and models in other areas like project management (Surowiecki, 2005; Giles, 2005). Table 1 gives an overview of these two groups.

Measures

We employed an improved version of the widely used Gutmann scale to objectively quantify the level of Alignment, Effort, and Capacity to change (van de Poll, 2021). This improvement technique asks employees about verifiable facts and -behavior, taps actual situation and the employees' ambition, caters to target setting, and provides additional managerial insights into, e.g., organizational Alignment and knowledge sharing. Here is an example of the Guttman-Poll format:

Table 1
Sample size

	N	Min	Max	Avg.	StDev.
Human (CM)					
Number of questionnaires	441				
Number of teams	3,362				
Number of employees	112,548				
Answers given	12,253,476				
Teams per questionnaire		1	80	7.6	9.7
Number of employees per team		5	835	33.5	67.7
Number of questions per questionnaire		9	234	54.3	29.2
Human + algorithm (CAM)					
Number of questionnaires	91				
Number of teams	1,041				
Number of employees	42,826				
Answers given	3,710,778				
Teams per questionnaire		1	92	11.4	16.9
Number of employees per team		5	992	41.1	92.3
Number of questions per questionnaire		8	92	40.9	13.1
Total database					
Number of questionnaires	532				
Number of teams	4,403				
Number of employees	155,374				
Answers given	15,964,254				

Min.: lowest value. Max: highest value. Avg: average value. StDev: standard deviation.

Q. How have you defined your team objectives?	Now	In 6 months
1. We have no team objectives (yet)	☐	☐
2. We have a qualitative description	☐	☐
3. We have formal, SMART key performance indicators.	☐	☐

Contrary to the original Guttman scaling, which works with current-status data (a term used by Diamond, McDonald, and Shah, 1986), we included a time dimension in the analysis. For example, the team might not have team objectives right now, but they might have in 6 months. The answers in the example above can be considered 'objectively real' (Ahrens & Chapman, 2006). To reduce interpretation bias, we forewent adjectives and adverbs that couldn't be verified (e.g., "good"). And we added "proof-words" like, e.g., 'periodically,' 'formally,' and 'documented,' to reduce self-reporting bias (discussed by Donaldson and Grans-Vallone, 2002). Objective and verifiable multiple-choice answers helped prevent employees from adding an emotional or cognitive meaning (Frese & Zapf, 1988). We then applied Levene's test (Levene, 1960) to test the homogeneity of variance across groups within the dataset. Levene's test is less sensitive than the Bartlett test to depart from normality. In this study, we failed to reject the null hypothesis (that the group variances are equal) since the value of Levene's test statistic (P=0.37) is less than the critical value (α=0.05).

Data analysis

Clustering is an essential tool in the literature to classify the data. The K-Means clustering is the simplest and most common clustering method that can group large amounts of data with relatively fast and efficient computation time, which is the case in this study (Bain et al., 2016). Table 2 shows which dimensions we used to cluster organizations for the three consequences.

Table 2
Consequences of a target: definitions

Measurement	Calculation
Organizational alignment	
1a. Alignment within the team	Dendrogram about the "In 6 months"-score
1b. Team alignment with the management target	Dendrogram between respondents and target
Effort	
2a. Relative amount of improvements	% respondent-questions to improve
2b. Division of improvements	Effort for top-¼ vs. for bottom-¼ improvers
Capacity to change	
3a. Time freed up by stopping non-priorities	% non-priorities versus % priorities
3b. Share knowledge & stop reinventing the wheel	% respondents that can share knowledge

For organizational Alignment, we used a dendrogram (cluster analysis) to measure to what extent employees differed in their outlook concerning their "In 6 months"-answers. The same dendrogram contained the management target to measure the Alignment (distance) between the individual respondents and this target. For each of these axes (1a and 1b in Table 2), we calculated where to divide the axes in a "low" and a "high" value, resulting in four quadrants. Here, the preferable consequence of organizational Alignment would be employees agreeing among themselves and with the target (van de Poll. 2018). We analyzed the "Effort to implement" using a similar construction. Two axes resulted in four quadrants, with each quadrant a consequence score (most to least favorable). Here, we looked at the percentage of (the number of respondents * the number of questions) that had to be improved. And we looked to what extent this 'burden of change' was equally divided over the respondents. For the "Capacity to change," we did not ask employees about their competencies and experience with change.

