Professional MBA
Entrepreneurship & Innovation

Success factors for the implementation of Artificial Intelligence in the cement industry: Mannersdorf plant case study

A Master's Thesis submitted for the degree of
“Master of Business Administration”

supervised by
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Vienna, 02.07.2019

Affidavit

I, **DEJAN DAMLJANOVIC, B.ENG**, hereby declare

1. that I am the sole author of the present Master's Thesis, "SUCCESS FACTORS FOR THE IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE IN THE CEMENT INDUSTRY: MANNERSDORF PLANT CASE STUDY", 47 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and
2. that I have not prior to this date submitted the topic of this Master's Thesis or parts of it in any form for assessment as an examination paper, either in Austria or abroad.

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ABSTRACT

The main objective of this master thesis is to define critical success factors in the implementation of Artificial Intelligence in the cement industry. First, the author decided to examine the literature, search for developed theoretical frameworks, and use these to evaluate and examine what the specific success factors of the Artificial Intelligence Expert System implemented in the Mannersdorf cement plant are. Research was done by examining two specific cases, which were evaluated using theoretical frameworks and a developed questionnaire. Due to the nature of business operations in the Mannersdorf plant, the questionnaire sample was not large enough to provide reliable statistical data. Therefore, this research is exploratory in nature and the conclusions derived describe the personal view of the author of this thesis. In the case of the Mannersdorf plant, the author defines five critical factors, these being Problem Importance, Developer's skill, Shell Characteristics, Expert Characteristic and User Involvement. Further, the author takes a critical look at these factors, concluding that this success is not part of some structural process; rather it is the result of the personal motivation of the local users and other circumstances, for example ease of use of the software. Finally, the author reflects on the two specific cases and gives his personal recommendations for the better adoption of Artificial Intelligence in the cement industry. These are: a clear AI strategy, investment in talents and skills and openness to new business models.

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1 INTRODUCTION

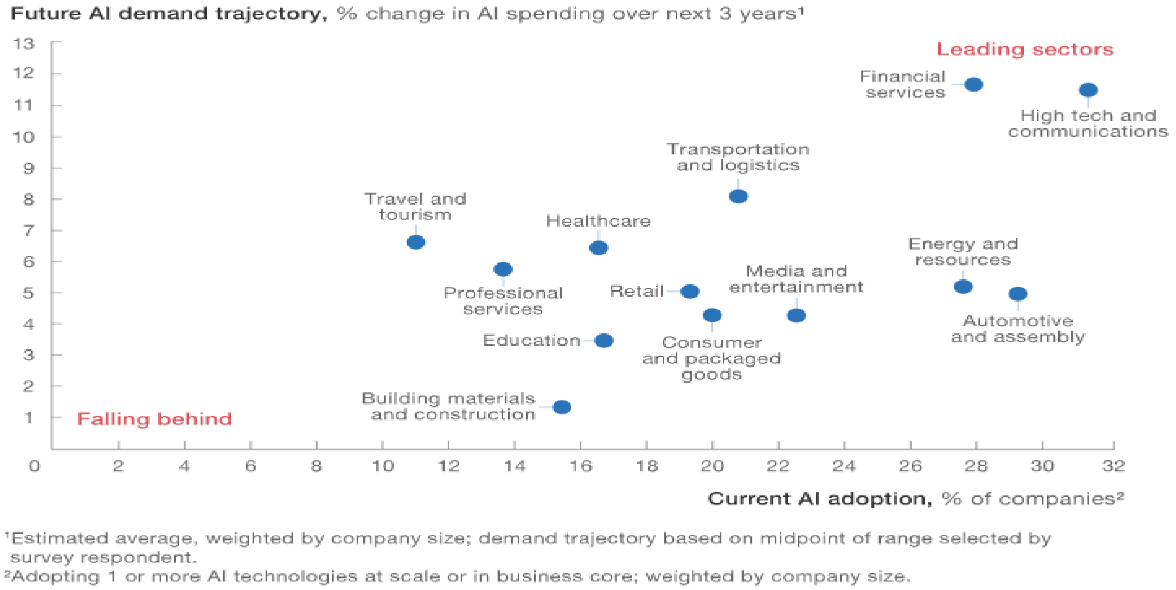
There are numerous analyses dealing with future trends in industry and use of Artificial Intelligence is probably one the most frequently mentioned. High computing power, new advanced algorithms and effective data collection and use has enabled large productivity gains. According to Bughin J. and Woetzel J. (2019), Artificial Intelligence and deep learning could account for as much as \$3.5 trillion to \$5.8 trillion in annual value, or 40 percent of the value created by all analytic techniques. Consequently, adoption of AI could have a significant impact on the global economy, raising global GDP by as much as \$13 trillion by 2030, or about 1.2 percent additional GDP growth per year, according to a simulation done by the McKinsey Global Institute.

In terms of heavy industry, particularly cement, use of artificial intelligence could bring enormous financial and competitive benefits. Robert McCaffrey, Editorial Director of Global Cement Magazine, writes in his article (McCaffrey, 2018) that artificial intelligence will play a role in the following areas:

- Fine-tuning pyro-processing systems to optimize fuel mix, flame attributes, air-flow, feed rates, damper settings etc., in order to achieve a better outcome than even the best operator;
- Listening-to and understanding the spectrum of vibrations from a mill or fan and diagnosing any problems, long before a human could do so;
- Optimizing delivery truck logistics and planning in real-time using GPS and neural networks, beyond the capabilities of any human handler.

However, according to the McKinsey Global Institute, which performed the study on AI adoption, the construction and construction material industry are at the bottom of the list in adopting the new technology, concluding that the cement industry as a construction material producer has a rather poor acceptance of AI technology (Figure 1).

