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Abstract

Performance measures shall enhance the performance of companies by directing the attention of decision makers towards the achievement of organizational goals. Therefore, *goal congruence* is regarded in literature as a major factor in the quality of such measures. As reality is affected by many variables, in practice one has tried to achieve a high degree of goal congruence by incorporating an increasing number of these variables into performance measures. However, a goal congruent measure does not lead automatically to superior decisions, because decision makers' restricted cognitive abilities can counteract the intended effects. This paper addresses the interplay between goal congruence and complexity of performance measures considering cognitively-restricted decision makers. Two types of decision quality are derived which allow a differentiated view on the influence of this interplay on decision quality and learning. The simulation experiments based on this differentiation provide results which allow a critical reflection on costs and benefits of goal congruence and the assumptions regarding the goal congruence of incentive systems.

JEL Classification: M10, M41

Keywords: Performance measurement, goal congruence, experience-based learning, simulation-based research

1 Introduction

Performance measures shall ensure a high level of decision makers' decision quality by directing their attention and actions towards aspects of reality which are relevant to organisational goals (Neely et al., 1997; Amaratunga & Baldry, 2002; Heineke, 2005). In this context, the literature addresses the following three areas of problems.

The *first area* encompasses the *congruence* between performance measures and economic reality (e.g. Kerr, 1975; Hirst, 1981; Prendergast & Topel, 1993). There is consensus that in order to achieve a useful performance measure, congruence between this measure and the *relevant parts* of reality (however defined) should be as high as possible (Baker, 2002; Bouwens & van Lent, 2006). Since reality is affected by many variables, a large number of them should be incorporated into performance measurement systems. In the past years the compliance with this requirement resulted in increasingly complex systems: First, instead of using isolated measures, whole performance measurement systems are proposed and used (Ridgway, 1956; Eccles, 1991; Marr & Schiuma, 2003). The balanced scorecard is a prominent example of this trend (Kaplan & Norton, 1992 & 1996; Hoque, 2003; Bessire & Baker, 2005). Second, more and more information is condensed into a single measure. The shareholder value discussion is a recent example of this development (Stewart, 1991; Stern & Stewart & Chew, 1995; Rogerson, 1997; Rappaport, 1998), as measures like the economic value added incorporate many elements. In general, the mentioned literature accepts this increase in complexity of performance measurement as an inevitable side-effect of its improvement.

However, the *second area* addresses the *user* of performance measures (e.g. Hopwood, 1972; Ittner & Larcker, 1998; Franco & Bourne, 2003). From this *behavioural* point of view, the influence of complexity on the efficiency of performance measurement is regarded as ambiguous. A user's limited information-processing capabilities might counteract the intended positive effect of goal congruence on decision quality: The simultaneous presentation of many measures can cause *information overload* (Stocks & Harrell, 1995; McWhorter, 2003; Eppler & Mengis, 2004). The mentioned rise of information condensation increases the need for interpretation that in case of cognitively-restricted decision makers can lead to *mis*interpretation (Hopwood, 1974; Hirst, 1981; Merchant, 1990; Otley, 2003). In essence, according to this stream of literature, complexity in performance measurement can compromise decision quality considerably.

Finally, the *third area* concentrates on the linkage between performance measures and incentive systems (e.g. Otley, 1978; Merchant, 1990; Neely et al., 1997; Bouwens & van Lent, 2006). This aspect is mainly addressed in the agency-theoretical literature (e.g. Baimann & Demski, 1980; Lambert & Larcker, 1987; Feltham & Xie, 1994; Araya & Fellingham & Schroeder, 2004; Ewert, 2006), which virtually ignores the effect of complexity. This neglect is reasonable with respect to rational decision makers, who are free of cognitive restrictions. In contrast, in case of cognitively-restricted decision makers complexity affects the usefulness of performance measures, and therefore it might also become an important obstacle to the effectiveness of incentive systems that are linked to these measures.

In summary, a high degree of goal congruence is accepted as important to achieve *effective* performance measures. Yet, goal congruence is accompanied to a certain degree by complexity, which in turn might counteract the positive effects of goal congruence due to decision makers' cognitive restrictions. On the one hand, as the discussion of the literature with respect to the second area of problems exhibits, this tension has already been analysed, yet from a rather static point of view. Decision makers are engaged in long-term decision processes using the same performance measures repeatedly. This fact raises the question, how the tension between goal congruence and complexity might influence decision makers' *learning* and the *improvement of their decision quality over time.* On the other hand, as the discussion of the literature regarding the third area of problems shows, the influence of the mentioned tension *on the long-term effectiveness of incentive systems* linked to performance measures needs further analysis with special emphasis on cognitively-restricted decision makers. This paper picks up both aspects and analyses the influence of the mentioned tension on decision quality from a long-term perspective. It makes several contributions to the literature.

First, it adds to the body of research concerning goal congruence a more differentiated picture regarding the influence of complexity by dividing the notion of decision quality into overall and internal quality. The former mirrors the quality of the measure regarding the *actual aim*. The latter exhibits the quality with respect to a target set with the same measure, i.e. the internal quality comprises what incentive systems in practice *actually reward for*. The following study shows that the interplay between goal congruence and complexity exerts *different effects* on each. This is an important result to the practice of performance measurement, because firms actually implement incentive systems to achieve goal congruent behaviour, assuming that internal decision quality reflects overall decision quality. Yet, as the results point out, this may not be the case. Hence, firms do not value the actual performance of their decision makers properly. Additionally, this result also is important to theory as it contradicts in a sense the notion spread in agency-theoretical literature that the more goal congruent a measure is, the better its effectiveness with respect to incentive systems (Baker, 2000 & 2002; Bouwens & van Lent, 2006).

Second, by analysing internal decision quality, the paper further contributes to the literature on incentive systems. It shows that under the premise of cognitive restrictions, targets calculated on the basis of complex measures become more different to achieve in the short-run. This may have discouraging effects. Hence, the possibility to become familiar with the measure over longer periods of time becomes crucial when highly complex measures are used. Depending on the situational context, this leads to the following conclusion: in less dynamical decision situations, long learning phases should be provided to the user of such measures before linking them to incentive systems. In dynamical environments with constantly changing requirements, incentive systems should only be linked to less complex measures.

Third, by studying overall decision quality the paper extends the body of research on performance measures and cognitive restrictions by adding a long-term perspective. The analysis shows that increasing complexity somewhat counteracts the positive effects of improving goal congruence and also inhibits full learning about reality in the long-run, even in the presence of a fully goal congruent performance measure. This outcome points to the question of efficient resource allocation when using complex performance measures: The results underline the importance of thorough cost-benefit analysis of the usefulness of more goal congruent measures. So far, the analyses comparing marginal benefits to marginal costs are relatively scarce when discussing new, presumably improved performance measurement systems.

Fourth, the situation analysed in this paper is analytically intractable due to the combination of multi-periodicity and cognitive restrictions. Therefore, computer-based simulation is used, as it has been applied successfully in many areas to examine learning processes, especially over longer periods of time (e.g. Herriott & Levinthal & March, 1985; March, 1991; Carley, 1992; Lant & Mezias, 1992; Marengo, 1992; Bell, 2001; Luna, 2002; Raghu & Sen & Rao, 2003). However, in the area of accounting research this method has been used relatively seldom so far. Hence, the following study delivers one possible starting point for a more intense usage of this method in the research of performance measurement and of other management accounting topics.

The remainder of the paper is structured as follows. In Section 2, five idealised performance measures are constructed, laying the basis of the analysis. Section 3 develops the multi-periodical decision model, in which the idealised performance measures are used. The study combines the premise of cognitive restrictions with experiential learning. However, in order to achieve a thorough analysis regarding the tension between goal congruence and complexity, the study has to be based on rather narrow assumptions regarding the mentioned psychological aspects. In Section 4 the decision model is transferred into a computer model and the used parameter values are presented. Section 5 distinguishes internal from overall decision quality and describes the metrics to evaluate both types. Moreover, it contains the simulation results. Section 6 is dedicated to the interpretation of the results and their consequences. Section 7 addresses the possibilities for future research.

2 Operationalisation of five idealised performance measures

A performance measure shall induce a decision maker to adjust his/her activities to meet a specific organisational goal. Nevertheless, a performance measure is only a *standardised* reflection of those parts of reality which are connected to this goal. The more *relevant* parts the measure incorporates, the higher its degree of goal congruence. The previous section mentioned a possible connection between goal congruence and complexity of a performance measure. However, increasing complexity does not *necessarily* lead to increasing goal congruence, because complex measures might also include parts of reality that are irrelevant to the organisational goal. In this case the possible negative or positive effects of complexity are mixed with effects of this mismatch. To pursue a clear analysis, one has therefore to construct the studied performance measures in a way ensuring that increasing complexity is caused by the integration of – and only of – relevant parts of reality. Then, the degree of complexity also reflects the degree of goal congruence and the tension between both can be studied properly. In effect, an object's degree of complexity is determined by its *different* characteristics (Stocks & Harrell, 1995; Heineke, 2005). This comprises the number of different characteristics (*quantitative* complexity) and their functional heterogeneity (*qualitative* complexity). In order to keep the analysis clear, this paper focuses on the first aspect of complexity. For the purpose of this analysis the number of parts integrated in a performance measure constitutes a useful operationalisation of its degree of complexity.

In order to be comparable, the analysed performance measures should be constructed on the same basis. Since *value-based* performance measures (Stewart, 1991; Stern & Stewart & Chew, 1995; Rogerson, 1997; Rappaport, 1998) have attracted a great deal of attention and are still discussed in accounting literature and widely used in practice, it is reasonable to use a stylised form of them as a starting point to derive measures of different complexity. The following study will be based on a stylised form of the economic value added (cf. Figure 1), as this measure is one of the most established ones in this field.

