Employees' Data Mining Readiness in the Malaysian Insurance Industry: A Preliminary Study

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Abstract

This paper addresses the readiness of employees in the insurance industry to adopt data mining technologies by looking at the influence of four predictor variables namely clarity of business strategy, user's skill & experience, data-driven culture, and data quality. Questionnaire survey on 200 employees working in 12 insurance companies in Penang and Kuala Lumpur reveal that the employees are non-committal to embrace data mining. This result is simply attributed to the newness of the technique, which has not caught on in Malaysia. A further analysis shows that the readiness level is only influenced by the users' skills and experience whereas clarity of business strategy, data-driven culture, and data quality has no influence on their readiness level. These findings suggest that readiness highly influenced by self-efficacy as reflected by skills and also past experience of using technology related products. Implications of the findings are further explored.

Key Words : Data Mining Readiness, Employees, Insurance Industry, Malaysia, Survey

Introduction

The twenty-first century is the age of Information and Knowledge. It is a century that is characterized by knowledge as the important resource that gains competitive advantage for companies. To acquire all these knowledge and information, organizations must rely on the data that they store. Data, the basic element, is gathered daily from different input sources. Information is extracted or learned from these sources of data, and this captured information is then transformed into knowledge that is eventually used to trigger actions or decisions (Anonymous, 1999a). By and large, organizations do not have any problem of not having enough data because most organizations are rich with data. The problem however is that many organizations are poor in information and knowledge (Anonymous, 1999c). This fact translates into one of the biggest challenge faced by organizations that is, how to

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transform raw data into information and eventually into knowledge, which if exploited correctly provides the capabilities to predict customers' behavior and business trends?

Today, the secret of success of many profitable businesses lie in their ability to process the data using advanced analytical methods. The business of information management encompasses more than just storing the data. It also covers data 'mining' or acquiring information by processing data using a new form of business intelligence (Anonymous, 1999a). Hence, organizations need to invest in data mining techniques (aided by statistical analysis, visualization and neural networks) to uncover hidden patterns, discover new knowledge, and as a consequence gain more insight into the current business situation. For example, a typical report is able to identify the best-selling product in a supermarket. However, a report aided by data mining or business intelligence, is not only able to identify the best-selling product in a supermarket but the report is also able to explain the reasons why the product is the best. This ability of knowing 'why' will therefore empower the organization to make the necessary strategic changes. For example, the organization should capitalize on the newfound knowledge by building a stronger, one-to-one relationship with its customers (Anonymous, 1999b). The application of data mining is wide-ranging, from market analysis to fraud detection (credit card business) to product development (say, pharmaceutical industry). It can also be used by manufacturing industries in determining the variety of production factors that influence the quality of the end product. In the financial industry, insurance companies and banks use data mining for risk analysis. For example, an insurance company may search its own databases to uncover relationships between personal characteristics and claim behavior (Basu, 1997). Usually the company is interested in the characteristics of insurants with a highly deviating claim behavior. According to META Group, Inc. a Connecticut-based market research firm, data mining application is expected to grow one hundred fifty percent from 1999 to 2000 (Bauer, 2000). Additionally, the report suggests that applications of data mining in insurance industries will grow at a steady rate of six percent during that period.

Data Mining and Insurance Industry

Dramatic changes have taken place; mergers and acquisitions together with deregulation and globalization have left their mark on the insurance industry (Anonymous, 1999c). The competitive landscape is also changing. Key competitors namely, banks and other financial institutions, are aggressively competing in the race for Internet success. As customers become more educated about the available options, they are more likely to choose the new marketing channels. In addition to the market situation, customers' needs are also changing. Customers now demand products to meet their needs or requirements. Thus, they are no longer interested in the traditional insurance products but are now demanding for 'financial solutions'. For example, EON CMG Life Assurance Berhad's Chief Executive Officer, Craig W. Dunn stressed that as the country develop economically, more people would realize the benefits of investing in the correct insurance plans (The STAR, 1999).