Figure 1 Adoption of AI across industries



Source https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence

1.1 Challenges related to AI adoption in Cement Industry

For decades, cement producers have been "digitalizing" their plants with distributed and supervisory control systems and, in some cases, advanced processes. While this has greatly improved visualizations for operators, most companies with heavy assets have not kept up with the latest advances in analytics and in decision-support solutions that apply AI controls (Charalambous E. et al. 2019). As stated before, in the cement industry the majority of leading producers have already implemented Expert Systems (ES), whose task is to mimic knowledge of experts in the domain and optimize operations in terms of production rate, fuel and power consumption, quality and other production related activities. However, as also stated before, in most cases these are rather old systems based on feedback control loops, if-then rules and traditional control system engineering techniques. Well-known examples are the Lafarge Universal Control Interference Engine used in Company Lafarge, or Kiln/Mill Master product used by Holcim, both companies being among the largest cement producers in the world (before their merger in 2016 to form LafargeHolcim). At that time these systems were categorized as Artificial Intelligence (AI) systems. However, both products are far removed from modern expert systems, lacking critical characteristics such as the ability to use historically available data, replicate system behavior, and calculate optimal output/solution for the given tasks. There are new products and solutions on the market that provide greater capabilities and new ways to control production processes from the ones currently used. Therefore, there is a lag in AI adoption among different industries and the most cited challenges among executive leaders are: developing AI strategy with clearly defined benefits, finding talent with the appropriate skill sets, overcoming functional silos that constrain end-to-end deployment, and a lack of ownership and commitment to AI on the part of leaders (Manyika, J., Bughin, J, 2018).

1.2 THESIS QUESTION AND THESIS STRUCTURE

. There are several aspects that should be considered for the successful implementation of AI, and overcoming the challenges mentioned. The purpose of this master thesis is to analyze those elements, and to do this in a structured way. First and foremost, we will perform a literature review and analyze existing theoretical frameworks. Next, the theoretical frameworks will be used to evaluate the critical factors for the successful implementation of an artificial system in two specific cases of AI implementation in the LafargeHolcim Mannersdorf cement plant, Austria. Here we formulate the thesis question:

> What are the critical factors for successful implementation of artificial intelligence in the cement industry?

The structure of the thesis is as follows:

Chapter 1 looks at industrial trends and the value of implementing artificial intelligence solutions in a company's operation. We place the focus on the cement industry and define the thesis question in relation to the success factors for implementing advanced technology in a cement plant.

Chapter 2 reviews the theoretical frameworks used to analyze success factors in the implementation of information systems in general, putting a focus on Expert Systems as a subgroup used on cement production sites.

Chapter 3 provides a short explanation of the methodology used to answer the research question.

Chapter 4 gives a short overview of the business environment of the Mannersdorf plant, explains the cement production process briefly, and elaborates on two cases of implementation of a new generation expert system in the Mannersdorf cement plant. Furthermore, this chapter deals with the critical success factors in the Mannersdorf plant by using the suggested frameworks and theoretical models. Chapter 4 summarizes the results from the exploratory research from the specific case studies. The author defines, in his opinion, the most critical elements for successful implementation of an artificial intelligence system in a cement plant in a specific business environment and supports his conclusions with the results of the exploratory research.

Chapter 5 gives the author's view on the presented results and discusses and gives recommendations for successful AI implementation and use in the cement industry.

2 LITERATURE REVIEW

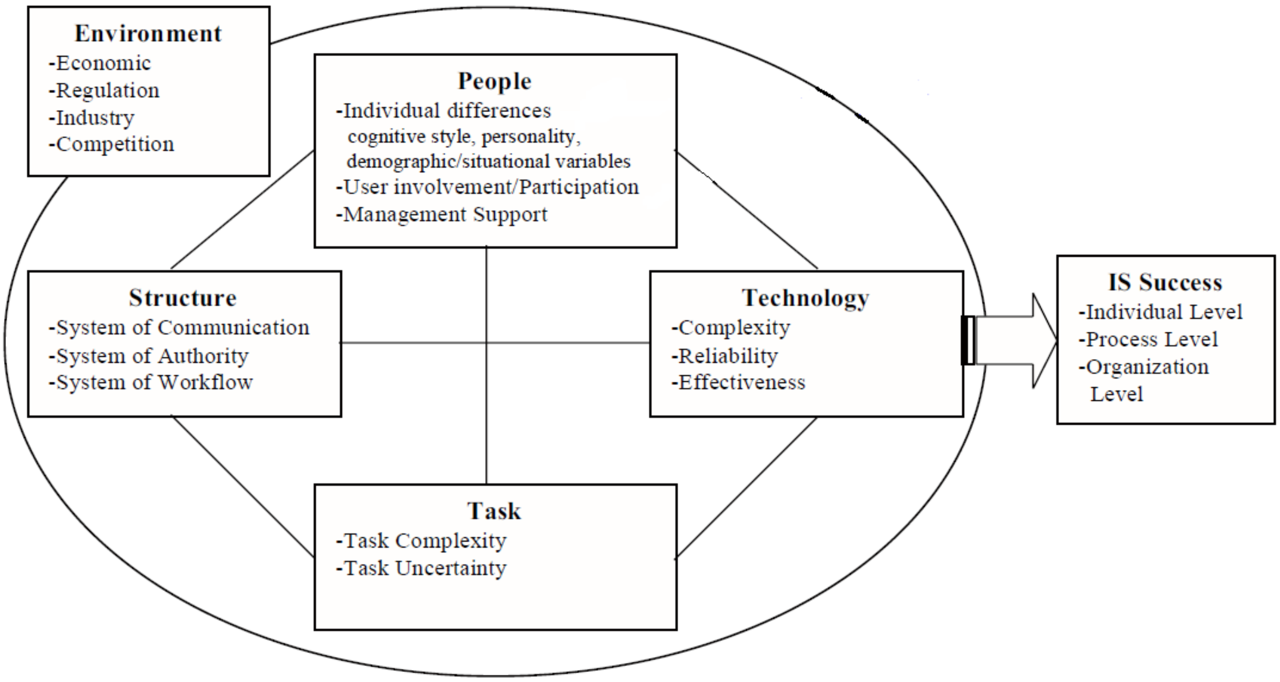
To start the review of literature we must clarify terminology in order to direct our research in the right direction. The review of literature started with a look at success factors related to the implementation of expert systems as this is the focal point of this research. The Encyclopedia Britannica defines an Expert system, as a "computer program that uses artificial-intelligence methods to solve problems within a specialized domain that ordinarily requires human expertise" (Encyclopedia Britannica, 2016). There are many previous studies on implementation success factors (Ignizio, 1991; Keyes, 1989b; Prerau, 1990; O'Neal, 1990; Turban, 1992b; Yoon et al., 1995). Here it is important to state that an Expert System is one of the defined types of Information Systems, others being data warehouses, enterprise resource planning, enterprise systems and others (Laudon, K.C. and Laudon, J.P, 1988), and success factors for other computer-based IS have been defined (Guimaraes et al., 1992; Liang, 1986).