EVA[1] = NOPAT – Invested capital x WACC,

NOPAT = Net Operating Profit After Tax, but before financing costs

$WACC = i_{\text{borrowed resources}} \times BR + (i_{\text{risk-free}} + (i_{\text{market}} - i_{\text{risk-free}}) \times beta) \times CR$

i = interest rate

BR = borrowed resources

CR = capital resources

beta = measure of systematic risk of the valued investment alternative

Figure 1: The economic value added as example of a value based performance measure (Source: Stern & Stewart, 1995, [1]EVA is a trademark of Stern Stewart & Co.)

Starting from this formula a step-wise simplification can be conducted, resulting in simpler but also economically reasonable measures. This way one ends up with five idealised performance measures. In practice, the economic value added only comprises approximations of those parts of reality that are important to achieve a goal congruent measure. However, for the purpose of this paper the stylised form of the economic value added used in this analysis shall be defined as perfect reflection of the organisational goal. Consequently, those measures that are constructed by diminishing the degree of complexity starting at this measure also exhibit lower goal congruence. The resulting five measures are presented in order of increasing complexity to show how they build on each other.

In the following analysis, the simplest, most reasonable measure to judge investment alternatives is their turnover (T) shown in (2.1), as it can give a good idea about their value creating potential. Because performance measure 1 consists of only one element, it has the complexity degree 1.

$$PM_1 = T \tag{2.1}$$

However, in most cases, it is reasonable to consider the costs of an investment alternative. Hence, the second measure incorporates additionally operating costs (C), i.e. in this case the degree of complexity is 2 and the measure is calculated via (2.2).

$$PM_2 = T - C \tag{2.2}$$

Besides the operating costs, costs of capital influence the value creating potential of investment alternatives. Therefore, the third measure considers these costs, i.e. capital (I) times the interest rate (i). This measure is calculated via formula (2.3) and its degree of complexity equals 4.

$$PM_3 = T - C - I * i \tag{2.3}$$

Because equity and debt might carry different costs of capital, one can introduce another measure that differentiates between these two types of capital. Hence, performance measure 4 is constructed by differentiating the interest rate for debt (i_d) from the rate of equity (i_e), and therefore also incorporates two types of capital invested, resulting either from debt (I_d) or from equity (I_e). Its degree of complexity is 6 and it is calculated with formula (2.4).

$$PM_4 = T - C - I_d * i_d - I_e * i_e \tag{2.4}$$

Finally, performance measure 5 is based on the idea of the Capital Asset Pricing Model and exhibits a stylised form of the economic value added. It incorporates the risk-free interest rate (i_{rf}), the market interest rate (i_m), and a measure of the investment risk beta (β). The measure has a complexity degree of 8 and is calculated via (2.5).

$$PM_5 = T - C - I_d * i_d - I_e * (i_{rf} + (i_m - i_{rf}) * \beta)) \tag{2.5}$$

3 Decision model

3.1 Cognitive restrictions and experiential learning

Human information-processing exhibits many restrictions which affect the perception, interpretation, storing and retrieving of information, the amount of available knowledge, and the ability to draw reasonable conclusions. In the following analysis it is unnecessary – and in fact impossible – to consider all of them, and the underlying psychological mechanisms will not be discussed in detail. In contrast, the discussion focuses on a typical situation with which a decision maker is faced in practice when using performance measures as decision basis and where cognitive restrictions in combination with learning processes come into play. As the general concept of experiential learning is accepted in management literature and serves as the basis of many models used in the context of learning in and of organisations (e.g. Cyert & March, 1963; March & Olson, 1975; Holmqvist, 2004), it also can be seen as reasonable modelling approach for the purpose of this paper.

Typically, decision makers have to make their decisions under conditions of uncertainty. In "classical" decision theory this uncertainty is given as an exogenous phenomenon that is *independent* of the decision maker. However, the precision of forecasts regarding future events not only depends on environmental uncertainty but also on the decision maker's experience (March & Simon, 1958; March & Olsen, 1975). An experienced decision maker is able to narrow the space of possible future states and thereby considerably improve the quality of his/her prognosis. Consequently, uncertainty in a decision context should be regarded as the result of external (environmental) and personal (cognitive) factors. Learning influences the personal factors and can reduce that part of uncertainty that is caused by them (George & Jones, 2005): After a decision a decision maker often receives feedback which tells her/him whether or not the prognosis was correct. When s/he is faced with a similar decision in the future, s/he can incorporate this feedback into the decision process and thereby improve the quality of his/her prognosis.

This experiential learning cycle exhibits a rather simplistic description of human learning processes and their interplay with cognitive restrictions. Yet, it includes the major principles of learning and grounds on results of the psychological learning literature (Kolb, 1984; Bower & Hilgard, 1998; Purdy et al., 2001). It has to be stressed that the concept of learning on which the following analysis is based does not say that learning has to be *positive* from the organisational point of view. Learning is rather conceptualised as an ongoing processing of feedback information to adapt actions to environmental requirements. This adaptation can result in productive *and* in non-productive behaviour from an organisational point of view.

3.2 Decision scenario

In this section the performance measures and a cognitively-restricted decision maker are put into a decision context. The analysis focuses on five decision makers who independently have to repeat an investment decision over several periods of time. Each decision maker has the same starting conditions, except for the used performance measure.

The decision makers act in a stable environment (i.e. the "true" values of the investment alternatives do not change from period to period). This assumption is certainly unrealistic, because in reality seldom several investment alternatives keep their values over a longer period of time. However, this premise is necessary to explore the effect caused *only* by the interplay between cognitive restrictions and different degrees of complexity, ignoring any effects due to changes in other factors. Hence, the decision makers do not face external uncertainty.

At the beginning of each period, each decision maker has to choose an investment alternative from a given set of projects. The selection is based on the values of the assigned performance measure that s/he has to calculate for each alternative. Each decision maker is motivated to select that alternative which exhibits the highest value with respect to his/her performance measure in use, i.e. in order to concentrate on the learning aspect the model abstracts from any diverging goals between the organisation and the decision makers. It shall be assumed that their degree of utility is linked to an incentive system based on the used performance measure. Hence, they are motivated to orientate their decision on their performance measures. In order to perform the calculation in the first period, the decision makers have to estimate (independently of each other) the values of those data (turnover, operating costs, etc.), which they need for their performance measure. Due to their lack of previous experience this estimation is erroneous. Consequently, although the environment is stable, the decision makers cannot foresee the correct values of the investment projects. Their cognitive restrictions lead to internal uncertainty.

At the end of each period, the selected project ends. (Since each investment project has a duration of one period, one can ignore the effects of compounded interest. Moreover, no budgeting constraints are considered, i.e. each project is assumed to lie within an acceptable range with respect to given resource constraints.) Each decision maker now receives the *correct* data of the *chosen* alternative. S/he uses these newly received data in period n to recalculate the respective performance measure for the selection in period n+1. Therefore, s/he should improve her/him set of data concerning the alternatives and learn over time which investment will yield the highest value concerning the used performance measure, but this learning process evolves stepwise:

In period 1, each decision maker has only estimated data based on forecasts regarding all N investment alternatives. Because s/he can only select and implement one alternative in each period, s/he also will only receive the correct data for this selected alternative at the end of period 1. The data sets of the other N-1 alternatives remain unchanged, i.e. they continue to contain only the – possibly false – estimated data. In period 2, each decision maker again has to calculate the expected values of all N alternatives using his/her performance measure. The previously chosen alternative is valued correctly, while the valuation of the other alternatives is still based on the estimated data. Again, on the basis of these values s/he selects one alternative. This can lead to a decision in which the same alternative as in period 1 is selected. It may also lead to the selection of another alternative. After the choice, s/he will receive the correct information for the chosen alternative and so on. In effect, each decision maker only gets the correct information for those alternatives which s/he actually has chosen at least once.

Although, this multi-step process is rather simplistic, it is adequate for the purpose of the following analysis for two reasons. First, it contains the experiential learning cycle. Second, it mirrors decision processes in reality in one important aspect: In most instances decision makers only receive feedback about the alternatives which they actually have implemented.

4 Procedure of the simulation and parameter values

4.1 Simulation as explorative method

Computer-based simulations combine theoretical and empirical approaches and are located between deduction and induction (Axelrod, 1997): They start with a set of assumptions like theoretical models, but do not lead to proofs of theorems. In contrast, they aim at generating data sets which can be analysed inductively, similar to empirical data. Simulations have the advantage of internal and statistical validity (Raghu & Sen & Rao, 2003). However, since the data does not come from the real world, the testing of hypotheses similar to empirical research is not possible. Therefore, the question of external validity is often raised, and results of simulation experiments cannot be used directly to predict and explain real world phenomena. Too many variables and factors are excluded from these models. Yet, this abstraction process also is beneficial (Simon, 1990; Miller et al., 1992; Raghu & Sen & Rao, 2003), because it allows for the exploration and discovery of stylised mechanisms which could not be handled by analytical means, like multi-periodical learning processes in an uncertain environment. Therefore, simulations are best characterised as thought experiments (Simon, 1981; Axelrod, 1997) linking theoretical and empirical research (Simon, 1990; Raghu & Sen & Rao, 2003).