As the insurance industry is becoming more information-centric, the wealth of the companies is based on the available data and the information accessed. Whether it is risk management, claims administration, underwriting or sales, all these services share a common trait they are all generated and managed by the client databases. In order to survive and to ensure sustainability, insurers therefore need to shift their focus from mere processing of insurance transactions to managing and exploiting information (Anonymous, 2000). In general, insurers need to realize the importance of quality information in their business and the advantages of having the ability to use this information to its advantage. In this evolving business, information becomes a strategic asset because the bulk of the data is available internally. Access to information in a timely manner is critical in order to enable the correct decisions to be made at the right time. However, most insurance companies are challenged to find the most efficient way to gain access to information. The interest in data mining within the insurance industry is widely spreading. Data mining technology has become an enzyme that enables data to be processed faster, better and cleaner (Anonymous, 1999a).

Research Objectives

This study explores the contributing factors to the adoption of data mining technology, and focuses on both the organizational issues as well as those related to the employees. The main purpose of this study is to uncover the relationship (if any) between the factors identified and the employees' data mining readiness. Two main research questions are addressed:

- What is the level of data mining readiness of the employees in the insurance industry in Malaysia?
- What are the factors that may affect the employees' readiness level?

Literature Review

Employees' Readiness in Adopting Data Mining

Adopting a new technology is not an easy task. Foremost, the employees are humans who are naturally fearful of the uncertainty of change. This fear is often translated to resistance to change. Additionally, the design of high-tech products sometimes fails to account for the way the users adopt and react to the technology. As suggested by Eby et al. (2000) understanding employees' readiness is crucial. The main question now is how to measure employees' readiness? Parasuraman and Rockbridge Associates (1996) develop a multiple-item scale in measuring readiness to embrace new technologies. The Technology Readiness Index (TRI) is designed to identify the propensity of a customer, an employee or even a manager to adopt new

Table I : Components of Technology Readiness Index (TRI)

Category	Definition
Optimism	the degree to which individuals believe that technology can benefit their lives and give them more control over their lives
Innovativeness	a natural desire to acquire and experiment with the newest technologies, as well as to be a thought leader
Discomfort	a feeling of lacking control over technology and lacking confidence in making it work properly
Insecurity	a need for assurance that a technology-based product, service or process will operate reliably and accurately

Optimistic individuals enjoy the control and freedom that technology provides. They also find technology to be mentally stimulating. On the other hand, pessimistic individuals have concerns in dealing with computers over people in conducting business. Naturally, innovative individuals are keen to keep up with the latest technological developments. However, individuals who prefer not to innovate usually do not have any interest in adopting new technology; especially so when the old technology still meets their expectations. Generally, employees with high discomfort level in using technology, often feel overwhelmed about the knowledge and skills required to operate the new technology. Often, they feel that technology is not only too complicated to be useful, but they also feel insecure of technology's ability to operate properly and safely. In contrast, employees who are comfortable with technology not only feel in control of the technology, but they also believe that computers are more reliable and consistent when performing a task than a person. Therefore, employees with high readiness level should exhibit optimism and innovativeness because they are comfortable using technology and they require little assurance on the performance level of the technology being used. The implication here is the applicability of TRI in measuring the employees' data mining readiness. In this study, TRI is used as a reference in assessing the employees' data mining readiness. Two components namely Optimism and Discomfort are used as a base in developing the data mining readiness assessment.