In order to have a structured overview of the literature and to grasp and consolidate different factors in the assessment of the implementation of computer-based information systems, theoretical frameworks related to Information Systems in general will be reviewed, and then a focused look at Expert Systems as a type of computer-based IS will be taken. In addition, we will have a brief look at the classification of expert systems in order to place the Mannersdorf case study and ES in the appropriate category.

2.1 DEFINITION OF INFORMATION SYSTEM SUCCESS

Jong Jin Kim at al. (1996) define Information Systems success as „a measure of the degree to which the person evaluating the system believes that the stakeholder is better off". Further, they argue that there are various internal and external interest groups within every organization who have stakes in different aspects of IS performance. According to the authors, these groups include stockholders, employees, customers, managers, creditors, and government. They claim that the focus of measuring IS success is on the investigation of the effect of a system on individual performance, business process performance, and organization performance. Next the authors present Figure 2, which is an adaptation of the famous “Leavitt Diamond” (Leavitt, 1964). Leavitt's organizational change framework views the organization as a complex system where variables are interrelated. These variables are task variables, structural variables, technological variables, and human variables. Further, Leavitt claims that a change in one has an effect on the others. Usually, efforts concentrate on structure, people, or technological variables in order to affect an improvement in the task variable, but other variables also react to the change. This framework is essential to understanding IS success because friction among task, technology, structure, people, and environment can subvert the purpose of a technology and prevent the success of the IS.

Figure 2. Framework to understand IS success



Source:
https://www.researchgate.net/publication/262369059_Information_systems_success_measurement

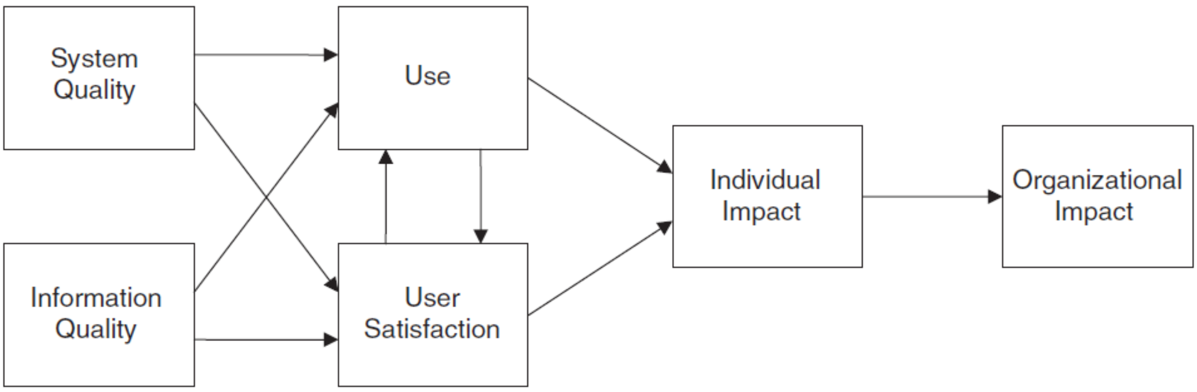
2.2 THE DEVELOPMENT OF A MODEL OF INFORMATION SYSTEM SUCCESS

In the last 3 decades, a lot of research has been done on assessing the success of IS (King and Rodriguez 1978; Matlin 1979; Myers et al. 1997; Rolefson 1978), and many models have been developed to give explanation of "successful" Information System. Due to the complexity, interdependent and multi-dimensional nature of IS, the first attempts to define IS success were not widely accepted.

DeLone & McLean (1992) performed a review of work on done on this topic and had deeper look on published papers during the period from 1981–1987, and based on this, they created classification of IS success factors. DeLone McLean in their 1992 paper, and based on the communications research of Shannon and Weaver (1949), and the information "influence" theory of Mason (1978), as well as empirical management information systems (MIS) research studies from 1981–87, they addressed six variables or components of IS success. According to DeLone and McLean those variables are system quality, information quality, use, user satisfaction, individual impact, and organizational impact.

The DeLone and McLean (1992) Information System success model has certainly one of the most frequently cited (Heo and Han 2002; Myers et al. 1997). In figure 3 we can see the original D&M IS model from 1992 illustrating the previously mentioned components of IS success.

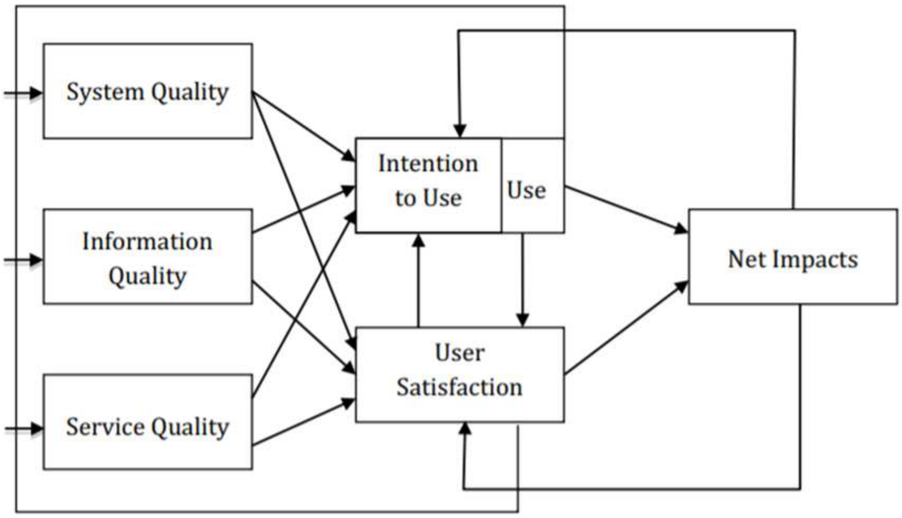
Figure 3. Original DeLone and McLean IS Success Model



Source: European Journal of Information Systems (2008) 17, 236–263. doi:10.1057/ejis.2008.15

Many researchers have questioned this model, tried to modify it or add different constructs. In their analysis (DeLone and McLean, 2008), DeLone and McLean reviewed the empirical studies and proposed modification to their model that had been performed since 1992, and revised the original model (DeLone & McLean, 2002, 2003). The updated model is shown in Figure 4.