Simulation-based research can use a wide range of different techniques and methodologies in order to fulfil different purposes (Gilbert & Troitzsch, 2005). With respect to the analysis of learning processes in an economic context especially two important applications can be identified: On the one hand, simulations are used to analyse the dynamics of interactional learning processes, which evolve in groups or whole organisations (e.g. like Dupouët & Yıldızoğlu, 2006). This category is termed a descriptive use of simulation models (Chattoe, 1996). On the other hand, simulations are used as substitute for an analytical analysis to generate comparative outcomes under different parametric settings (e.g. like Raghu & Sen & Rao, 2003). This type of application is also called instrumental (Chattoe, 1996). As the deduction of the decision situation in Section 3.2 shows, the focus of this paper lies in the learning processes of individual decision makers using a specific performance measure under the premise of internal uncertainty. In order to focus clearly on this aspect, the following study abstracts from interactional processes. Hence, the simulation model serves the second purpose.

4.2 Step 1: Generation of investment alternatives

The simulation is written in Java and structured according the previously developed decision scenario. In order to conduct a thorough analysis of the decision quality, full information concerning the investment alternatives is needed. Therefore, the study is not based on real world investment alternatives, but on a generated set of them. Each simulation run consists of three main steps: (1) the generation of investment alternatives, (2) the generation of decision makers and their estimated information sets and (3) the repeated choice by the decision makers based on their performance measures and personal information. This section is dedicated to the first step and the next one to the second and third steps. Appendix I.1 exhibits a pseudo-code containing the major elements of the simulation model and Appendix I.2 provides an exemplary simulation run.

At the beginning of each simulation run, N investment alternatives are generated. Each investment alternative gets a set of data which contains all information that is relevant to the five performance measures. Since it probably takes more time to learn about a set of two alternatives than it does to learn about a set of ten, it is reasonable to assume that simulation results will vary according to the number of investment alternatives. Therefore, the simulation experiments have been repeated with a varying number N of alternatives, where the results of $N \in \{2, 5, 10\}$ are presented in this paper. Since the initial information sets are randomly generated, each experiment was repeated 2000 times to obtain a significant sample on which statistically-based conclusions can be drawn.

Two aspects must be considered when generating the data sets for the decision alternatives. First, they should remain within a reasonable range, which makes a thorough analysis possible. Second, during each simulation run a differing set should be generated to protect the analysis from being biased by a specific constellation of data. Therefore, the simulation experiments are based on investment alternatives whose data are discrete uniformly distributed random variables drawn from the following intervals or have the following fixed values (s_{Id} denotes the estimated share that I_d comprises of I. Consequently, I_e equals $(1-s_{Id})*I$. I_d and I_e are calculated this way to ensure comparability between PM_3, PM_4 and PM_5):

$C \in \{150; 199\}$; $T \in \{250; 349\}$; $I \in \{400; 499\}$; $s_{Id} \in [0; 1]$;

$\beta \sim N(1; 0.05^2)$; $i, i_d = 0.08$; $i_e, i_m = 0.12$; $i_{rf} = 0.03$.

The randomly-generated values of turnover, operating costs, etc. ensure a variability of the initial data sets. The uniform distribution has been selected to avoid any bias. The values of the interest rates have been fixed, because they have only a very small impact on the learning process: Since they are the same when calculating with the same performance measure, their correct values are unveiled to the decision maker at the end of the first period.

Table 1 provides statistical information concerning the values of the investment alternatives with respect to the five performance measures. It shows the spread of an average alternative set, given by the average values of the five performance measures with respect to the best (maximum) and the worst (minimum) investment alternatives. Moreover, standard deviation, kurtosis, and skewness of the sample data are given.

In addition, the column RD_1 in Table 1 shows that the assumption of the relation between degree of complexity and degree of goal reflection underlying the construction of the five performance measures holds in the assumed decision context. By definition PM_5 is the performance measure that best reflects reality in sense of goal congruence. To judge the degree of goal reflection regarding the other four measures, RD_1 is used. It is calculated as the relative difference between the correct value of the best alternative b in period t concerning PM_k and the correct value of the best alternative b in period t concerning PM_5, i.e.:

$$RD_1(t) = |PM_{k,b} - PM_{5,b}|/PM_{5,b} \qquad (k \in \{1, 2, 3, 4, 5\}) \qquad (4.1)$$

It was assumed that the less complex the measure, the farer away it is from a correct reflection of the goal because fewer factors that influence the goal are taken into consideration. As Table 1 shows, the sample data exhibit this decrease of RD_1 from PM_1 to PM_5. Consequently, the assumed increase of goal reflection with increasing complexity from PM_1 to PM_5 holds in the simulation experiments. Hence, the start assumption of this study is correctly implemented in the simulation model.

		RD1		Maximum				Minimum			
No. Altern.	PM	Mean	Std. dev.	Mean	Std.dev.	Kurtosis	Skewness	Mean	Std. dev.	Kurtosis	Skewness
	PM1	288.77	264.86	316.71	22.54	-0.48	-0.57	284.05	23.67	-0.68	0.50
	PM2	68.06	60.19	144.31	25.84	-0.39	-0.29	107.41	26.52	-0.42	0.31
2	PM3	22.66	19.83	108.45	25.93	-0.39	-0.28	71.32	26.63	-0.40	0.30
	PM4	11.20	15.19	99.29	26.65	-0.42	-0.22	62.07	27.26	-0.35	0.30
	PM5	0.00	0.00	90.56	26.09	-0.39	-0.27	53.23	26.71	-0.39	0.29
	PM1	214.23	50.76	332.72	14.12	1.12	-1.15	266.05	14.10	0.99	1.13
	PM2	51.22	11.11	162.54	18.16	-0.15	-0.44	87.26	18.47	-0.16	0.40
5	PM3	17.04	3.86	126.63	18.21	-0.18	-0.41	51.07	18.57	-0.11	0.40
	PM4	8.35	5.96	117.48	19.08	-0.19	-0.33	41.78	19.57	-0.10	0.34
	PM5	0.00	0.00	108.72	18.29	-0.20	-0.40	32.89	18.72	-0.08	0.39
	PM1	188.80	31.81	340.19	8.22	2.80	-1.45	258.44	8.24	3.31	1.61
	PM2	45.72	6.92	172.93	13.27	-0.19	-0.40	76.63	13.62	0.05	0.53
10	PM3	15.16	2.46	137.04	13.40	-0.18	-0.39	40.54	13.75	0.04	0.50
	PM4	7.21	5.12	127.72	14.77	-0.25	-0.26	31.04	14.92	-0.04	0.38
	PM5	0.00	0.00	119.24	13.56	-0.15	-0.36	22.37	13.95	0.03	0.47

Table 1: Descriptive statistics regarding the sets of investment alternatives underlying the decision makers' selection (RD_1 in %).

4.3 Steps 2 and 3: Construction of decision makers and repeated decisions

In the second step of each simulation run, five decision makers are constructed. Each gets one of the five performance measures and receives a set of data relevant to his/her performance measure for each investment alternative. To implement the internal uncertainty, these data sets are only estimations of the correct data that were generated previously. This estimation is implemented by a normally-distributed random variable which has the correct value of the considered piece of data as mean μ and the standard deviation $\sigma = 0.2*\mu$, i.e. on average each decision maker estimates each piece of data correctly. However, the single estimated pieces of data deviate on average from the correct value by ±20% of this value and follow a normal distribution.

Because the assumption regarding this initial estimation error can be assumed to be a crucial one, higher and lower estimation errors were also used in the testing phase of the simulation. Although the absolute values of the simulation results changed, the qualitative outcomes did not (see Appendix II). Since the analysis uses the simulation as a "thought-experiment", it does not aim at quantitative but at exactly these qualitative aspects. Hence, the following results are robust with respect to the changes of the estimation error.

The third step of each simulation run comprises the repeated decision processes. As described in the previous section, each decision maker evaluates the N alternatives based on his/her personal set of estimated data and selects the alternative, which accordingly exhibits the highest value. At the end of the period the decision makers get the correct information regarding the selected alternatives to update their data sets. Based on this adjusted information set they perform their selection at the beginning of the next period and so on. The following sections provide the results regarding a time frame of 12 periods. The discussion of the simulation outcomes can concentrate on this time frame, because decision quality does not change any more thereafter.

5 Simulation results

5.1 Evaluation of decision quality and of learning

In order to analyse the impact of the five performance measures on long-term decision quality, one has to define a measure of this quality and the degree of learning.

Under the premise of cognitive restrictions, one can compare decisions based on performance measures of different degrees of complexity (a) regarding their deviation from a *globally optimal* decision and (b) regarding their deviation from the *optimal decision using the same performance measure*.

The first aspect focuses on the decision quality and learning with respect to "reality". This type of quality actually reflects the intended effect of performance measures: Performance measures are used to support managers and direct their decisions to select alternatives that are optimal for organisational goals. Consequently, the closer the "real" value of the selected decision alternative to the "real" value of the overall optimal alternative is, the better the decision in terms of goal achievement. A high-quality decision leads to a difference of zero between the mentioned values because the selected alternative is actually the optimal alternative. This type of decision quality shall be named the *overall* quality and the mentioned difference the *overall* deviation. It is operationalised via the relative deviation (RD_2) between the correct value of the (via PM_k) selected alternative s in period t concerning PM_5 and the correct value of the best alternative b in period t concerning PM_5:

$$RD_2(t) = |PM_{5,s} - PM_{5,b}|/PM_{5,b} \qquad (5.1)$$

The value of PM_5 is an adequate basis of comparison, because according to the initial assumption it is a perfect reflection of reality. One can illustrate the meaning of (5.1) by the following example: A decision maker uses PM_2 to evaluate the performance of the N alternatives. Based on this measure, s/he selects alternative s. However, in order to judge the "true" value of s in terms of perfect goal congruence, one has to calculate its value using PM_5, as it perfectly reflects "reality", and then take the difference between this value and the PM_5-value of the truly optimal alternative b. To make several simulation runs with differing starting values comparable, one finally calculates the relative deviation, by dividing the mentioned difference by the PM_5-value of the truly optimal alternative b.