Instead, we created two 'proxy' dimensions. We calculated how the amount of work indicated by the management target would be higher or lower than the ambition the employees had set for themselves (comparing the "Now"- and "In 6 months"-scores). A lower amount of work than planned by respondents would free-up time by not spending any capacity on non-priorities. The other dimension was the % of respondents already scoring close enough to the target (with their "Now"-scores) that they could be considered an extra force to help with the implementation. Again, these two axes resulted in four quadrants. We deliberately "dumbed down" our clusters into four quadrants for each of the three aspects (Alignment, Effort, Capacity) in order not to overwhelm managers with an incomprehensible range of consequences. Already, with three 2×2 quadrants, there were 64 (4^3) possible consequence combinations from which to choose.

Results
Table 3 summarizes the results of the two groups.

Table 3
Comparing two target setting approaches

Measurement	Human (CM)	Human +Alg. (CAM)	Factor
Team scores containing:			
Any score '1' (negative)	74%	26%	3
Any scores '1' or '2' (negative)	95%	47%	2
Perfect score (12 out 12, positive)	2%	65%	33
Overall "consequence score"			
Average per team	7.3	9.9	
Teams scoring a "consequence score" of:			
Score = 3	100%	100%	1
Score = 4	99%	100%	1
Score = 5	91%	100%	1
Score = 6	82%	98%	1
Score = 7	68%	96%	1
Score = 8	49%	93%	2
Score = 9	34%	81%	2
Score = 10	**11%**	**61%**	**6**
Score = 11	4%	44%	11
Score = 12	2%	19%	10

Human +Alg.: an upper manager/management team aided by our algorithm

We calculated per team and maturity level a "consequence score." For each consequence (Alignment, Effort, capacity), the score ranged from "1" (being in the worst quadrant) to "4" (being in the best quadrant). Consequently, the overall score started at "3" (1+1+1) if a target reached the worst possible quadrant for each of the three consequences. The maximum score was "12" (4+4+4) when a target landed everywhere in the most favorable quadrant. For example, Table 3 shows that 74% of the targets contained the worst score for one or more of the three consequences with just the manager setting the target. In 95% of teams, there were one or more "1"- and "2"-scores. Only 2% of the teams chose a 'perfect score' (the target ended three times in the best quadrant). Adding the algorithm changed the quality of the selected targets considerably. First, the maturity levels added variety and immediately gave managers something they could choose from. Only 26% of the targets (five different maturity levels for each team) contained one or more "1"-scores. Similarly, any scores '1' or '2' (negative) dropped from 95% to 47%. More importantly, 65% of the teams had a target/maturity level to choose from that had a perfect consequence score. Clearly, with just the managers setting the target (the CM group), the selected target was purely based on 'external considerations' (e.g., market forces or technological developments). However, with the aid of the development algorithm (by obtaining employee input), the CAM group set much smarter targets. We postulate that a "consequence score" of 10 or higher is a sensible choice regarding Alignment, Effort, and Capacity to change. In 11% of the CM teams, managers selected a target with a consequence score of 10 or higher while it increased to 61% for managers in the CAM group, almost a six-fold increase. With the algorithm's aid, the average consequence score improved from 7.3 to 9.9 (on a scale from 3 to 12). This score of 9.9 is almost the consequence score of 10 or higher we deemed a requirement. We have visualized the percentage of teams scoring a specific consequence score in Figure 1.

The bottom half of Table 3 (the column "Manager + Alg.") shows managers do not set targets *solely* based on our consequence score. We infer that the consequence score alone was not the only deciding factor for managers to choose a target: the content of the improvement target was a factor as well. In that latter case, we would see 65% of teams choosing the maturity level with the perfect consequence score; in reality, this happened only in 19% of the teams. We found that CAM consistently produces smarter improvement targets with more manageable organizational consequences compared to CM. Fig. 1 compares the performances of CM and CAM methodologies.

