Chapter 13

A Tale of Two Approaches: How and Why a Person-centred Approach would Provide New Insight into the Leadership of Innovation

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Introduction

In managing innovation, leaders set out to make sense of large chunks of information. This consists of the constant processing of data from a variety of sources, such as performance data, financial reports, market analyses, insight from employee surveys and management literature. Analysing and comparing information from a variety of sources can be experienced as a daunting and technical task. One of the risks lies in using conservative and 'best practice' types of data analysis. This chapter will outline why this limits insight in complex processes, which is particularly the case managing innovation.

Data related buzz words pop up continuously, introducing the 'next big thing' in data collection and analysis, including: open data, data-mining, linked data, and big data. It is both the increasing volume and diversity of information becoming available for analysis, as well as the techniques for data gathering, handling and analysis developing in a furiously fast pace. Together this opens up a whole new space of opportunities of data available for analysis. New techniques create opportunities for looking at new types of information in different ways, which is a basis for innovation by itself.

The role of leaders is to find a balance between making optimal use of new data opportunities at the limits of organisational processing capacity. The excitement about new opportunities goes hand-in-hand with anxiety and reluctance. This is based on variety of reasons, varying from reluctance to change, ethical considerations, concerns about information security and the personal angst of 'not getting it'. Organisational difficulties can lie in the (quick) development of analytical skills, the organisation of data flows and keeping up with market requirements.

Another set of risks lies in limited insight into the management of human resources by using the most common types of analysis. In this case, core assumptions of the 'most common' approach may be breached when the decision-maker fails to consider the fuller range of approaches. Unsuccessful in identifying the most optimal technique limits the usefulness of results, reducing trusts in the data and method. Eventually, this can lead to withdrawal from any type of quantitative data analysis, basing decisions on experience and intuition only. In sum, there is scope to make better use of information and data streams in organisations, which is essential in gaining insight into complex innovative processes.

This chapter does not set out to prescribe how to analyse data for kick-starting innovative processes. It is neither a practical tool to improve your understanding of data analysis using the latest techniques, since there are plenty of practical guides for this purpose (e.g., Davenport & Kim, 2013). This chapter aims to outline two general approaches in analysing data, which are very specific in purpose, and the underlying fundamental assumptions about the nature of innovation and its leadership. Regardless of the new techniques being developed, awareness of the underlying differences of these two approaches is essential in summarising data, finding meaning in it, and extracting its value. Outlining and distinguishing between the two approaches shows opportunities for data analysis which are particularly relevant in the management of innovation.

Distinguishing between variable-centred and person-centred types of analysis is not new. This chapter outlines these two basic perspectives and assumptions in the light of technical developments which enable new ways of measuring, connecting and analysing aspects of the organisational environment. Applications of the person-centred approach in recent management research are provided, as well as practical examples of this approach in the management of innovation. In particular, a case presenting results from innovation data analysed using a person-centred approach shows the value of the person-centred approach in managing innovation. To conclude, this chapter points out the importance of making a distinction between types of data analysis and discusses the value of juxtaposing the two perspectives in the analysis of business data.

A tale of two approaches

This chapter sets out to go back to a fundamental understanding about approaches to analysing data. Developments in information technology have caused (1) more data and a large variety of data to be available for analysis in business, but also (2) more advanced types of analysis to be available as a result of a general increase in computing power. While only a decade ago we would be limited in what types of analysis could be used, the possibilities now seem to be unlimited. In this multitude of new opportunities it becomes more important to identify what exactly we are after researching and which technique would provide this information, rather than analysing the data available using techniques we are familiar with. The two approaches to data analysis presented in this chapter underlie all research in business, however these are rarely recognised and considered.

The two general approaches are the variable-centred approach and the person-centred approach, an overview of the differences is provided in Table 13.1. A variable-centred approach towards the analysis of data assumes all the subjects in the data (employees, teams, organisations) to contribute to variance in the data. This variance may be explained by general trends on how subjects score on indicators and how these indicators relate to each other. These trends hold for all subjects for which data have been collected. This assumes that all subjects in the react in a similar way to conditions in the work environment, in other words subjects are homogeneous. In this way, research has found that transformational leadership has a direct and positive effect on organisational innovation (Jung, Chow & Wu, 2003), with transformational leadership to have a general positive effect on empowerment and the innovation-supporting organisational climate.