Factors Affecting Data Mining Readiness

David (1998) points out that being successful in business demands for continuous attention to changing external and internal conditions. Many business leaders do not fully understand the nature of the benefits that data mining technology can provide (Anonymous, 2000). Though some insurers have enjoyed notable success, many have failed. These initiatives are strategic; often they do not directly address an immediate need. Thus, as far as the business strategies are concerned data mining stands at a low priority. Without a strategic context, a company will not know which data to focus on, how to allocate analytic resources, or what it is trying to accomplish in transforming data to knowledge. A clear business strategy will help provide the data and analytic capabilities required by the organizations (Davenport et al., 2001). These arguments are aligned to those made by Armenakis et al. (1993), and Ivancevich et al. (1999). Revised policies, procedures, as well redefined roles and responsibilities of the employees are indeed crucial when organizations face new changes. Seybold (1998) suggests "advancement in the insurance industry has been hampered by lack of investment industry-wide in data warehousing and data mining technology". In addition, Seybold states that in the absence of the investment, product (policy) designers work with limited data about policyholders and claims. They mostly rely on data summarization supplemented by intuitive hunches to guide their new policy development. This is an example when the organization does not budget appropriate resource in moving strategically. This is also a case where the business strategy is not data-driven. Davenport et al. (2001) report that two-thirds of the companies surveyed are challenged with concerns on recruitment, development and retention of highly skilled employees. Thong (1999) also agrees that the importance of employees' knowledge on a system lies in adopting the system itself. Fox, Ellison and Keith (1988) as cited by Armenakis et al. (1993) propose "effective management practices (such as planning, delegating, and communicating) influenced employee cooperation and perceived equity. These were associated with higher employee readiness for implementing improvements in procedures and problem solving". Further, Corrado (1994) suggests that employees are highly motivated and contribute the most to the business when there is full and open communication at work.

In short, organization should promote data-oriented culture through establishment of policies, procedures and excellent communication system. One of the critical success factors in maintaining manageable and profitable information systems is through its data quality (DQ). DQ is defined as data that is fit for use by the users (Huang, Lee, & Wang, 1999). Among commonly identified data quality include accuracy, timeliness, completeness and consistency (Xu, Nord, Brown & Nord, 2002). DQ is an important aspect during the system conversion process as well as when providing users with quality findings. Thong (1999) emphasizes the relevance of the intensity of information available to the organizations in adopting IT.

Research Model and Hypotheses

This study aims to understand the contextual factors in the insurance organizations that influence employees' data mining readiness index (DMRI). The theoretical framework is adapted from the Model for Building an Analytical Capability (Davenport et al., 2001), which states that the more analytically capable the individual, the higher the readiness. Fig. I illustrates the dependent variable (employees' DMR) and the independent variables (business strategy, users' skills and experience, data-driven culture, and data quality).

Clarity of the Business Strategy

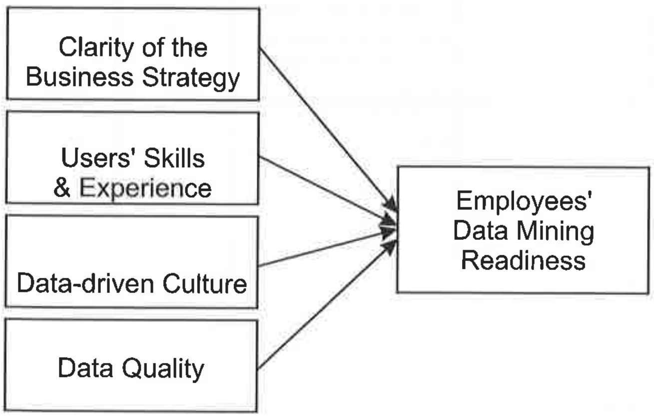

Figure I : Conceptual Framework

Clarity of the business strategy requires the top management to convey a clear definition of the purpose for change, to continually improve, and to align the core processes with organizational goals (Hassan, 2000). Additionally, change must be top-down to provide vision and create structure and it must also be bottom-up to encourage participation and support. The clearer and more detailed the business strategy, the more obvious what data and analytical capabilities the organization requires. Thus, the first hypothesis:

H1 : The clearer the business strategy's definition, the higher the employees' data mining readiness

Users' Skills and Experience

Users skills and experience are accounted by the level and structure of skills needed to support data analysis capabilities (Davenport et al., 2001). As for the requisite skills that are aligned to the business strategy, four dimensions are proposed: technology management skills, business functional skills, interpersonal skills, and technical skills (Bryd & Turner, 2001). Empirical evidence reveals that tech-savvy employees are likely to use more innovations (Thong, 1999), and there is a positive link between computing technology experience and outcomes such as affinity towards computers and computing skill (Agarwal & Prasad, 1999). Thus, the second hypothesis:

H2 : The better the users' skills and experience in analytic capabilities, the higher the employees' data mining readiness

Data-Driven Culture

A CEO's characteristic plays an active role in the allocation of resources and is crucial to the organization's technological direction (Thong, 1999). For example, sixty-two percent of the managers responding in an informal survey indicate that organizational and cultural factors are the greatest barriers to the returns on system investments (Davenport et al., 2001). A major concern is creating a data-driven culture that requires for the logistics and systems' support to be part of strategic policy (Schneider & Bowen, 1993). As culture dictates acceptance of all organizational change, issues such as policies and practices dictate individual's actions and interactions within a culture (McNabb & Sepic, 1995). Any large-scale change should involve the reshaping of the organizational culture in ways that will motivate its employees to care for the business as their own (Moran & Avergun, 1997). For example, in investigating the impact of organizational resources on innovation adoption, adaptors and innovators are identified as the two extreme ends of the innovativeness continuum (Kirton, 1980). To ensure successful analytical capability, the entire organization needs to value data-based analysis and to adopt a data-driven culture. Thus, the third hypothesis:

H3 : The higher the data-driven culture, the higher the employees' data mining readiness

Data Quality

The quality of the data used for data mining-related activities is crucial to successful data mining because quality data must be organized into an accessible and extendible data warehouse. The data must be of the right age and richness (depth) for the task (Baker & Baker, 1998). Without good quality data, data mining loses its central function of providing managers with meaningful patterns and trends. In other words, the dynamic nature of business data affects the quality of information retrieved. The technology underlying analytic processes includes the hardware and software used in the data capture, cleaning, extractions, and analysis, as well as the networking and infrastructure capabilities needed to transfer data and provide end-user access (Davenport et al., 2001). As a result, the technological infrastructure conducive for an analytic capability to succeed is critical to get the data-driven organization to the goal of converting data-to-knowledge-to-results. Thus, the fourth hypothesis:

H4 : The better the data quality, the higher the employees' data mining readiness

Methodology

Data is collected using e-mail questionnaire. The questionnaires are mailed to selected employees working in the insurance industry. The questionnaires contain multiple measurement items relating to each of the constructs in the theoretical framework. For the independent variables (the contextual factors of the organization namely: clarity of the business strategy, users' skills and experience, data-driven culture, and data quality), these are based on reviews of relevant literature (Davenport et al, 2001; Eby et al., 2000; Thong, 1999). For the dependent variable (employees' DMR), it is adapted from Parasuraman's Technology Readiness Index (Parasuraman, 2000).

Results of Study

A total of 200 questionnaire sets were mailed and distributed personally. A total of 114 sets were returned giving a response rate of 57%. However 11 sets were rejected due to significant omissions. As such the useable response rate is 51.5%. A total of 114 employees from 12 insurance companies responded to this study. The sample profile is as shown in Table II. Insurance is a service industry; thus it is not surprising to note that more than two-third of respondents is from the Sales or Marketing department and Customer Service (51.5% from the former department while 17.5% from the latter).

Goodness of Measures

Factor Analysis

A factor analysis with varimax rotation was done to validate how the respondents perceived the dependent variable of data mining readiness. The results showed a two factor solution with eigenvalues greater than 1.0 and the total variance explained was 60.22% of the total variance. KMO measure of sampling adequacy was 0.657 indicating sufficient intercorrelations while the Bartlett's Test of Sphericity was significant (2=188.765, p< 0.01). We used the criteria used by Igbaria et al. (1995) to identify and interpret factors which were: each item should load 0.50 or greater on one factor and 0.35 or lower on the other factor. Table III shows that result of the factor analysis. These results confirm that each of