The second aspect is important for analysing decision quality and learning concerning only the pieces of data that are relevant for the *considered* performance measure. In practice, decision makers only learn ex post the realised values of the performance measure *in use*. They never learn the "true" real value (whatever this may be) of their decisions. Consequently, their actual performance is always compared to benchmarks which are calculated in the same way as their performance targets. From this perspective, a high-quality decision leads to the selection of those alternatives whose correct performance values are the highest regarding the performance measure *in use*. This type of decision quality shall be called *internal* quality and the difference between the values of the – in this sense – optimal alternative and the selected alternative shall be named *internal* deviation. In case of correctly estimated data, this difference is always zero. However, if erroneous data are incorporated into the performance measure, the evaluation of decision alternatives is erroneous, too, and a sub-optimal alternative might be chosen. The internal deviation is calculated as the relative difference (RD_3) between the correct value of PM_k regarding the selected alternative s in period t and the correct value of PM_k regarding the best alternative (in terms of PM_k) b in period t:

$$RD_3(t) = |PM_{k,s} - PM_{k,b}|/PM_{k,b} \qquad (k \in \{1, 2, 3, 4, 5\}) \qquad (5.2)$$

In order to judge the influence of the performance measures on *learning*, the analysis concentrates on the difference between the overall internal deviation of the first and the last periods. If this difference is positive, the analysed performance measure allows for an improvement in decision quality. In this case, the learning process was favourable also from an organisational point of view. In case of a negative difference, the performance measure leads to a decrease in decision quality, what is unfavourable from an organisational perspective. Beside this long-term change in decision quality, the following tables also provide the short term change from the first to the second period.

5.2 Development of internal decision quality

Figure 2 and Table 2 provide the results of the development of internal decision quality. Figure 2 shows the average values of RD_3 in each period for each performance measure. The lines between the data points have been introduced for reasons of visualisation. Table 2 presents the averaged values of RD_3 of the first and the last periods, strength of short- and long-term learning, and some statistics regarding the sample data.

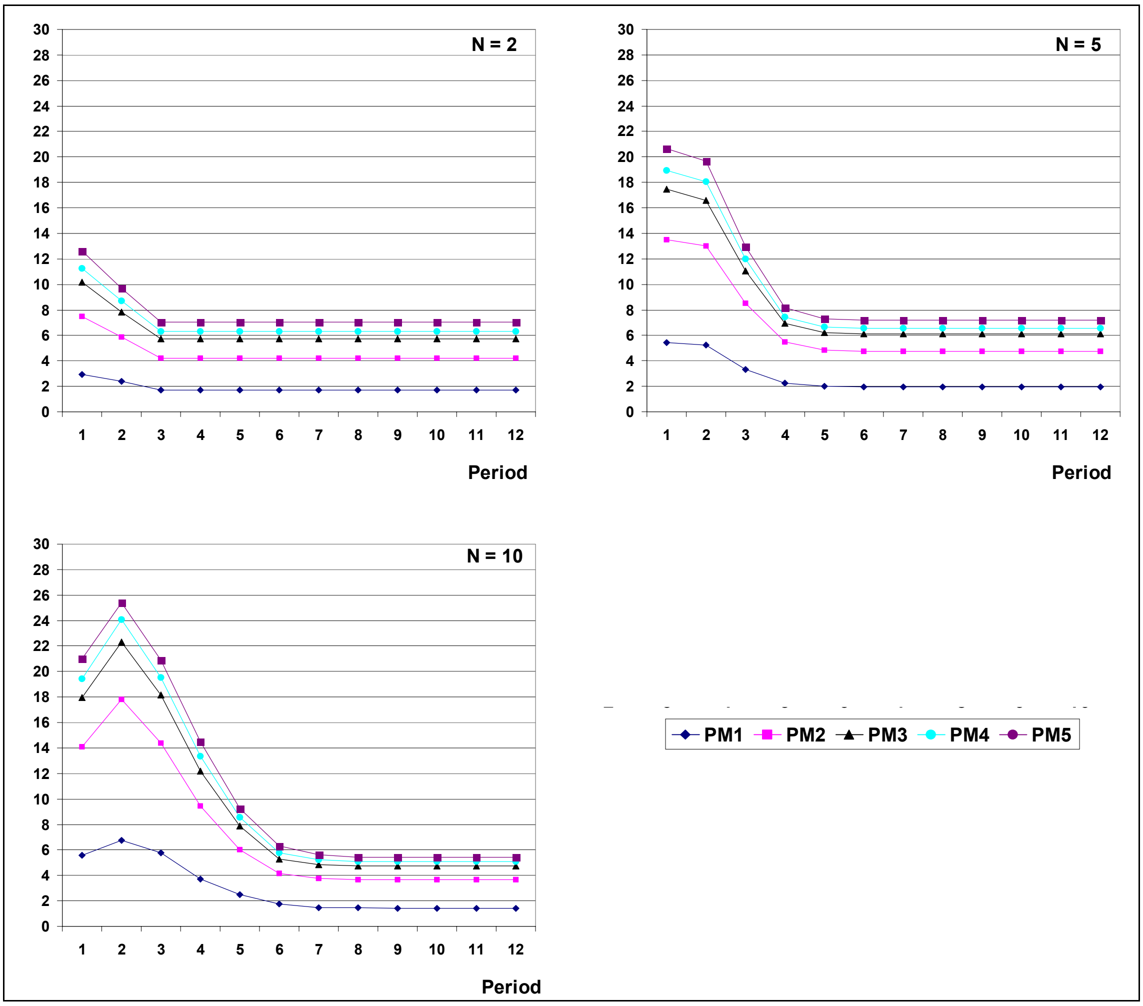

Figure 2: Values of RD_3 in % (average of 2000 simulation runs, N = number of alternatives).

No. Altern.	PM		First period RD3 Mean	Std.dev.	Skewness		Last period RD3 Mean	Std. dev.	Skewness	strength of learning long-term	short-term
	PM1	***	2.95	5.34	1.89	***	1.72	4.13	2.70	1.23	0.53
	PM2	***	7.48	12.90	1.78	***	4.23	9.82	2.60	3.25	1.62
2	PM3	***	10.19	17.54	1.77	***	5.71	13.54	2.72	4.48	2.37
	PM4	***	11.24	19.43	1.79	***	6.33	15.09	2.75	4.91	2.52
	PM5		12.64	21.83	1.77		7.06	16.92	2.80	5.58	2.93
	PM1	***	5.42	6.54	1.18	***	1.97	3.78	2.35	3.45	0.18
	PM2	***	13.50	15.51	1.02	***	4.76	8.99	2.19	8.74	0.49
5	PM3	***	17.49	20.01	1.03	***	6.11	11.54	2.17	11.38	0.89
	PM4	***	18.95	21.89	1.07	***	6.55	12.44	2.19	12.40	0.92
	PM5		20.67	23.70	1.03		7.20	13.52	2.16	13.47	1.02
	PM1	***	5.56	6.11	1.11	***	1.44	2.63	2.36	4.12	-1.19
	PM2	***	14.12	14.23	0.96	***	3.69	6.50	2.07	10.43	-3.67
10	PM3	***	17.95	17.91	0.92	***	4.73	8.24	2.05	13.22	-4.35
	PM4	***	19.41	19.45	0.96	***	5.07	8.83	2.03	14.34	-4.66
	PM5		20.99	21.03	0.94		5.44	9.44	1.98	15.55	-4.41

Table 2: Values of RD_3 in the first and the last period and strength of learning (in %). The data is tested regarding a significant difference to the performance measure with next higher RD_3 using a Wilcoxon-Test because the values are not statistically independent due to their partially equal starting sets of information parts and they are not normally distributed. (*** significant in 99%-Interval.)

Before looking at the long-run influence of the tension between goal congruence and complexity, the degrees of internal decision quality regarding the five measures in the first period (which is equivalent to a single periodical decision situation) are worth noting. Independently of the number of alternatives, the five performance measures start on average at different levels of internal deviation. Each measure starts at a significantly higher level than the measure with the next lower degree of complexity and goal congruence. In effect, increasing complexity leads to lower internal decision quality in the first period, i.e. the impact of cognitive restrictions increases compared to a measure with a lower level of complexity. Hence, the simulation experiments provide an expected outcome with respect to the influence of complexity in the short-run: As was discussed in Section 1, in the literature the effect of complexity on decision quality has been discussed from such a short-run point of view and the existing results point to its dysfunctional effect on decision quality. The fact that the simulation provides results that are in line with existing literature can be seen as evidence of the usefulness of the incorporated assumptions.