Include Table 13.1 about here

The name ‘variable-centred’ refers to the idea of grouping items in the most optimal way representing underlying variables. An example would be the variable work engagement consisting of the three elements – absorption, vigour and dedication – which are measured by three items for each sub-category. A factor analysis is used to explore the relationship between items, exploring underlying groups in a set of questions. This type of analysis finds a number of questions together to represent a latent variable. The aim of this grouping of items is to represent the variance in the data in the most optimal way, in such that the grouping of the items into variables explains the most of the variance of each subject.

A person-centred approach can be seen as the exact opposite. This approach assumes subjects to be heterogeneous, with underlying groups of subjects to be responsible for explaining the variance in the data. In other words, the data is explored on the existence of underlying typical groups of subjects existing of typical employees, teams and organisations. People, teams, projects or organisations are grouped on the basis of similarity, in the way the groups explain most of the variance in the data. Within these groups, the relation between all variables and indicators measured in the data is assumed to be the same. This approach has been used in various fields of research, more frequently in marketing (exploring consumers on specific consumption patterns) and in the medical sciences (exploring groups of symptoms by grouping patients into medical conditions).

Following the person-centred approach, the grouping is not based on variables but on subjects, which can be organisations and teams but are very often persons, hence the name. In other words, grouping individuals into unique and distinct profiles, for which the relations with other constructs and outcomes may differ, creates typologies. A wide variety of names are used for the groupings that are found using a person-centred approach, including typologies, clusters, types, classes, profiles, modes, and so forth.

An example of research on the leadership of innovation using a person-centred perspective is the identification of collaborative research and innovation clusters (Liyanage, 1995), and the exploration of modes of innovation, including the Science, Technology and Innovation (STI) mode versus the Doing, Using and Interacting (DUI) mode (Jensen, Johnson, Lorenz & Lunvall, 2007). The person-centred approach allows to explore complex interactions between individual characteristics, team specifics and organisational contexts which may be too complex to hypothesise using a variable-centred approach.

Dominance of the variable-centred approach

The two approaches are not only a specific type of analysis but are related closely to more general research approaches. By analysing data in a variable-centred approach, the aim is to find sub-groups of questions that measure a similar underlying constructs (factor analysis) which are then related to the other constructs in the data. This approach is grounded in a more confirmative research nature, in which variables are measured and effects between variables are tested. An explorative element in the variable-centred approach lies only in the development of new measures or improvement of existing measures by exploring how items represent variables.

This approach seems to be dominant in the analysis of data in businesses, which may be explained by a number of reasons. When a positivistic epistemology is followed, research is often deductive and confirmatory in nature. For this type of research testing hypotheses follows a variable-centred approach to analysis, which is directed to be the appropriate analytical approach in business degrees. A person-centred approach to analysis can work for confirmatory types of research, however it may be problematic since it requires sufficient theoretical understanding of the complex interactions between the variables to develop hypotheses on which profiles are expected to be found. In other words, research following a positivistic confirmative hypothesis-testing tradition is mostly likely to succeed when applying a variable-centred approach towards data, since the person-centred approach requires an understanding of complex interactions.

On the other hand, more constructivist and critical approaches are more likely to explore phenomena using qualitative methodologies following a person-centred approach. The person-centred approach is explorative by nature, analysis techniques following a person-centred approach explore data on the existence of underlying groups. This 'misfit' as well as a distance between quantitative and qualitative types of research together have led to only few studies that apply analysis technologies following a person-centred approach to analysing quantitative data. This may have to do with another limitation of the person-centred approach, which is the poor reputation of cluster analysis. This method has received substantial disapproval from researchers, due to considerable reliance on researcher judgement that is inherent in using cluster analysis (Ketchen & Shook, 1996). The researcher decides the number of clusters on the basis of the dendrogram, which may be interpreted in different ways, and is considered a highly subjective way of choosing a final cluster structure.

Difficulties with the variable-centred approach may occur when subjects are nested in specific contexts, for example with employees nested within teams that are nested within organisations. Multi-level issues appear when the variance in the data is not independent between subjects, but their grouping showing similar answer patterns rather than representing independent observations that show what influences subjects. Multi-level analysis techniques can provide insight into nested data using a variable-centred approach but only as long as: (1) this nesting or grouping is known and included in the data, (2) situational or context variables are independent or interactions or buffering effects are 'simple', and (3) the differences between groups and interactions between climate effects are not of interest. In other words, if you are looking for overall trends and effects regardless of context, these effects can be 'controlled for' or statistically be held constant.