Table II : Summary Profile of the Respondents

Variable	Category	Respondents	
		Number	Percentage
Gender	Male	59	57.3
	Female	44	42.7
Race	Malay	35	34.0
	Chinese	59	57.3
	Indian	7	6.8
	Other	2	1.9
Education Level	Post graduate	16	15.5
	Undergraduate	21	20.4
	Diploma	34	33.0
	Certificate	8	7.8
	Secondary	24	23.3
Position	Clerical	24	23.3
	Lower level management	22	21.4
	Middle level management	31	30.1
	Top level management	3	2.9
	Others	23	22.3
Job Function	Finance/ Accounting	7	6.8
	Sales/ Marketing	53	51.5
	Customer Service	18	17.5
	Administration	9	8.7
	Operation	14	13.6
	Information Technology	1	1.0
	Others	1	1.0
Age	Less than 21 years	3	2.9
	21 - 30 years	46	44.7
	31 - 40 years	37	35.9
	41 - 50 years	12	11.7
	more than 50 years	5	4.9
Length of Service	Less than 1 year	8	7.8
	1 - 5 years	55	53.4
	6 o 10 years	30	29.1
	more than 10 years	10	9.7

these constructs is unidimensional and factorially distinct and that all items used to measure a particular construct loaded on a single factor.

Table III: Rotated Components of Dependent Variables

Items	Factor 1	Factor 2
Optimism		
Optimism4	0.581	-0.294
Optimism6	0.792	-0.007
Optimism7	0.794	0.007
Optimism8	0.808	-0.003
Optimism9	0.698	-0.009
Discomfort		
Discomfort8	0.004	0.829
Discomfort9	-0.161	0.812
Eigenvalue	2.764	1.451
Variance (60.22%)	39.482	20.734
Cronbach Alpha	0.792	0.561
Mean	3.91	3.51
Std. Deviation	0.54	0.62

* 5 items were dropped due to low anti image correlation

Another factor analysis with varimax rotation was done to validate how the respondents perceived the independent variables. The results in Table IV show a four factor solution with eigenvalues greater than 1.0 and the total variance explained was 60.33% of the total variance. KMO measure of sampling adequacy was 0.736 indicating sufficient intercorrelations while the Bartlett's Test of Sphericity was significant (2=1449.335, p< 0.01).

Multiple Regression Analysis

The multiple regression output in Table V shows that there is a significant linear model. The F statistic produced (F=12.258) is significant at the 0.01 level. It shows an adequate model. The R2 value of 0.333 reveals that the model is able to explain 33% of the variations in data mining readiness. This result indicates that among the four independent variables, the skills and experience (=0.563) are the most important variables in explaining the variance in DMRI. The positive beta value indicates that as the skills and experience increase the higher will be the data mining readiness. The other three variables (clarity of business strategy, data-driven culture and data quality) are not found to be significant in explaining the employees' data mining readiness. Thus hypotheses H1, H3 and H4 on clarity of business strategy, data-driven culture and data quality were not supported; but supported the H2 hypothesis:

Table IV: Rotated Components of Independent Variables

Items	Factor 1	Factor 2	Factor 3	Factor 4
Clarity of Business Strategy				
Strategy2	0.275	-0.007	0.004	0.767
Strategy3	0.002	0.003	0.144	0.787
Strategy4	0.010	0.008	0.009	0.745
Strategy9	0.157	0.556	0.278	0.514
User's Skills and Experience				
Skills1	0.691	-0.267	0.007	0.147
Skills2	0.746	0.167	0.001	0.117
Skills3	0.791	0.009	0.106	-0.006
Skills4	0.879	0.010	-0.002	-0.005
Skills5	0.787	0.004	0.005	0.203
Skills6	0.771	0.183	0.265	0.176
Skills7	0.687	0.269	0.104	0.135
Data Driven Culture				
Culture3	0.003	0.645	-0.005	0.404
Culture4	0.227	0.634	0.001	0.232
Culture5	0.003	0.627	0.333	0.000
Culture6	0.009	0.664	0.214	0.000
Culture7	0.008	0.854	0.181	0.004
Culture8	-0.004	0.607	0.234	-0.146
Culture9	0.135	0.609	0.395	-0.202
Culture10*	0.002	0.126	0.812	-0.009
Culture11*	-0.002	0.230	0.839	0.007
Culture12**	0.120	0.457	0.353	0.006
Data Quality				
Data3	0.155	0.216	0.716	0.191
Data4	0.168	0.253	0.535	0.219
Data7	0.217	0.310	0.613	0.288
Eigenvalue	4.429	4.150	3.274	2.627
Variance (60.33%)	18.453	17.293	13.641	10.946
Cronbach Alpha	0.749	0.893	0.829	0.627
Mean	3.838	3.394	3.695	3.576
Std. Deviation	0.540	0.682	0.468	0.585