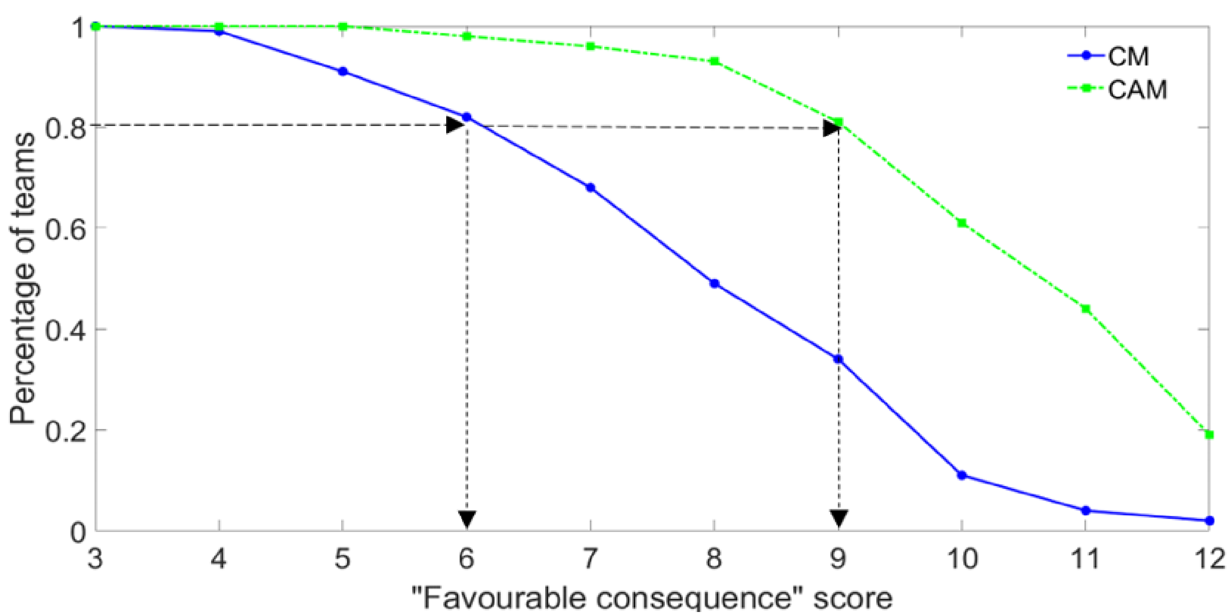

Figure 1. Comparing two target setting approaches

The difference between the two approaches increases slowly initially (around Favorable consequence score 4), but the gains increase rapidly. For example, 80% of teams produced a score of 6 with CM. However, it increased to a score of 9 with CAM. Based on the results of this research, CAM appears to be a promising technique for setting strategic targets in organizations and contributing to the Robo-advisers the Hard Business Review referred to Davenport et al. (2018).

Discussion

Organizational transformations usually determine whether an organization will thrive or not survive. Then, the quality of target setting is paramount. The wisdom of the crowd in combination with artificial intelligence improved our "consequence score" almost an order of magnitude. Not 6% or 60%, but 600%. This percentage could be even higher, but managers also opted for targets that made business sense: our "consequence score" was not the only deciding factor.

It was not possible to compare the effects of a CM and a CAM target in the *same* organization. There wasn't a board of directors that wanted to forego smarter targets for a part of their organization, just to hand us an A/B test in the name of science. Additionally, we understand that Alignment, Effort, and Capacity to change - though of great importance – aren't the only factors that determine a successful target setting. We also realize that our three factors purely look at the consequences for the workload of those who have to implement the transformation. We did not factor in aspects like, e.g., financial consequences or technological implications.

Limitations and future research

Even just focusing on the target's workload for the organization, some cautionary remarks are to be made about our research. In Alignment, we calculate with the ambition of the respondents (Table 2, item 1a). But the plan or intention to improve something does not mean employees will start everything they plan to improve. The literature about *goal* clarity, as referenced in the introduction, does not automatically imply *roadmap* clarity on how to reach that goal.

In Effort, we calculate the improvement workload among the employees (Table 2, item 2b). Literature on "stretched goals" usually focuses on the organization as a whole, not on those parts that undoubtedly will be *over*stretched.

In terms of Capacity, we limit that Capacity to change to non-priorities and knowledge sharing (Table 2, items 3a and 3b). As such, our approach is a proxy of Capacity to change at best: basic parameters as the competencies of employees or the available technology haven't been factored in. Future research will help find generally applicable ways to integrate such parameters and create even more positive "consequence scores."

Conclusions

Managers hardly consider the internal organizational consequences when setting strategic targets. This study presents a new technique integrating the classical management (CM) approach with computer-aided management (CAM). We observed that CAM shows 65% of the teams with an alternative target featuring the most favorable consequences (12 out of 12). When managers develop an improvement target themselves (CM), only 2% of the targets qualify for "most favorable" consequences. This percentage indicates that the managers in the second group (CAM) factored in both the external factors and the internal consequences. We are confident we can break to the "10 times better" threshold in future studies by further refining our algorithm. We want to highlight that our definition of organizational Alignment, Effort to implement, and Capacity to change is a workable proxy, not an entirely theoretically underpinned approach covering all aspects of these three consequences. More research is needed to develop more refined definitions that hold their ground in organizations' daily practice.

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