In only few research areas, both variable-centred and person-centred approaches are applied. This results in two separate streams of research providing insight into the same phenomenon, however the two streams find difficulty integrating. This is the case in commitment studies, particularly in research where commitment is measured in multiple types (affective, normative, continuance) and multiple foci of commitment (including: organisation, team, project, profession, industry, career, job, client). Commitment has been studied mainly using a variable-centred approach. In which items together represent the underlying latent construct of commitment, and this construct is related to antecedents and effects, for example, absenteeism, turnover and organisation citizenship behaviour. The person-centred approach has been used to explore commitment typologies which describe how people experience multiple (types or foci of) commitments represented in mindsets. The employees within one commitment profile show a similar level of commitment to a set of commitment targets, these being significantly different from levels of commitment in other profiles.

This person-centred approach towards the study of the multiple foci of commitment, as opposed to a variable-centred approach, captures the complex interplay among multiple mind sets of commitment (Klein, et al., 2009; Meyer & Herscovitch, 2001). This seems a more appropriate approach for studying the multiple types and foci of commitment, particularly because previous studies have found the direct effects of the multiple foci of commitment to interact with one another (Morin et al., 2011). In the field of research on commitment, the person-centred approach is therefore encouraged (Klein et al., 2009), rather than the more traditional variable-centred view.

In relation to the use of the person-centred approach in HR research, Morin et al (2011, p. 61) make an important remark:

> ‘*The identification of […] profiles would be an important improvement in the field of human resources management and organizational psychology. Indeed, results regarding employee profiles are easier to communicate to managers and make cognitively more sense than abstract results from variable-centred multivariate analyses. Additionally, identifying Work Affective Commitment (WAC) profiles may serve as a first step in the development of differential strategies targeting specific profiles of employees.*’

New data analysis techniques and research opportunities

Fortunately, the person-centred approach is no longer limited to cluster analysis. Several techniques allow for profiling and clustering, which can even be combined with other techniques such as regression analysis and structural equation modelling. The emerging mixture modelling methodologies (latent profile analysis, factor mixture analyses) are turning into highly promising advanced statistical methods for clustering cross-sectional data (Klein, Becker & Meyer, 2009). In addition to Morin et al.’s (2011) study of commitment profiles, research anchored in the person-centred approach using mixture modelling techniques has yielded interesting insights beyond the results from more classical variable-centred analyses (Marsh et al., 2009; Kam, Morin, Meyer, & Topolnytsky, 2013). Statistical improvements include: (a) more opportunities of exploring profiles in different ways (1-step, and 3-step), (b) development in various data types (binary, ordinal, categorical and continuous, even combined), (c) and opportunities of regressing profiles (including profiles in further models), (d) chances in profiles over time (Latent Growth and Latent transition analysis).

Implications for studying innovation

The development of techniques enabling the use of person-centred approaches is particularly important in the study of innovation. Innovation has been found to be highly circumstantial and context specific. Starting at the employee level, the foundation of all innovative improvements is ideas (Scott & Bruce, 1994) and it is argued that the person or individual develops, carries, reacts to, and modifies these ideas (Van de Ven, 1986). Development, reaction and modification can only take place in interaction with the organisational environment. Firstly, it is therefore vital to take into account the groupings and nesting of innovation which may not always be easy to identify. Secondly, variable-centred types of analysis are unable to take into account the complex interaction between the variety of aspects of the various environments of which we are currently not yet fully aware to affect innovative processes. Acknowledging employees as being part of particular research and development teams which are nested in organisations, (creative) industries, as well as personal networks providing access to particular information allows to explore potential interactions relevant to innovation.

The place or environment in which innovation takes place (geographical, industrial, organisational, and departmental) is considered to play a key role in simulating and allowing for innovative initiatives. An example of this type of research is how Framback and Schillewaert (2002) identify the differences between individual level and organisational level decision-making processes which together influence how organisations adopt innovations. These environmentally specific effects and their interactions may be explored taking a person-centred approach, however this complexity is lost in variable-centred approaches, which assumed subjects to be homogeneous. The person-centred approach enables the exploration of groups of employees with different behavioural reactions to a variety of leadership styles. This would give insight into which leadership style is applicable in stimulating innovative behaviour specific to a group of employees who may have a common context, a nested structure or a set of individual preferences.