Figure 4. Modified DeLone & McLean IS Success Model



Source: European Journal of Information Systems (2008) 17, p 238

DeLone and McLean updated their model by accepting recommendation from from work of Pitt et al. (1995) to include service quality as a construct. Next, Myers et al. (1997) and Seddon et al. (1999) claimed in their work that information system could have an impact on other level apart from individual and organization ones, so DeLone and McLean replaced those variables with Net Benefits, so taking in consideration benefits on different levels of analysis. These changes allowed the model to be much more versatile and used as a framework in any type of analysis which could be considered as most relevant one. Next, final improvement of DeLone and McLean model was a further clarification of the "use" construct. DeLone & McLean (2003) write following: "'Use' must precede 'user satisfaction' in a process sense, but positive experience with 'use' will lead to greater 'user satisfaction'' in a causal sense' ". Hence, they went on to state that if the user satisfaction is increasing, this would lead to higher intention to use IS, and this will consequently have results on Use. DeLone and McLean (2003) give description of mentioned dimensions of success as the following:

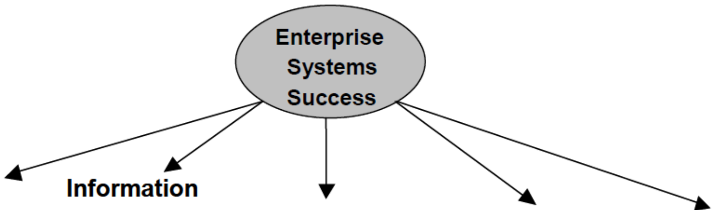
- *"System quality – the desirable characteristics of an information system, which includes the following elements: ease of use, system flexibility, system reliability, and ease of learning, as well as system features of intuitiveness, sophistication, flexibility, and* *response times."*

- *"Information quality – the desirable characteristics of the system outputs. This is for example: relevance, accuracy, conciseness, completeness, understandability, currency, timeliness, and usability."*
- *"Service quality – the quality of the support that system users receive from the IS department and IT support personnel or IS provider. This includes responsiveness, accuracy, reliability, technical competence, and empathy of the personnel staff."*
- *"System use – the degree and manner in which staff and customers utilize the capabilities of an information system. This means amount of use, frequency of use, nature of use, appropriateness of use, extent of use, and purpose of use."*
- *"User satisfaction – users' level of satisfaction with reports, Web sites, and support services."*
- *"Net benefits – the extent to which the IS contributes to the success of individuals, groups, organizations, industries, and nations. This considers improved decision-making, improved productivity, increased sales, cost reductions, improved profits, market efficiency, consumer welfare, creation of jobs, and economic development. "*

It is extremely important to say that in the D&M IS model, all constructs are interdependent and that, compared to the old model, there are additional feedback loops. For example, the model shows that if there are positive impacts of IS implementation, this will lead to more Use and higher User Satisfaction. Further, DeLone and McLean (2016) explain that with increased experience in using a system, problems become known and possible improvements are recognized, leading to requests for changes and updates to the system, or what is commonly called "maintenance." These changes are the next steps in the evolving process of the life cycle of the system. To capture this graphically, feedback arrows are shown leading from "Use" and "User Satisfaction" back to "System Quality," "Information Quality," and "Service Quality."

In their article, DeLone & Mclean (2008) point to the work of Sedera et al. (2004) as an effective measurement system for IS success. Sedera et al. have developed and validated a *priori* model of multidimensional IS success instrument for enterprise systems. Unlike the original DeLone and McLean model, the *a priori* model (Figure 5) is simply a measurement model for assessing the multidimensional phenomenon of Enterprise System success using five separate dimensions of success: system quality, information quality, satisfaction, individual impact, and organizational impact. The model does not propose any connections among dimensions in the model, rather it is postulated that they are correlated and additive measures of the same multidimensional phenomenon—Enterprise System success.

Figure 5. Enterprise System Success



System Quality		Information Quality		Satisfaction		Individual Impact		Organizational Impact	
SQ1	Data accuracy	IQ1	Importance	S1	Information	II1	Learning	OI1	Organizational costs
SQ2	Data currency	IQ2	Availability	S2	Systems	II2	Awareness / Recall	OI2	Staff requirements
SQ3	Database contents	IQ3	Usability	S3	Overall	II3	Decision effectiveness	OI3	Cost reduction
SQ4	Ease of use	IQ4	Understandability	S4	Enjoyment	II4	Individual productivity	OI4	Overall productivity
SQ5	Ease of learning	IQ5	Relevance				*accurate interpretation+*	OI5	Improved outcomes/outputs
SQ6	Access	IQ6	Format		*decision making^^*		*problem identification++*	OI6	**Increased capacity****
SQ7	User requirements	IQ7	Content Accuracy		*specifications^^*		*task performance+++*	OI7	**e-government****
SQ8	System features	IQ8	Conciseness					OI8	**Business Process Change****
SQ9	System accuracy	IQ9	Timeliness						*application portfolio^*
SQ10	Flexibility	IQ10	Uniqueness						*no. of critical applications^*
SQ11	Reliability		*usefulness#*						*increased work volume^^*
SQ12	Efficiency		*completeness#*						
SQ13	Sophistication		*informative#*						
SQ14	Integration		*currency#*						
SQ15	**Customization****		*reliability##*						
			readability###						
			clarity###						
			appearance###						

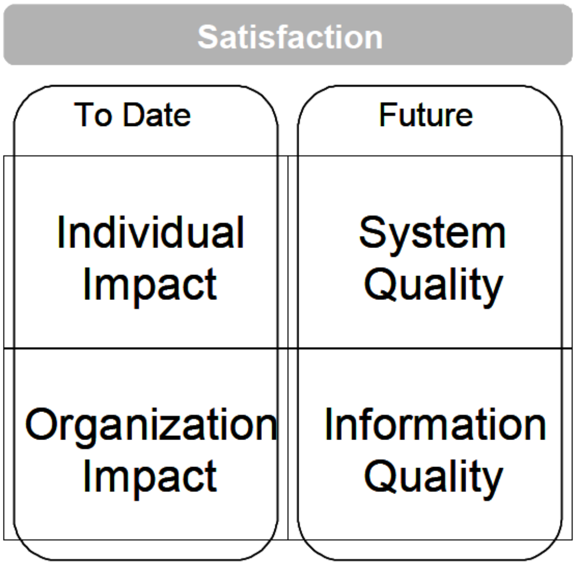
Source: https://eprints.qut.edu.au/4743/1/4743.pdf