* Item Culture10 and Culture11 was dropped because it loaded on a different factor

** Item Culture12 was dropped due to high cross loading

*** Other items dropped due to low anti image correlations

Table V: Multiple Regression Analysis (Summary Output)

Variables	Std. Beta
Clarity of Business Strategy	-0.007
User's Skill & Experience	0.563**
Data-Driven Culture	0.146
Data Quality	-0.107
Multiple R	0.577
R2	0.333
Adjusted R2	0.306
F value	12.258**

** p< 0.01

We further examined whether data mining readiness differed by race, educational level, position and job function by using a one-way ANOVA analysis, by sex using a t-test analysis and by age, service length using a Pearson correlation analysis. The results show that data mining readiness does not differ across the variables examined.

Additionally, we examined the descriptive statistics for DMRI and two DMRI components. As shown in Table VI, the mean value for both optimism and discomfort is high. This means that although the employees are optimistic, they are also experiencing high discomfort.

Table VI: Descriptive Statistics for Data Mining Readiness Index (DMRI)

Components	Mean	Standard Dev.	Skewness
Optimism	3.91	.54	-.11
Discomfort	3.50	.62	-.20
Overall DMRI	3.27	.45	-.59

Note: The overall DMRI was calculated after reverse coding the discomfort index.

Discussion and Conclusions

Employees' Data Mining Readiness Index

A total of 103 employees of different insurance companies (based on the DMRI) indicate that generally they feel neutral when asked of their readiness in adopting data mining technology. A DMRI mean of 3.27 explains this situation. Zooming in to the components of the data mining readiness, the mean of about 4.0 suggests that in general employees are optimistic about data mining. Nonetheless, from the mean of discomfort which is about 3.5 indicate that they also experience a considerable amount of discomfort. Additionally, the findings of this study also corroborated that of Parasuraman (2000). As he suggested, people are generally optimistic about technology and yet they also experience a considerable amount of discomfort in handling technology. He also pointed that even optimists and innovators apparently experience technology-related anxieties. This is similar to those experienced by employees' who are less enthusiastic about technology.

Factors Affecting Data Mining Readiness in Insurance Industry

A recent study on bank employees reveals that the higher the users' skills and experience and data-driven culture, the higher the employees' data mining readiness (Dahlan, Ramayah and Koay, 2002). In contrast, a study involving telecommunication employees suggests that the clearer and well-defined the business strategy, the higher the readiness in technology adoption and the greater ability to understand requirements such as data and analytical capabilities required in technology adoption (Dahlan, Ramayah and Looi, 2002). In this study, the regression analysis results show that only one variable has a significant impact on employees' data mining readiness, which is the skills and experience variable. The strongest link is also shown by this variable. This confirms that the more skills and experience that the employees possess, the higher their readiness levels are. These findings corroborate with works done by Davenport et al. (2001) and Thong (1999). Davenport et al. (2001) state that two-thirds of the companies they studied shows the major challenge faced by them is in recruiting, developing, and retaining highly skilled employees with analytic capabilities (transforming data to knowledge). The employees here are referred to all the users of the data mining systems. There are different users which require different skills and experience in handling the data mining related works. Users can be the administrators who deal with data extraction or decision makers who use data to develop the business strategy. The skills and experience ranges from ability to extract data, managing data quality, to data visualization. Inadequacy of skills and experience will be a stumbling factor for the organizations in getting full value from its transaction data. Thong (1999) suggests that employees who are more knowledgeable about systems are more like to be ready in adopting the systems.