CIPD case: leadership of innovation through a person-centred view

This section will demonstrate the value of the person-centred approach in analysis of data concerning leadership of innovation. In 2013, the CIPD commissioned the Work and Employment Research Centre (WERC) from the University of Bath, School of Management, to produce a series of reports around the theme of innovation. The project partners directly involved were Professor Veronica Hope-Hailey, Professor Juani Swart, Professor Nick Kinnie, Dr John McGurk, Dr. Yvonne van Rossenberg and Nichola Peachey. The programme consisted of four research pieces including innovation in networked organisations, innovation in local government, innovative outputs and the role of HR in the innovation imperative. The results from these four research streams are available online to CIPD members.

The data we draw on consists of 766 responses to the Learning and Talent Development survey, which was sent out to CIPD members worldwide in 2012. The data was provided by HR managers (20%), heads of learning and development (15%), senior managers and directors (15%), line managers and organisational development managers (15%), consultants and advisors (12%) and owners/CEO (5%). The industries are also very diverse, with 14% in manufacturing and production, 44% in the private sector, 26% in the public sector, and 10% in voluntary, community and not-for-profit organisations. A large proportion of the data comes from organisations based in London (30%), elsewhere in England (76%), and elsewhere in the UK (86%). However, respondents are also located in Europe (5%), the USA (5%) and other non-European countries (4%). Data has been collected from organisations varying significantly in size, from fewer than 10 employees (7%), and smaller organisations (33% of less than 250 employees), to also a fair proportion of very large organisations (24% of 5000 or more employees).

In the CIPD 2012 Learning and Talent Development survey, managers have answered a series of questions on their organisation concerning the management of personnel, learning and training as well as questions on innovation-related activities and strategies. Before this project started, the data from this survey has been collected and analysed by the CIPD, resulting in a report including on general trends in the data. For this particular research project, we set out to analyse this data again using a person-centred approach, exploring the data on patterns providing complementary insight into the management of innovation. For the following reasons aa person-centred approach was deemed more suitable rather than a variable-centre approach towards the analysis of the data. Firstly, previous research and theoretical framework could not provide clear expectations on how training and learning would be related to innovation. This research was, therefore, explorative rather than confirmative, which suits a person-centred approach rather than a variable-centred approach. Secondly, the subjects in the sample include managers providing information about their organisation. These managers representing a wide variety of industries and organisations were not expected to be a homogenous group. The only common denominator between these respondents was their membership of the CIPD. Since homogeneity could not be assumed, general trends in the data would not be representative of the variety of subjects contained in the data. Hence the choice for an approach which allows for underlying subgroups in the data.Thirdly, in the case of innovation strategies, we expected contextual, industry- and organisation-specific effects to interact. In other words, it may be the industry in relation to the type of organisation in relation to the particular learning and training strategy which together created a unique situation in which innovation takes place.

Methodology and analysis

A latent class analysis using the statistical package MPlus version 7 (Muthén & Muthén, 2013), was used to explore the data on underlying groups. This analysis uses the expectation-maximisation algorithm of the robust maximum likelihood estimator (MLR) to estimate mixture model parameters (Muthén & Sedden, 1999). Similar data analysis could be performed using the statistical package LatentGold and other packages are available. The program assigns respondents into groups which in this case will be called profiles, but depending on the data analysis technique, research field and audience, these groupings are called also clusters, classes, bundles, collections or agglomerates.

In our case, HR managers provided information on a variety of questions related to the innovation strategy. The 13 questions on the basis of which the data is explored on profiles include questions concerning (1) the types of innovation strategy and approach are used in the organisation, and (2) who in the organisation is involved in innovation and creativity. An example of a question is: ‘Innovation is about specialist and technical product development over long timescales’ and ‘We employ technical specialists to deliver innovation’. The program starts an iterative process, applying a series of algorithms optimising the cluster or class solution on the basis of the answer patterns of the respondents on the 13 questions. The result is the grouping of respondents in such a way that the profiles represent most of the variance in the data. In other words, it maximises the similarity of answer patterns within the groups, and maximises the differences in the answer pattern between the groups.