The uniqueness of this particular instrument to measure the success of an Information System is that it captures the multidimensional and complex nature of IS success by measuring five key success dimensions and by using at least four measurements for each dimension. DeLone and McLean claim that “the instrument has strong construct validity in that it captures multiple aspects of each variable”. According to DeLone and McLean (2008) this is a quite a big change from much of the measurement of IS success constructs that focus on only one aspect of the construct. Further, DeLone and McLean claim that another strength of this model is that its validity has been rigorously tested within the context of enterprise systems. In the model of the system under investigation, Sedera et al. eliminated the “User Satisfaction” construct from the success measurement model because it added little explanatory power after the four primary constructs. Use was also eliminated because the system under study was mandatory causing little measurable variation in use. Revised model is presented in figure 6, and it has the four quadrants „representing four distinct but related dimensions of the multidimensional phenomenon: Enterprise Systems success “. According to

Sedera et al., the revised model for ES success deviates from the traditional DeLone and McLean model in the following ways:

1. *„it depicts a measurement model and does not purport a causal/process model of success."*
2. *„it omits the Use construct. "*
3. *„ satisfaction is treated as an overall measure of success, rather than as a dimension of success. "*
4. *„new measures were added to reflect the contemporary IS context and organizational characteristics. "*
5. *„It includes additional measures to probe a more holistic organizational impacts construct. "*

Figure 6. Revised Sedera et al. Enterprise Success Model

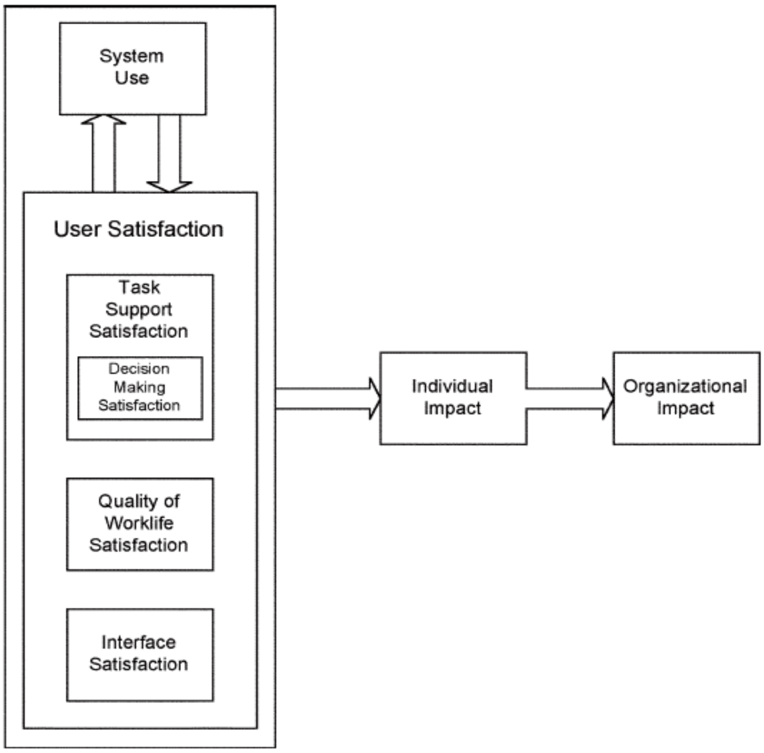


Source: https://eprints.qut.edu.au/4743/1/4743.pdf , page 12

After a further analysis of literature, other IS success models were analyzed and consider for use in the assessment of IS success factors in the Mannersdorf plant. The Garrity and Sanders model, as an extension of D&M, was looked at in more detail. Kim at el. (1996) write that, although IS are generally designed to fit within the existing organizational or administrative structure, firms have achieved the most dramatic improvements in performance when they have redesigned their entire work systems to take advantage of changes in technology. So, new work practices, such as decentralized decision-making, self-directed work teams, and incentive systems that encourage and reward high team performance, when combined with technology investment have been shown to provide the greatest payoff for organizations. In addition, computers and information technology are being used as advanced communication devices that can have a dramatic effect on organizational structure and communication patterns. Finally, the Garrity and Sanders model of IS success adapts the DeLone and McLean model by incorporating four dimensions of IS success: task support satisfaction, decision support satisfaction, interface satisfaction, and quality of work life satisfaction. The model presented in Figure 7 is an extension of the work of Leavitt and various scholars of organizational science and draws on general systems theory to provide a parsimonious representation of the major factors involved in IS success. Further, we will elaborate on these four constructs and give a brief explanation.

Figure 7 Garrity and Sanders' IS Success Model

Source:https://www.researchgate.net/publication/262369059_Information_systems_success_measurement/figures?lo=1



According to Kim at al. (1996) the *"task support satisfaction"* dimension measures how well the system helps or hinders the individual in accomplishing his or her job responsibilities and fulfilling task requirements. Very often, newly developed systems, while technically robust, fail to carry out their intended roles if designers do not pay close attention to achieving a close fit with the task requirements of users and gaining a thorough understanding of how users accomplish work. In this context, the task support satisfaction dimension is concerned with the fit between the system, the user, and the task. In this context, the appropriate deployment of information technologies for each task is critical to the success of the IS. In measuring task support satisfaction, the concepts of productivity and effectiveness, and the difference between expectation and perceived quality should be incorporated because task support satisfaction is assumed to come from the individuals' perception of fulfilling task requirements. In the following table are measurement statements that assess the success of this particular dimension.

Table 1. Measurement Items for Task Support Satisfaction

1.	This information system is more useful than I had expected.
2.	This information system assists me in performing my tasks better.
3.	This information system is extremely useful.
4.	Using this information system enables me to accomplish tasks more quickly.
5.	This information system makes it easier to do my tasks

"Decision support satisfaction", as Kim at al. (1996) formulate, can be defined in terms of the capability of an IS when system intervention assists in decision-making and better performance of the user's job. The use of decision support from IS helps to simplify the decision process and make it linear, particularly in complex environments when the decision-making activities involve choosing from a number of alternatives. Measurement items for Decision Support Satisfaction attempt to determine whether the system supports the individual in recognizing problems, structuring problems, and/or making decisions related to the goal of controlling a business process. Examples of measurement items for decision support satisfaction are shown in Table II

Table 2 Measurement Items for Decision Support Satisfaction

1.	This information system improves the quality of my decision making.
2.	Use of the information system enables me to make better decisions.
3.	This information system assists me in making decisions more effectively.
4.	Use of the information system enables me to set my priorities in decision making

The focus of measuring the "*interface satisfaction"* dimension is on presentation, format, ease of use, and efficiency. Interface satisfaction is assumed to incorporate most parts of information quality because the vehicle for presenting the information (e.g., a textbox, table, graph, list box, or form) cannot be separated from the information itself. Table III shows several examples of measurement items for interface satisfaction

Table 3. Interface Satisfaction

1.	The information provided by this information system is clear and understandable.
2.	Learning to use this information system was easy for me.
3.	This information system is user friendly.
4.	This information system is easy to use.
5.	I found it easy to get this information system to do what I want it to do.
6.	My interaction with this information system was clear and understandable.
7.	It would be easy for me to become skillful at using this information system.