The business strategy factor explains the importance of strategic context in managing the data to knowledge process. Davenport et al. (2000) highlight that the clearer a firm business strategy, the more obvious what data and analytic capabilities it requires. However, this study is not able to conclude as Davenport et al. (2000) because the scope of organizational and cultural factors is wide. Thus, organizations seeking to put more emphasis on using data to make strategic decisions need to start from the top management. However top management involvement alone will not suffice. The users at all levels should be involved according to their needs, roles and responsibilities with regards to managing data. The dynamism and interaction between and among the users also are affected (Eby et al. 2001).

In addition to the above, this study does not reveal any significant relationship between the cultural factors and readiness level. This is not consistent with Eby et al.

(2001) who suggest that creating conducive conditions will help ensure success. Further, the findings do not agree with the other studies done on technology acceptance. For instance, Armenakis et al. (1993) reveal that organizations are most likely to be successful when they have the characteristics that support and creates conducive climate for change to happen. This is also supported by Davenport et al. (2001) who conclude that organizational and cultural factors are the greatest barrier in achieving significant return upon their data-to-knowledge related investment.

It was interesting to find that data quality factors do not have any significant impact on readiness. This result disagrees with Davenport et al. (2001) that emphasizes the importance of maintaining high levels of data quality to ensure data is acceptable for analysis and reporting. Another study on data quality related matters also stresses the criticality of quality data to an organization's success (Xu, 2002). Further, Xu proposes that inaccurate and incomplete data may adversely affect the organization success.

Implications

The DMRI value indicates that the employees are optimistic and yet experience discomfort in handling data mining. Parasuraman et al. (1993) highlight the feeling of technology-related anxieties experience by the employees who are optimistic about technology is similar to those experienced by those who are less enthusiastic. Indirectly, organizations need to identify who these people are and in which categories they belong to. Therefore, organizations should consider strategically, different sets of system or structure that needs to be in place to tackle the different levels of employees' readiness. The organization may also need to establish a system or structure that can motivate the employees to adopt data mining technology. As a consequence, the relevant resources (such as human and budget) needed to be in place even before attempting to adopt the technology.

As skills and experience are identified to be positively correlated to employees' readiness, the insurance companies should focus on issues pertaining to the human resources management (HRM), specifically on the quality of the current and future workforce. The implication here is on the IS and IT personnel regardless of whether the organization uses the internal experts or outsource, because the IT personnel needs to acquire the necessary skills and knowledge of data mining in order to strategically and effectively manage the data mining technology in the organization.

Other studies have shown that the clearer the business strategy, the higher the readiness in technology adoption and the greater ability to understand requirements such as data and analytical capabilities required in technology adoption. Since this study does not prove such situation, potentially it may be caused by the employees' lack of awareness of the business strategy. Therefore, they may not see the relevance of clear business strategy to the categories of data that they need to focus on. The implication is the organization may need to revisit its techniques, and perhaps the communication channels in propagating its business strategy.

Data quality is also identified as an important factor in the adoption of IS and IT related technology. However, this study does not conclude as such. Nonetheless it is worth highlighting the criticality of the data captured and the data quality. Quality data extraction begins with quality data warehousing. Perhaps at this juncture most of the insurance industries have not exercised most of the data captured in making strategic decisions. Perhaps the conventional way of establishing rapport with customers is still the main way of marketing to customers. This implies the need for the organizations to shift their paradigm from purely customer-based relationship to data-driven culture as well as strategy. Establishing data-driven strategy will force the organizations to manage a better data quality.

Conclusion

The DMRI results suggest that in general employees are optimistic about data mining, but they also experience a considerable amount of discomfort in handling this technology. In addition it also highlights the employees' neutral feeling towards adoption of data mining. The findings also show that skills and experience has an impact on employees' readiness. It appears that the other three variables namely business strategy, cultural factors and data quality do not have a significant impact on readiness.

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