In the Mplus programme there are several tests that can be performed to determine the optimum number of profiles in our data, representing groups of organisations with similar innovation strategies in UK. This is a comparison and test in the fit of the cluster solution with the fit of the cluster solution plus one more cluster (one profile versus two profiles, two profiles versus three profiles and so forth). Two tests are available including Likelihood Ratio Test and Bootstrap LRT, (Li & Nyholt, 2001; Muthén, 2004; Lubke & Muthén 2005).The choice for the optimal number of profiles can also be assessed by a number of other fit-indices, including log likelihood values (comparable to the dendrogram in a cluster analysis) and the lowest value in the three information criteria (AIC, BIC, and ABIC).

In our case, this indicated that the fit of the five profile solution was significantly better than the four profile solution. Fitting a six profile solution did not increase the explained variance of the data significantly more than the five profile solution. After finding this 'best clustering solution', more solutions with a higher number of profiles should be tried, to check if there is another, better solution. The five profile solution in our case showed the best indices, optimising the explained variance in the data. Analysis shows an overall of 92% of the original grouped cases were correctly classified indicating differentiation between the profiles and acceptable levels of mis-specification of the developed groups.

Along with the cluster solution, the MPlus programme produces a diverse series of fit measures which indicate how well the solution represents the data. Entropy is a value indicating how well the class membership represents the data; entropy with values approaching 1 indicates clear delineation of classes (Celeux & Soromenho, 1996). The cut-off point of an entropy value of .8 is used for using class membership is as a categorical variable in further analysis. In case values are below .8, further analysis is recommended to be conducted using factor mixture models, which represent the probability of class membership rather than final and fixed class membership (Muthén, 2004, Muthén & Muthén, 2013). The analysis finds the entropy for our five class solution to be .804, which is sufficient to consider the profile membership as a grouping variable in further analysis.

Results

The profiles are presented in order of how important innovation is to their organisation and their distinct features are presented in table 13. 2. The profiles of the organisations cannot be identified on the basis of other (known) variables in the data. In other words, these explored profiles are not representing organisations in, for example, five distinct types of industries. These profiles exist across industries and across organisational size, however profile 1 is found more often in the public sector and profile 5 consists of a large proportion of small and medium-sized organisations.

Insert Table 13.2 about here

More interestingly, the membership of the five profiles has been linked empirically to training and skills development and learning and training activities. It is found these innovation profiles link to specific training and development activities, in the following way: The (1) *Cautious Innovators*, use more traditional and distant learning and training methods, including coaching by line managers, formal education courses and e-learning. The least talent management activities are undertaken. Also managers received the least skills development training on promotion. For the (2) *Distributed Innovators* innovation is also not very important for their organisation and innovation is concentrated around the exploration of new market opportunities. In these organisations, there is a bit more of a variety of learning and training activities compared to the cautious innovators, including audio-video resources and action learning sets.

For the (3) *Specialist Innovators* (18%) innovation is seen as a technical task focusing on which is undertaken by specialised teams designing and improving products. This highly specialist knowledge is developed through job rotation, secondment and job shadowing. Mentoring and buddying schemes are less common. Talent management activities are plentiful, however managers do not receive a very high level of training after promotion.

The (4) *Open Innovators* have the widest approach to innovation in such that innovation is important for processes, products, delivery and efficiency, and new market opportunity.. Innovation involves the widest variety of people in their innovation strategy, including managers, specialist teams and departments, technical specialists, all members of the organisation through suggestion schemes and external collaboration. Knowledge and training activities focus on informal learning by internal knowledge- sharing events and mentoring and buddying schemes. The organisations in this profile undertake the highest number of talent management activities as well as providing the highest levels of skills development training when managers are promoted.

For the (5) *Managerial Innovators* (14%) innovation is viewed most crucial to bring new markets and opportunities in comparison to the other profiles. Rather than a wide search for innovative applications, like the organisations in the open innovation profile, this profile focuses on market opportunities. Managers encouraged innovation and employees are asked to participate in the innovation process by suggestion schemes. This innovation strategy goes hand-in-hand with training based on actor learning sets and on-the-job training. This group of organisations does not use e-learning and formal courses. Although innovation is deemed critical, employee skills are not developed widely, and particular innovative skills training to improve business performance is not common.