Measurement items for "*Work Life Satisfaction"* attempt to determine whether the introduction of a new IS changes the perceived quality of work life in terms of changes in five job characteristics: task autonomy, skill variety, task identity, task significance, and task feedback. Examples of measurement items for the quality of work life satisfaction are shown in Table IV

Table 4. Measurement Items for Quality of Work Life Satisfaction

1.	The information system has improved my overall quality of work life.
2.	The information system helps alleviate time pressure.
3.	The information system gives me the right level of autonomy.
4.	The use of the information system makes my job more challenging.
5.	The information system makes my job more important.
6.	The information system makes my skills more important.
7.	The use of the information system improves my relationship with other employees.
8.	Learning the information system allows more promotion opportunities.

2.3 SUCCESS FACTORS FOR THE EXPERT SYSTEMS IMPLEMENTATION

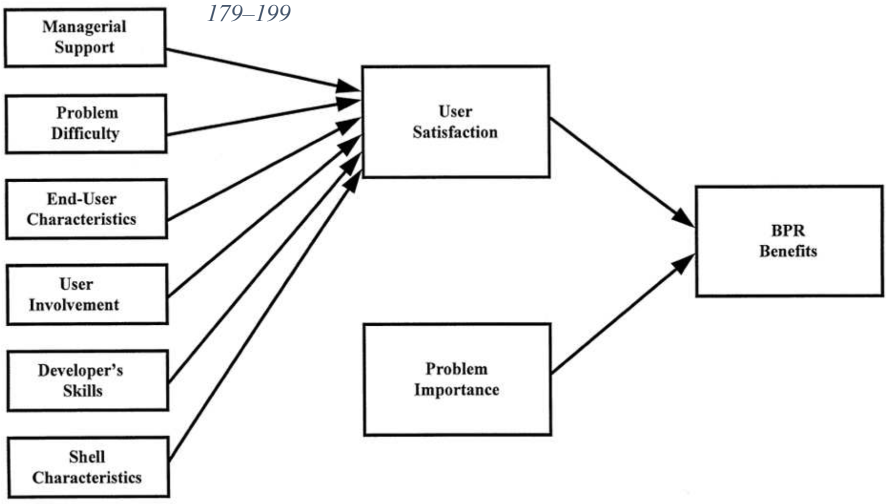
As has already been mentioned, two cases from the Mannersdorf plant will be used to assess the success factors in the installation of artificial intelligence systems. By their nature, IS used for plant operation are Expert Systems. We will review literature that places focus on Expert

Systems as a sub-group of IS. First, we will explore the differences among different groups of IS.

Guimaraes at al. (1997) performed literature review and realized that many studies deal with other types of computer-based Information besides ES. JIH (1990) in this case refers the term ES to systems that "comprise at least a knowledge base, an inference engine, an explanation module, and a user interface in order to mimic expert decision-making". Further, t Guimaraes at al. (1997) noted that ES are different quite a lot from other IS, although they have some similarities. They write that the "basis for ES is the capture and use of knowledge from high-level experts to assist less proficient ES end-users". To summarize, Guimaraes at al. (1997) summarize some important factors that are unique to ES, such as " their "expert mimicking" nature, the domain-oriented problems addressed, the characteristics of ES shells, the required activities and characteristics of domain experts and knowledge engineers, and their unique relationship with end-users."

Figure 8. Yoon et al. Model of ES success

Source: Y. Yoon et al.J. Eng. Technol. Manage. 15 (1998) 179–199



Based on DeLone and McLean (1992), Yoon et al. (1995), conducted research and employed various measurements for ES success as dependent variables, including user satisfaction (Yoon et al., 1995), and impact on end-users' jobs (Yoon and Guimaraes, 1995). Next, Yoon et al. (1998) deal with Business Process Re-engineering (BPR), a term that describes changes in business processes driven by implementation of some computer-based systems, particularly ES. The authors state that while system usage and user satisfaction are important measures for ES success, the business benefits it provides to the organization may arguably be the ultimate measure. Further, they write there are other aspects of changes in BPR project success that are not dependent on the technology used to support the new processes. Therefore, BPR project success, or specifically ES to support BPR success, very likely must be defined in much broader terms than those used here to measure ES success. Figure 8 graphically depicts the model studied. The model contains three sets of variables: six exogenous variables (managerial support for the use of ES technology, business problem difficulty, end-user characteristics, user involvement, developer's skills, and shell characteristics), which are positively related to one endogenous variable (user satisfaction with the ES). Business problem importance to the end-users and user satisfaction with the ES, in turn, are positively related to the outcome variable (the business benefits from using the ES in the BPR project).

Next, in their study Yoon, Guimaraes and O'Neil (1997) and Yoon, Guimaraes and Clevenson (1998) identified and empirically tested nine major variables overall proposed in the literature as determinants of ES success. Hypotheses are listed below, and the questionnaire used to evaluate each of mentioned variable is presented in Appendix B.

"H1: Problem difficulty is positively related to ES success."

"H2: Developer(s) skill is positively related to ES success."

"H3: Domain expert quality is positively related to ES success."

"H4: End-user characteristics is positively related to ES success."

"H5: ES desirable impact on end-user(s) is positively related to ES success."

"H6: Shell characteristics is positively related to ES success."

"H7: User involvement is positively related to ES success."

"H8: Management support is positively related to ES success."

"H9. Problem importance is positively related to ES success."