With respect to the research question, the following two aspects can be observed: First, on average the degree of long-term learning is the highest with respect to PM_5, because it exhibits the highest decrease of RD_3 from period 1 to period 12. From PM_5 to PM_1 the degree of long-term learning diminishes. Hence, as the results regarding the first period show, the increasing complexity negatively influences the internal decision quality. However, through the process of learning the decision makers have the possibility to considerably improve their degree of internal decision quality over time. Moreover, the degree of complexity does not inhibit learning in the same manner as it influences the degree of decision quality in the first period. In contrast, the worse the initial internal decision quality is due to complexity, the higher the degree of learning. So in essence, it holds:

Proposition 1: *Increasing complexity does not counteract the improvement of internal decision quality through learning in the long-term.*

However, second, with respect to the long-term development of internal decision quality, on average one observes that the order regarding the measures remains the same through all twelve periods: PM_5 shows the highest degree of deviation, followed by PM_4, PM_3 and then PM_2, while PM_1 exhibits by far the lowest degree of internal deviation. Hence:

Proposition 2: *Increasing complexity has a negative effect on the long-term level of internal decision quality.*

Beside the two previously derived aspects the number of decision alternatives also has an effect. However, it affects all performance measures equally and therefore does not change the qualitative results. In essence, with an increasing number of alternatives the possibility to subsequently choose wrong alternatives emerges, which in the short-run can lead to an increase in internal deviation.

5.3 Development of overall decision quality

Figure 3 and Table 3 provide the results of the development of overall decision quality. Figure 3 shows the average values of RD_2 in each period for each performance measure. The lines between the data points have been introduced for the sake of visualisation. Table 3 presents the average values of RD_2 of the first and the last periods, strength of short- and long-term learning, and some statistics about the sample data.

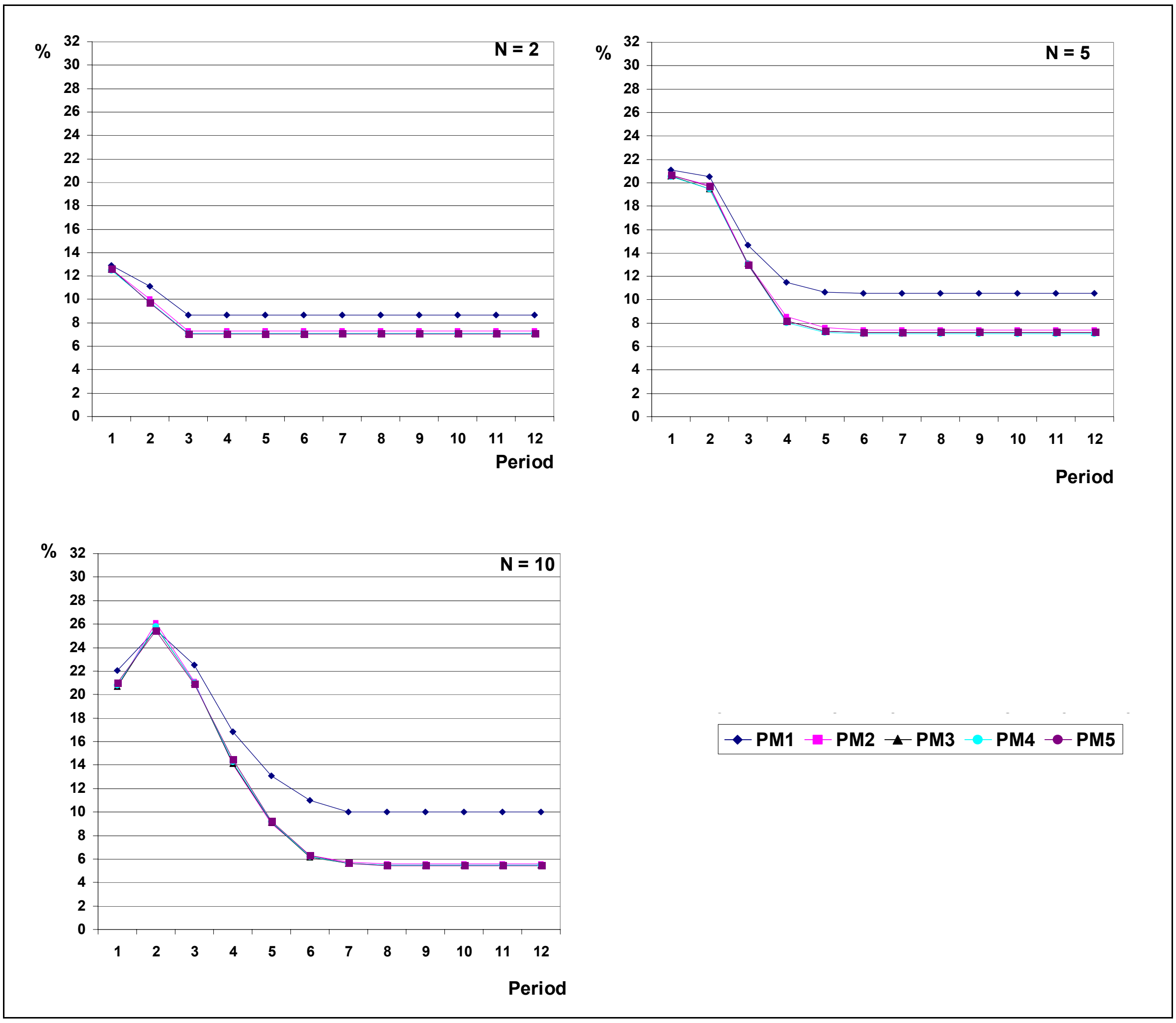

Figure 3: Values of RD_2 in % (average of 2000 simulation runs, N = number of alternatives).

			First period RD2				Last period RD2			strength of learning	
No. Altern.	PM		Mean	Std.dev.	Skewness		Mean	Std. dev.	Skewness	long-term	short-term
2	PM1	n	12.90	22.20	1.80	***	8.69	18.06	2.39	4.21	1.81
	PM2	n	12.58	21.55	1.76	**	7.31	16.87	2.69	5.27	2.56
	PM3	n	12.57	21.65	1.78	n	7.11	16.88	2.78	5.46	2.84
	PM4		12.48	21.60	1.78	n	7.07	16.90	2.77	5.40	2.7
	PM5	n	12.64	21.83	1.77		7.06	16.92	2.80	5.58	2.93
5	PM1	n	21.10	23.41	1.00	***	10.55	15.55	1.70	10.55	0.59
	PM2	n	20.60	23.53	1.00	***	7.44	13.65	2.13	13.16	0.84
	PM3	n	20.55	23.51	1.04	n	7.22	13.51	2.14	13.33	1.07
	PM4		20.51	23.60	1.04		7.10	13.40	2.17	13.40	1.03
	PM5	n	20.67	23.70	1.03	n	7.20	13.52	2.16	13.47	1.02
10	PM1	***	22.06	20.97	0.86	***	9.99	12.32	1.23	12.07	-3.46
	PM2		20.66	20.77	0.95	***	5.60	9.58	2.06	15.06	-5.43
	PM3	n	20.71	20.68	0.92	***	5.50	9.53	2.05	15.21	-5.05
	PM4	n	20.80	20.77	0.93	n	5.45	9.51	2.06	15.34	-4.97
	PM5	n	20.99	21.03	0.94		5.44	9.44	1.98	15.55	-4.41

Table 3: Values of RD_2 in the first and the last periods and strength of learning (in %). (The data is tested regarding a significant difference to the performance measure with next lower RD_2 using a Wilcoxon-Test because the values are not statistically independent due to their partially equal starting sets of information parts and they are not normally distributed. *** significant in 99%-Interval, ** significant in 95%-Interval, n = no significance.)

First, on average in case of $N \in \{2, 5\}$ all decision makers start at about the same level of overall deviation, in case of $N = 10$, only PM_1 exhibits a significantly higher deviation, i.e. its initial overall decision quality is lower than the initial overall decision quality of PM_2 to PM_5. Hence, although measures with higher degree of complexity also have a higher degree of goal congruence, there is virtually no significant difference of decision quality in the initial period (which is equivalent to a single periodical decision situation). The increasing number of possibly wrong estimated input data due to cognitive restrictions counteracts the positive effect of increasing goal congruence. Again, the results can be seen to be in line with the findings of the literature mentioned in Section 1. In addition to the outcomes regarding the internal decision quality, the results presented in this section are based on the combined effect of complexity *and* goal congruence, as it is also analysed in the literature regarding information overload. Again, the fact that the provided results are in line with the findings of the mentioned literature can be interpreted as evidence of the usefulness of the assumptions.

With respect to the research question the following two observations are of special interest: First, independently of the number of decision alternatives, on average the final level of overall deviation is significantly lower for PM_2 compared to PM_1 and for PM_2 compared to PM_3. In case of $N=10$, there is also a significant difference between PM_3 and PM_4. However, there is no significant difference between PM_3 and PM_4 and between PM_4 and PM_5 in case of $N \in \{2, 5\}$, and no significant difference between PM_4 and PM_5 in case of $N=10$. Moreover, in terms of the absolute values of RD_2, the five measures exhibit a less differentiated behaviour than in case of the internal deviation. Consequently, from PM_2 on increasing goal congruence hardly leads to any improvement of overall long-term decision quality through learning. The negative effects of complexity counteract the positive effects of increasing goal congruence. This can be summed up in Proposition 3:

> ***Proposition 3:*** *Increasing complexity counteracts the positive effects of increasing goal congruence regarding the improvement of overall decision quality through learning.*

Second, on average none of the performance measures allow to gain full information about the relevant reality, i.e. none reaches an overall deviation of zero, independently of the number of alternatives. Obviously, the decision makers do not get the chance to try each alternative and therefore in some cases repeatedly misjudge some alternatives. This result can be explained as follows. In each period the decision maker chooses the alternative that has the best value concerning his/her performance measure. Incorrectly estimated input data leads to situations in which actually good alternatives are undervalued and therefore never get the chance to be used and re-valued with the correct data. This result can be expressed in Proposition 4:

> ***Proposition 4:*** *Even a fully goal congruent performance measure does not reduce the overall deviation to zero over time in case of cognitively-restricted decision makers.*

Beside the mentioned effects, again the number of alternatives influences the outcomes but does not change the qualitative results, as it affects all performance measures equally.