Conclusion and discussion

Managers can benefit from the increasing variety of data analysis techniques available and computing capacity seems unlimited. It becomes, therefore, more critical to choose the right type and technique of analysis which fitting to your research question or managerial issue. Until recently, one family of data analysis techniques using the variable-centred approach ‘covariance structure analysis’, which also includes structural equation modelling (SEM), developed in isolation of other extended latent variable families following a person-centred approach, such as latent class analysis, latent class regression, and latent transition models (Kline, 2011).

Advances in data analysis techniques have opened up the possibility to test mixture models, and the program MPlus is indicated to be especially suitable in analysing a variety of latent variable models (Kline, 2011). Future empirical research may provide unique and (more) complete insight into innovation by juxtaposing empirical results using both variable-centred and person-centred approaches. The first empirical attempts of this type of empirical cross-fertilisation of the two research approaches show promising results (Marsh et al., 2009). This chapter contributes to the encouragement of these opportunities making the point that, especially in the study of innovation and its leadership person-centred approaches, these are worth exploring.

The case material presented shows the potential for studies regarding leadership and innovation in following this promising path. Firstly, the case shows how the person-centred types of analysis are particularly relevant in relation to multi-level and other types of grouping structures. The variable-centred types of analysis, looking for overall trends, generalising organisations in the way they managed innovation, assumed that the underlying innovation profiles did not exist. Secondly, the explorative approach shows to be more relevant and able to provide insight into the complex processes and interactions central to innovation, in which context conditions interact as well as are nested within the (multi-level) groupings. Finally, the person-centred types of analysis has enabled the first step in the development of differential strategies, policies and management, targeting specific innovation profiles of organisations. Future studies on the management of innovation may explore the possibility of multi-level person-centred approaches, which may lead to differential strategies on managing people targeting specific embedded profiles of individuals, which may be embedded in the profiles of organisations.

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Table 13.1 A tale of two approaches

	Variable-centred approach	**Person-centred approach**
Nature	Confirmative, deductive, specific	Explorative, holistic, intensive, integrative, inductive
Research question	What is the (latent) structure of subjects' case scores in a number of variables?	Which way of grouping of subjects/respondents/ cases can explain the most variance?
Grouping of…	Variables/questions/items into factors representing underlying variables/factors	Subjects/persons/organisations into groups representing underlying groups
Assumption	Homogeneity	Heterogeneity
	Normal distributed data	Underlying groups for which the effects are specific
	Climate/context conditions are independent	Existing variables cannot identify these groups
Necessary condition	All groups in the data are 'known'	Very large variety of cases in the data
	All climate conditions are measured	Intensive data: much is known for each respondent
A good approach if…	There are clear expectations which can be summarised in the hypotheses	Expectations are unclear, effects cannot be hypothesised
	To test the effect of one specific condition	Exploration of big data, data-mining
	The research field is theoretically developed	The research field is theoretically less developed
Analysis technique	Exploratory/Confirmatory Factor Analysis	Cluster analysis, Latent Profile Class Analysis
	Reliability Analysis	Fuzzy set Qualitative Comparative Analysis
Follow up analysis	Continuous variables created can be analysed using regression analysis, correlations, Structural Equation Modelling (SEM)	Probabilities of class membership can be analysed using ANOVA, (Wald) Chi-square test, Latent Mixture Models

Table 13.2 Profiles

Profile	Percentage	Innovation strategy?	Who is involved?
1 Cautious Innovators	23%	Innovation not viewed as important	Innovation concerns managers and key project teams
3 Distributed Innovators	27%	Innovation is used for new market opportunities Innovation is not used to increase efficiency to customers	Basically all employees, through external ideas, Project teams and managers to encourage innovation
		Innovation focuses on project design and development	Specialists in specific departments to deliver innovation
2 Specialist Innovators	18%	Innovation is specialists and technical	Technical specialists are employed
4 Open Innovators	17%	Strongest focus on process innovation Innovation for design, development and new markets	Everybody in the organisation is involved External collaboration and specialist consultants
5 Managerial Innovators	14%	Innovation is crucial for new market opportunities	Only managers are encouraged to innovate Employees are involved through suggestion schemes