Yoon at el. (1998) write in their work that there are several motivating reasons for the introduction of BPR: incremental process improvements not meeting expectations, large gaps between the current and target level of company productivity performance, loss of market share due to customer dissatisfaction and product or services becoming commodities (Tsang, 1993). Further, among various computer-based information systems, ES have been recognized as important implementation vehicles for BPR. The increasing use of ES techniques in BPR has raised the importance of understanding the various factors affecting the success of ES for such purposes. By capturing expert knowledge and experience, an expert system provides the means to deliver expertise in the field and change the way an organization performs its business processes. Finally, Yoon at el. state that ultimately, ES success is measured by whether or not the ES has decreased the time taken to perform the tasks in the business process, decreased the number of steps involved in performing the required tasks, simplified the business process, increased the derived benefits, and/or decreased the associated costs. To derive these business benefits from ES use, the ES must satisfy end-users in terms of its ability to provide good quality information. Below, we give a description of each independent variable.

2.3.1 User Satisfaction

Previous studies have proposed User Satisfaction as a determinant of ES success (Yoon and Guimaraes, 1995). A reasonable assumption is that without user satisfaction, a system is less likely to be used and to produce beneficial results to the user community and the organization. Therefore, user satisfaction is considered as an important factor to ES success (DeLone and McLean, 1992; Yoon and Guimaraes, 1995). Further, Yoon at el. (1998) write that user satisfaction with an ES is particularly important in cases where the system is used for dramatically changing business processes and how end-users perform their work. In their study, the authors measure user satisfaction with the ES in terms of its information quality (the value of the output, reliability, timeliness, etc.) and usefulness. So, unless the ES provides good quality information, it will not aid in deriving BPR benefits.

2.3.2 Problem importance

Earlier studies have stressed that the ES should address a needed and useful task so that the ES solution has a high payoff (Casey, 1989; Hayes-Roth and Jacobstein, 1994; Medsker and Liebowitz, 1994; Mumford and MacDonald, 1989; Slagle and Wick, 1988; Yoon et al., 1995). A useful task must be non-trivial and important to the organization. Successful ES were found to address problems core to the business (Barsanti, 1990), and perform functions which are essential for their user organizations to obtain competitive advantages. Managers' support is vital for developing good quality ES by facilitating the acquisition of the necessary tools, proper training and end-user support. Choosing an application of interest to managers is likely to be important in gaining their support.

2.3.3 Management support

Management commitment to ES development, utilization and maintenance has been recognized as a critical success factor of ES development by several authors (Hayes-Roth and Jacobstein, 1994; Leonard-Barton, 1987; Leonard-Barton and Deschamps, 1988; Liebowitz, 1991, 1993; Keyes, 1989b; Smith, 1988; Turban, 1992a). Such support is thought to be more critical in the case of ES vs. other IS because of the more threatening nature of the ES to end-user jobs and the need for management reassurances in this area (Yoon and Guimaraes, 1995). Keyes (1989b) has written that a critical barrier for ES success was lack of management support. Barsanti (1990) wrote that" a key predictor of ES success in an organization is the existence of top management support".

2.3.4 Problem difficulty

Many studies have emphasized the importance of selecting an appropriate domain for successful ES implementation (Barsanti, 1990; Beckman, 1991; Keyes, 1989b; Liebowitz, 1989; Medsker and Liebowitz, 1994; Slagle and Wick, 1988; Turban, 1992a; Waterman, 1986; Will et al., 1994). Business problem difficulty has previously been proposed as an important determinant of ES success (Yoon et al., 1995; Yoon and Guimaraes, 1995) because when an ES is able to assist end-users with a difficult problem, they are likely to appreciate the help more than if the ES dealt with a simpler problem. On the other hand, difficult problems may create obstacles to ensuring user satisfaction with the information provided by the ES.

2.3.5 Developer(s) skills

Several authors (Couger and McIntyre, 1987–1988; Fellers, 1987; Liebowitz, 1993; Mykytyn et al., 1994; Payne and Awad, 1990; Shacklett, 1990; Turban, 1992a; Will et al., 1994) have emphasized the importance of skillful ES developers. Developers' ability to capture the necessary knowledge, communicate with experts and end-users, and use ES development tools are required for an ES capable of producing quality information. These prior studies have recognized knowledge engineers as critical members of ES development teams and emphasized that a qualified knowledge engineer is a prerequisite for successful development.

2.3.6 End-user(s) characteristics

Research studies have stressed the importance of end-user(s) characteristics for ES success (Hayes-Roth and Jacobstein, 1994; Liebowitz, 1991; Slagle and Wick, 1988; Smith, 1988). The central end-user characteristics that affect ES success are user attitude, user expectations and user knowledge of computer and ES technology (Smith, 1988), user confidence with the system (Will et al., 1994), and user commitment to learning how to use the system (Hayes-

Roth and Jacobstein, 1994; Liebowitz, 1991; Slagle and Wick, 1988). Yoon et al. (1998), write that “user attitude is considered an important factor to ES success since end-users with a negative attitude toward an ES will not utilize the system, completely, wasting development costs”. Users often have fears about the ES affecting their job security, thus they develop negative attitudes and challenge the system implementation (Byrd, 1992, 1993; Lu and Guimaraes, 1988). The problem of negative user attitude and resistance is more apparent in the ES field since an ES can substitute tasks done by the humans with artificial systems.

2.3.7 Shell characteristics

Employing a proper shell is enormously significant to ES success. Keyes 81989a) and Liebowitz (1991) write that “for many applications, shells must enable the ES to be easily integrated with existing database and other systems, but many ES are capable of only limited interface”. Equally, a shell providing a user-friendly interface enables ES developers to develop a user-friendly interface for the ES. The execution time of the shell is also very important to ES success since it determines the response time of the ES (Plant and Salinas, 1994).

2.3.8 User Involvement

In most DSS development and information requirements, definition is heavily dependent2 on user involvement (Guimaraes, *et al*, 1992). On the other side, Guimaraes et al. write that in the ES development domain, in most cases experts are the primary source of knowledge and inference about the problem”. Still, Smith (1988) writes that “high levels of user involvement is important to ES success”, and that “users who initiated an ES project and were involved in establishing its goals/objectives are more likely to be satisfied with the system”. Keyes (1989) claimed that “if the end-users were excluded up front, they would exclude themselves at the end and not use the ES”. At least, it could be said that user involvement in ES development will improve the chances that the system will produce more useful information.