6 Interpretation of the results and implications

6.1 Costs and benefits of goal congruence

Taking into consideration the usual caveat regarding the generalisability of results obtained by simulation experiments, the previous propositions nevertheless provide some useful insights and may help to put some aspects regarding the influence of performance measures on organisational (long-term) performance partly into a new and broader perspective. In this section the consequences of overall decision quality are discussed in more detail. The next section describes the consequences of the findings regarding internal decision quality for the usage of incentive systems.

As previously stated, overall decision quality is directly linked to organisational performance by means of goal congruence and goal achievement. It shows how close the decision maker comes to an overall best decision. The benchmark of this decision quality lies outside the organisation; it is determined by environmental factors. However, in practice overall decision quality never can be measured, for environmental complexity undermines the possibility to find any "truly correct measure" as metric for the achievement of organisational goals. Any measure can only be an approximation. The better this approximation, the more goal-relevant parts have to be incorporated and – on average – the more complex a measure becomes. The possible dysfunctional effects that can arise when decision makers with restricted information-processing capabilities are confronted with complex performance measurement systems have been discussed and accepted in literature. However, the focus of this discussion was put on a relatively short-term perspective. The simulation results add to this by taking the discussion one step further. They point to the fact that even learning cannot eradicate these dysfunctional effects, as Propositions 4 shows: Performance measures with higher degree of goal congruence exhibit the least overall deviation in the final period, but there is no significant improvement from PM_3 to PM_5 respectively from PM_4 to PM_5. The incorporation of more pieces of information is not *equivalent* to an improvement of overall decision quality in the long-run, as cognitive restrictions may lead to *continuous* distortion of measures that are actually goal congruent. The mentioned long-term aspect is of importance, as in many instances in practice and in theory the implicit assumption can be observed, according which initial problems of performance measurement systems will disappear after some learning phase. In this sense, the repeated use of a more goal congruent measure always should allow a decision maker to learn more about "reality" than a less goal congruent measure, at least in the long-run. However, as the simulation results indicate, under the assumption of cognitively-restricted decision makers, this might not be the case. One has to consider additionally, that the study has focused only on a single aspect of cognitive restrictions. Problems in perception and interpretation, which were ignored in this paper, would probably exacerbate the dysfunctional effects. The mentioned aspects have implications for theory and practice.

With respect to the practice of performance measurement the following can be concluded: Decision makers in firms are frequently confronted with new performance measurement systems, not only as users but in their capacity to decide whether or not to implement them. One major reason for the implementation of new performance measurement systems is certainly the inadequacy of existing systems (Ittner & Larcker, 1998). However, new trends in performance measurement are often aggressively marketed by consulting firms. The pressure to pick up such new developments is additionally increased when competitors have already implemented such systems and may benefit from improved management processes. The sole conjecture that any improvements could be gained from the new system by competitors can similarly enhance a decision to implement the system. Hence, the actual need for new measurement systems that better fit to a changing environmental context in combination with pressure to implement new “managerial fashions” have led firms to introduce a wide range of highly complex performance measurement systems without previously testing to see whether they actually fit. For example, recent empirical studies show, that the additional informational value of the economic value added to classical accounting data is marginal (Tsuji, 2006; Kyriais & Anastassis, 2007). Yet, due to its complex calculation modus and the high amount of data needed, presumably its expense compared to that of classical accounting information is considerable.

In essence, as complexity raises the costs of gathering, selecting, saving and distributing the needed data, one should have a closer look at the actual quality improvement through increasing goal congruence. This is particularly important as the used stylised performance measures are quite simplistic compared to the actual performance measures used in practice. In particular, the past and current discussions of value-based performance measures and of the balanced scorecard highlight the need to gather a high number of information parts and to apply many adjustments to them before arriving at an adequate measure. These processes consume many resources, but their additional benefit remains vague. The results of this study point to the supposition, that in some situations a less goal congruent but easier to process measure would produce the same degree of overall decision quality. However, since it is simpler, its calculation consumes fewer resources. Therefore, it leads to the same benefit but at lower cost and therefore has a better impact on organisational performance than a more goal congruent one, in the short-run *and* in the long-run.

From a theoretical point of view, one should start to analyse the influence of *specific* performance measurement systems on long-term learning of single decision makers in order to judge their value compared to more classical performance measures as decision basis. Surely, the analysis of the information value of general information systems has a long standing tradition in accounting theory. However, it tackles the problem from a relative abstract point of view. In contrast, only the combined consideration of cognitive restrictions and the characteristics of a specific performance measurement system allow for its judgment in a practically useful way. Additionally, the mentioned learning aspect should be taken more prominently into consideration, as performance measures are one of the most important information systems that are used – mainly in an unconscious way – by decision makers to learn about environmental requirements.

6.2 Incentive systems and goal congruence

What organisations actually want to achieve is highly goal congruent behaviour of their decision makers. This is equivalent to decisions with high degree of overall decision quality. Yet, organisations reward internal decision quality: Often performance measures and incentive systems are linked insofar as incentives are bound to target values regarding these measures, which should be reached by decision makers. However, this is exactly what internal decision quality means. It reflects how well a decision maker adapts his/her decisions to a decision that is optimal to the performance measure in use. Consequently, by using incentive systems, decision makers are motivated to improve the internal quality of decisions. Hence, in practice one assumes that using a highly goal congruent measure and by rewarding internal decision quality a high degree of overall decision quality is achieved and thereby, the decision maker's and the organisational performance improve. Actually, if this assumption holds, the order of the five performance measures should be the same in their internal and overall decision quality. However, as the simulation results show, at least under the used assumptions, this is not the case: the higher the degree of complexity, the lower internal decision quality, as Proposition 2 shows.

Translated to the practice of incentive systems, this means the higher the degree of complexity, the harder it might be to match the preset target value of the used performance in the short-run and in the long-run. Hence, on the one hand, using highly goal congruent measures aligns decisions to organisational goals by providing a relatively high degree of overall decision quality. On the other hand, this is not valued by incentive systems, since due to their high degree of complexity, highly goal congruent measures also have a relatively low degree of internal decision quality. The impossibility of matching given targets negatively affects the motivation of decision makers and can reduce their interest in meeting organisational goals. The motivational effect of incentive systems is counteracted by the de-motivational effect of their sensitivity to errors caused by cognitive restrictions.

Consequently, the actual aim of motivating decision makers to pursue the correct action fails. The incentive system becomes less effective.

This casts the theoretical discussion regarding distorted performance measures in the literature into a new light. There is a considerable body of research on the influence of distorted performance measures on the effectiveness of incentive systems (e.g. Feltham & Xie, 1994; Baker, 2000 & 2002; Bouwens & van Lent, 2006). In this stream of literature, distortion is synonymous with what this paper has called overall deviation. The authors come to the conclusion, that the less distorted a measure is, the more effective is its application in incentive systems. However, as the previous analysis demonstrates, when cognitive restrictions come into play, this notion might not hold. In the simulation study only the missing experience to perform a reasonable forecast, was considered. In practice, cognitive restrictions might also lead to misperception of the perceived data, wrong interpretations etc., which can additionally increase the mentioned effect. In effect, similar to environmental factors cognitive restrictions introduce noise into performance measurement processes. In literature, noise and distortion are discussed as affecting the quality of incentive systems in the same manner (e.g. Baker, 2002). Additionally, some authors accept them as two phenomena that are linked to each other in a reverse manner (e.g. Baker, 2002). The simulation study adds to this discussion one possible reason for this trade-off and exhibits its long-term consequences.

With respect to practical consequences, especially Proposition 1 is of interest. It exhibits a positive effect of goal congruence on the improvement of decision quality over time. This leads to two further conclusions on the linkage of more or less goal congruent and therefore complex performance measures to incentive systems under the premise of learning.

First, the more complex a measure gets, the more important it becomes for the decision maker to improve his decisions over time, because the more complex a measure is, the higher is the probable deviation between a preset target value and the reached value when it is used for the first time. Therefore, it is recommended to use highly complex measures only in relatively stable decision situations where the circumstances change slightly over time and the decision maker has time to learn. Moreover, in order to prevent from de-motivational effects, a learning phase should be provided, in which the measure is not yet linked to any incentive systems. In more dynamic environments, less complex measures are more useful. They may have a lower degree of goal congruence. However, as the environment changes constantly, the decision maker has not sufficient time to learn and the negative effects of complexity would counteract the positive effects of goal congruence.

Second, it would make sense to have a closer look at this learning perspective instead of pure goal reaching, when linking incentives to more complex performance measures, i.e. especially for highly complex measures incentives probably could be linked to improvements from period to period instead to pure target reaching. Alternatively, one can think of a more differentiated performance measurement system incorporating more and less complex measures: the former are used for learning purposes only, the latter are linked to incentive systems. However, this dichotomy would probably be hard to communicate.

7 Conclusion and further research

This paper studies the interplay between goal congruence and complexity of performance measures and its influence on decision quality and learning. The results of this study add several aspects to the existing literature. First, the modelling process showed that there are two kinds of decision quality, which have to be studied separately from each other to reach a better understanding regarding the influence of performance measures on decision makers' learning. *Overall* decision quality reflects what organisations actually want to achieve when they implement performance measures. It comprises the degree of "real" goal achievement. The higher the degree of overall decision quality is, the closer the outcome of a decision comes to the outcome of an overall best decision. *Internal* decision quality reflects what organisations actually measure and reward their decision makers for. It mirrors the quality of a decision under a given set of assumptions about reality that are incorporated in the used performance measurement system. Second, the simulation experiments exhibited that complexity which to a certain degree always accompanies goal congruence, differently influences both types of decision quality. This aspect is important to the practical use of performance measures, as that use is based on the implicit assumption that both kinds of decision quality are linked to each other and by rewarding internal decision quality one will also achieve overall decision quality. As this seems not to be the case, the question regarding costs and benefits of an increasing number of presumably more goal congruent but also more complex modern performance measurement systems rises. Third, the study points to the influence of performance measures on decision makers' learning processes and highlights the importance of further research in this area. As was stated in Section 3.1, learning comprises a process of adaptation to environmental requirements through the perception and interpretation of feedback information. Performance measurement systems are one of the most important feedback systems in organisations. They cast decision makers' learning processes regarding "reality" in a strong way, and have the potential to lead to outcomes that are unfavourable from an organisation's point of view.

The analysis was conducted in the context of restrictive premises. Therefore, at this point it shall be stressed that the study was done explicitly under the premise of exploration and its results are a starting point for further research. Beside the already mentioned aspects, the simulation experiments reveal the following promising research directions.

First, as stated in Section 6, in practice the inquiry of the different pieces of a complex performance measure consumes resources and thereby results in expense. The more parts a measure has, the more resources it needs. So far this resource consumption was only mentioned but not introduced in the simulation model. It would be interesting to analyse on the basis of a simulation model the trade-off between the expense incurred by the number of information parts and their additional informational value – measured as a decrease of overall deviation. Since those costs of inquiry can be considerable, one may assume that the incorporation of this trade-off in the presented model would be worthwhile.

Second, this study is based on a rather simple decision situation. The decision maker has to repeat his selection of investment alternatives several times, while there are no changes in the alternatives. This was conducted to isolate the influence of complexity on personal uncertainty, ignoring external uncertainty caused by changing investment alternatives. However, because in practice decision makers have to cope with both types of uncertainty, the external one should be introduced in a future model. Moreover, errors of perception and interpretation when receiving the feedback might be valuable to introduce in a future model as additional aspects of cognitive restriction.

Finally, the simulation results show that under the given premises, the ranking of the five analysed performance measures is quite different in both types of decision quality. As mentioned in Section 6, incentive systems assume that both types of decision quality go in the same direction. Consequently, a deeper analysis of the linkage between internal and overall decision quality would be of interest.

Appendix I: Simulation

A I.1 Pseudo-code

Regarding the five performance measures, the following algorithm was performed during one simulation run (k = number of alternatives, j = index of performance measure ($j \in \{1,\ldots,5\}$), n_j = index of pieces of information ($n_j \in \{1,\ldots,N_{j,}\}$, N_j = number of pieces of information needed for calculating performance measure j):

(1) Generate sets of k vectors $v_{i,j}$ ($i \in \{1, \ldots, k\}$) that contain the correct pieces of information for the respective alternative i and the performance measure j.

Those pieces of information that are used for several performance measures are the same regarding the respective alternative.

(2) Based on these values generate the vectors $\tilde{v}_{i,j}$ containing the estimated values of the pieces of information adding an error term $\varepsilon_{i,j}^{(nj)} \sim N(0, (0.2*v_{i,j}^{(nj)})^2)$.

Those parts of information that are used for several performance measures get the same initial misjudgement regarding the respective alternative.

(3) For (1 to 12) /* The simulation comprises 12 periods. */

```
{
    For (m = 1 to 5)    /* The decision makers calculate the values of the
                           alternatives based on their performance measure. */
    {
        Calculate the values of the decision alternatives based on the set of
        estimated values ṽ_{i,j}^{(nj)} using formulas (2.m).
        Chose the alternative with the highest performance value.
    }
    For (m = 1 to 5)    /* The decision makers receive the correct values for the
                           selected alternative l_m and recalibrate their information
                           set. */
    {Substitute the values in the vector ṽ_{lm,m} by the correct values v_{lm,m}.}
}
```

A I.2 Example

The following example shows a simulation run in which the decision makers have to choose between *two* decision alternatives.

Step 1: Generation of the information sets regarding the decision alternatives 1 and 2

Alternative 1: T_1=270; C_1=151; I_1= 420; s_{Ib}=0.5; β_1=1.05; i, i_b=0.08; i_e, i_m=0.12; i_{rf}=0.03

Alternative 2: T_2=300; C_2=187; I_2= 460; s_{Ib}=0.5; β_2=1.006; i, i_b=0.08; i_e, i_m=0.12; i_{rf}=0.03

Step 2: Generation of the estimated information sets by the decision makers

(PM_i^j indicates the value of performance measure i with respect to alternative j)

Decision maker 1 using PM_1:

Alternative 1: T'_1=285, i.e. PM_1^1=285

Alternative 2: T'_2=290, i.e. PM_1^2=290

Decision maker 2 using PM_2:

Alternative 1: T'_1=285; C'_1=150, i.e. PM_2^1=135

Alternative 2: T'_2=290; C'_2=177, i.e. PM_2^2=113

Decision maker 3 using PM_3:

Alternative 1: T'_1=285; C'_1=150; I'_1=423; i'=0.08, i.e. PM_3^1 = 101.16

Alternative 2: T'_2=290; C'_2=177; I'_2=457; i'=0.08, i.e. PM_3^2 = 76.44

Etc.

Step 3: Repeated decisions

Period 1

Decision maker 1 selects alternative 2, as $PM_1^1 < PM_1^2$, and receives the correct value of T_2=300.

Decision maker 2 selects alternative 1, as $PM_2^1 > PM_2^2$, and receives the correct values of T_1=270; C_1=151.

Decision maker 3 selects alternative 1, as $PM_3^1 > PM_3^2$, and receives the correct values of T_1=270; C_1=151; I_1= 420; i=0.08.

Etc.

Period 2

Each agent recalculates the values of the alternatives using his performance measure and selects the alternative with the highest value, and so on.

Appendix II: Sensitivity analysis regarding the degree of error

Figure 4 and Table 4 show the simulation results regarding the internal deviation with varying errors. As the different degrees of error influence all performance measures equally, the qualitative results summarised in Propositions 1 to 3 remain unchanged.

Figure 5 and Table 5 show the results concerning the overall deviation. Regarding the first period, a lower degree of error leads to a significant higher overall deviation of PM_1 also in case of five decision alternatives, while in case of a high error there is no significant difference any more independently of the number of alternatives. Hence, a high degree of error equalises decision quality in the first period between PM_1 and the other performance measures. This aspect is consistent with Proposition 4. Moreover the differences in error also have an influence on the significant difference among the five performance measures in the last period. However, the qualitative results captured in Propositions 5 and 6 remain unchanged.

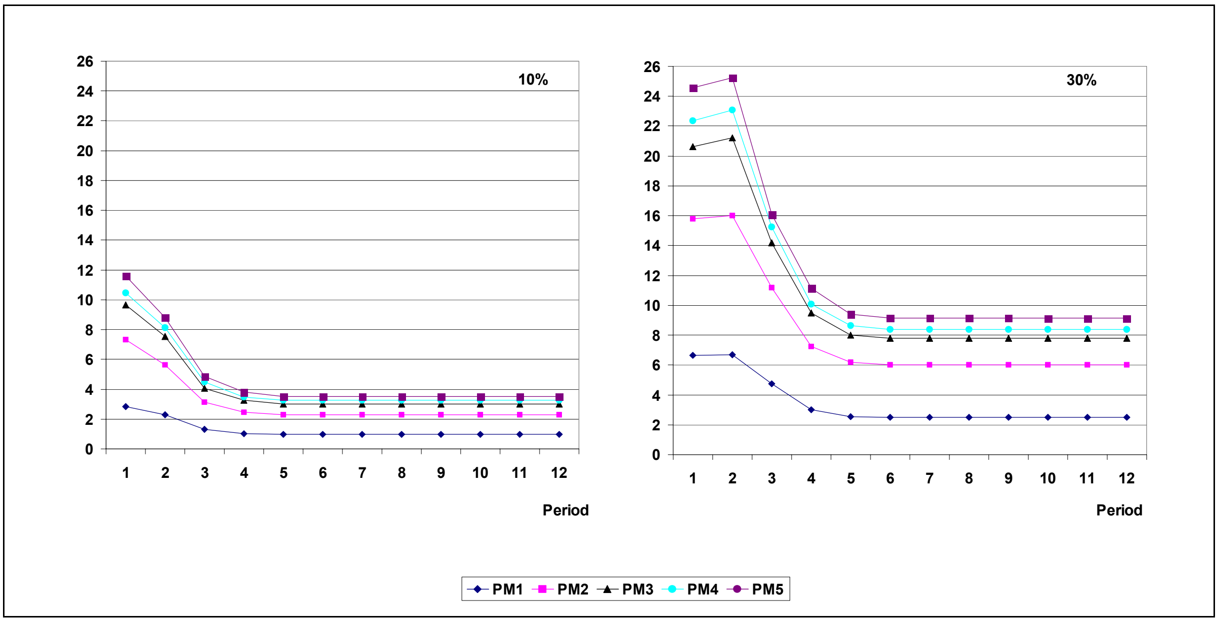

Figure 4: Values of RD_3 in % (average of 2000 simulation runs, 5 alternatives, degree of error $\in$ {10%, 30%}).

error in %	No. Altern.	PM		First period RD3 Mean	Std.dev.	Skewness		Last period RD3 Mean	Std. dev.	Skewness	strength of learning long-term	short-term
10%	2	PM1	***	1.61	3.82	2.99	***	0.75	2.36	3.96	0.86	0.63
		PM2	***	4.39	9.87	2.61	***	1.91	6.07	3.95	2.48	1.67
		PM3	***	5.93	13.30	2.57	***	2.64	8.37	3.97	3.29	2.26
		PM4	***	6.51	14.60	2.58	***	2.90	9.25	4.05	3.60	2.47
		PM5		7.39	16.62	2.58		3.40	11.00	4.20	4.00	2.70
	5	PM1	***	2.85	4.47	1.83	***	1.00	2.35	2.98	1.85	0.55
		PM2	***	7.31	11.06	1.72	***	2.29	5.38	2.92	5.03	1.66
		PM3	***	9.67	14.46	1.70	***	3.03	7.05	2.93	6.64	2.14
		PM4	***	10.47	15.68	1.71	***	3.25	7.53	2.88	7.23	2.34
		PM5		11.62	17.14	1.65		3.51	8.13	2.89	8.11	2.81
	10	PM1	***	3.37	4.23	1.48	***	0.93	1.86	2.52	2.43	-0.13
		PM2	***	8.58	10.40	1.33	***	2.39	4.74	2.36	6.20	-0.36
		PM3	***	11.10	13.34	1.36	***	2.94	5.83	2.27	8.16	-0.10
		PM4	***	11.94	14.39	1.39	***	3.17	6.27	2.25	8.78	-0.06
		PM5		12.78	15.53	1.40		3.39	6.76	2.30	9.40	-0.12
30%	2	PM1	***	3.55	6.10	1.79	***	2.26	5.01	2.49	1.29	0.44
		PM2	***	8.73	14.64	1.70	***	5.29	11.87	2.53	3.44	1.14
		PM3	***	12.21	19.97	1.60	***	7.44	16.32	2.41	4.77	1.59
		PM4	***	13.50	22.02	1.61	***	8.27	18.09	2.42	5.23	1.66
		PM5		14.93	24.21	1.57		9.18	19.86	2.35	5.75	1.75
	5	PM1	***	6.66	7.26	0.91	***	2.49	4.43	2.08	4.18	-0.05
		PM2	***	15.79	16.43	0.84	***	5.99	10.31	1.99	9.80	-0.22
		PM3	***	20.64	21.30	0.81	***	7.79	13.45	1.98	12.85	-0.58
		PM4	***	22.35	23.00	0.79	***	8.37	14.45	1.98	13.99	-0.71
		PM5		24.54	25.02	0.78		9.15	15.72	1.95	15.39	-0.71
	10	PM1	***	7.26	7.12	0.90	***	1.75	3.10	2.34	5.51	-1.49
		PM2	***	18.85	16.44	0.66	***	4.86	7.89	1.81	13.99	-1.79
		PM3	***	23.79	20.65	0.66	***	6.15	9.97	1.86	17.64	-2.68
		PM4	***	25.44	22.10	0.67	***	6.61	10.76	1.90	18.84	-3.25
		PM5		27.48	23.93	0.65		7.19	11.63	1.87	20.29	-3.34

Table 4: Values of RD3 in the first and the last periods and strength of learning (in %). (The data are tested regarding a significant difference to the performance measure with next lower RD2 using a Wilcoxon-Test because the values are not statistically independent due to their partially equal starting sets of information parts and they are not normally distributed. *** significant in 99%-Interval, ** significant in 95%-Interval, n = no significance.)

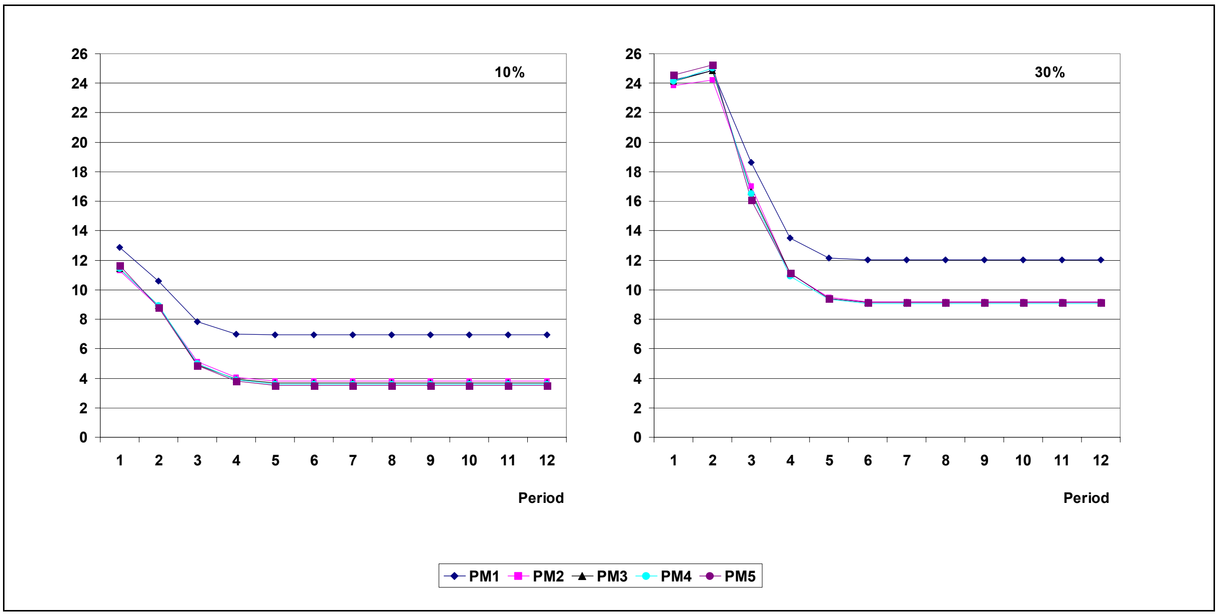

Figure 5: Values of RD2 in % (average of 2000 simulation runs, 5 alternatives, degree of error ∈ {10%, 30%}).

			First period RD2				Last period RD2				strength of learning	
error in %	No. Altern.	PM		Mean	Std.dev.	Skewness		Mean	Std. dev.	Skewness	long-term	short-term
		PM1	n	7.88	16.95	2.45	***	5.20	12.92	2.99	2.67	1.66
		PM2	n	7.47	16.48	2.52	n	3.46	10.67	3.88	4.00	2.59
	2	PM3	n	7.36	16.42	2.54	n	3.33	10.54	3.96	4.03	2.73
		PM4		7.35	16.38	2.53		3.30	10.50	3.99	4.05	2.78
		PM5	n	7.39	16.62	2.58	n	3.40	11.00	4.20	4.00	2.70
		PM1	***	12.87	17.65	1.50	***	6.94	11.90	2.02	5.93	2.30
		PM2		11.31	16.84	1.65	**	3.80	8.60	2.84	7.50	2.45
10%	5	PM3	n	11.44	16.98	1.68	n	3.67	8.42	2.88	7.77	2.49
		PM4	n	11.45	17.04	1.69	**	3.62	8.31	2.87	7.83	2.52
		PM5	n	11.62	17.14	1.65		3.51	8.13	2.89	8.11	2.81
		PM1	***	15.45	16.25	1.05	***	8.67	11.07	1.21	6.77	-0.28
		PM2		12.66	15.31	1.31	***	3.65	7.13	2.33	9.00	-0.56
	10	PM3	n	12.80	15.41	1.34	n	3.42	6.76	2.30	9.38	-0.18
		PM4	n	12.84	15.45	1.35	n	3.43	6.77	2.27	9.41	-0.10
		PM5	n	12.78	15.53	1.40		3.39	6.76	2.30	9.40	-0.12
		PM1	n	15.22	24.50	1.61	***	10.60	20.80	2.16	4.62	1.82
		PM2		14.68	24.01	1.59		8.97	19.58	2.40	5.71	1.94
	2	PM3	n	15.03	24.40	1.57	n	9.21	20.03	2.37	5.82	1.89
		PM4	n	15.05	24.42	1.57	n	9.21	20.04	2.37	5.83	1.88
		PM5	n	14.93	24.21	1.57	n	9.18	19.86	2.35	5.75	1.75
		PM1	n	24.20	24.65	0.80	***	12.01	17.17	1.56	12.20	-0.64
		PM2		23.85	24.68	0.81	n	9.19	15.56	1.93	14.66	-0.37
30%	5	PM3	n	24.15	24.87	0.80	n	9.13	15.74	1.97	15.02	-0.71
		PM4	n	24.15	24.80	0.79		9.06	15.62	1.95	15.08	-0.86
		PM5	n	24.54	25.02	0.78	n	9.15	15.72	1.95	15.39	-0.71
		PM1		27.06	23.39	0.70	***	11.52	13.86	1.22	15.55	-4.08
		PM2	n	27.65	23.95	0.65	***	7.33	11.60	1.78	20.31	-2.60
	10	PM3	n	27.48	23.85	0.66		7.13	11.48	1.85	20.35	-3.12
		PM4	n	27.42	23.79	0.66	n	7.15	11.55	1.87	20.28	-3.46
		PM5	n	27.48	23.93	0.65	n	7.19	11.63	1.87	20.29	-3.34

Table 5: Values of RD2 in the first and the last periods and strength of learning (in %). (The data are tested regarding a significant difference to the performance measure with next lower RD2 using a Wilcoxon-Test because the values are not statistically independent due to their partially equal starting sets of information parts and they are not normally distributed. *** significant in 99%-Interval, ** significant in 95%-Interval, n = no significance.)

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