2.4 SELECTED FRAMEWORK USED IN RESEARCH

After performing literature review, we consider that using model for measuring ES success developed by Yoon at al. as one that best fits to the presented cases coming from the cement plant Mannersdorf. We believe that model considers all important elements in ES implementation, it is based and build on widely accepted framework, and, in our opinion, compare to other mentioned models, it considers much more end-user characteristics, user involvement and developer skills, variables which could be the main determinant in ES implementation success.

3 RESEARCH METHOD

The practical application of any model is naturally dependent on the information system and organization under study. In the case of the Mannersdorf plant, we will examine the implementation of an artificial intelligence Expert System, which is a sub-group of IS. Therefore, the focus of this study is on the success factors of ES implementation. The Mannersdorf cement plant is the first LafargeHolcim plant to implement an Expert System based on artificial neural networks. Therefore, there is no reference for this specific case, and there were only a limited number of users involved in the ES installation. Consequently, we had a very limited number of people that we could interview and as a result our sample is a very limited one. For this reason, our research must be considered as exploratory, and the conclusions developed taken with caution. To point out the main factors of success, the author will use the presented models as a framework, evaluate all constructs based on personal experience and compare two cases, one considered as relatively unsuccessful, and one with full implementation success. The author, as project leader for both cases, will use a questionnaire specially designed for Expert Systems developed to support the Yoon Model and perform an assessment of each measured component. Rating is done on scale from 1 to 5 and it represents personal assessment on a given point. This structured approach and assessment of the differences between the two cases will eventually isolate the main success factors for AI installation in the Mannersdorf cement plant. A descriptive view of the success factors will be presented, and this view represents the personal and subjective view of the author of this thesis.

4 Mannersdorf Case Studies and Results

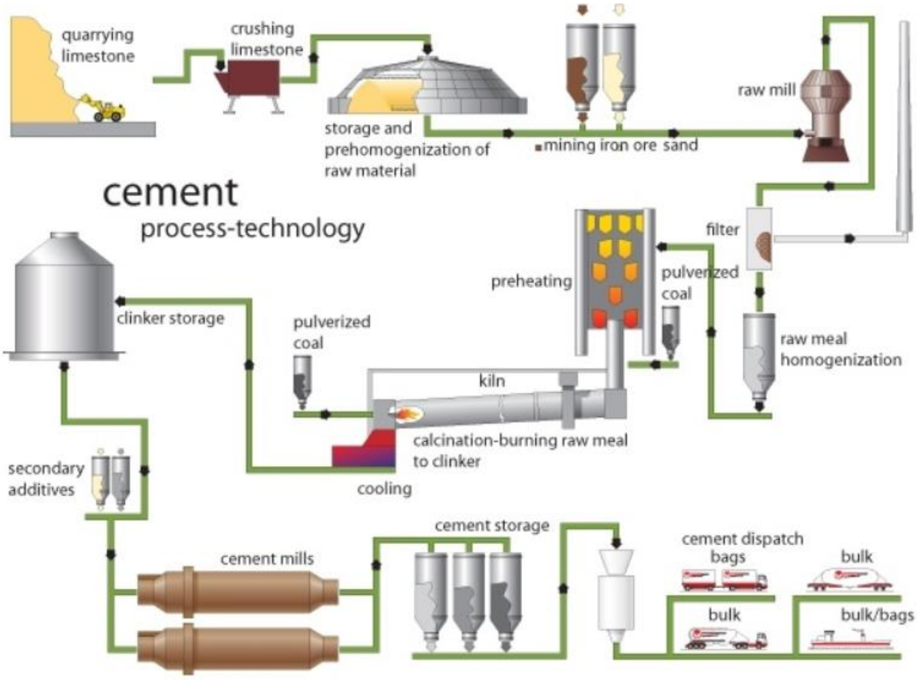
4.1 LH Mannersdorf Cement Plant – Business Environment Summary

The Mannersdorf Cement Plant belongs to the Central Europe Cluster LH Cluster, and is located near the city of Vienna, Austria. Generally, the plant is currently in a sold-out market with high pressure on production output. To satisfy the high demand, the plant must import clinker (a semi-product used for cement production). On the other hand, due to the significant capex backlog in recent years, the plant is not in perfect condition with a desperate need for investments to maintain operations and output. Furthermore, the high salaries in Austria in comparison to its neighboring countries represent the main driver of the plant's higher fixed costs. For that reason, the plant runs with a very limited number of highly educated people, and generally, it is a very lean organization.

4.2 Brief description of the Cement Production Process

Cement manufacturing is a complex process that begins with mining and then grinding of raw materials, which include limestone and clay, to a fine powder, called raw meal. Further, the raw meal is then heated to a sintering temperature as high as 1450 °C in a cement kiln. In this process, the chemical bonds of the raw materials are broken down, and then they are recombined into new compounds called clinker, which are rounded nodules between 1 and 25mm across. The clinker is ground to a fine powder in a cement mill, and it is mixed with gypsum to create cement (Figure 9).

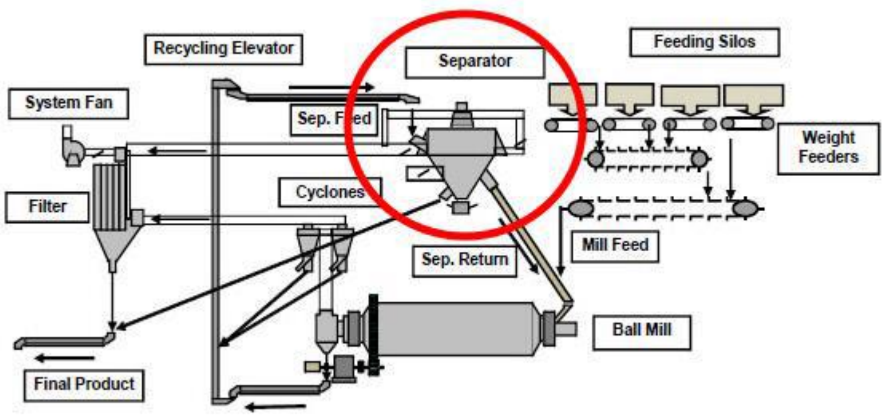
Figure 9. Cement Production Process



Source: https://www.quora.com/What-is-the-manufacturing-process-of-cement

The fineness of cement is regulated by changing the speed of rotation of the cement mill separator (Figure 10) The powdered cement is then mixed with water and aggregates to form the concrete that is used in construction (Leetham, 2015).

Figure 10. Cement Mill Separator



Source: http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0104-66322014000100015

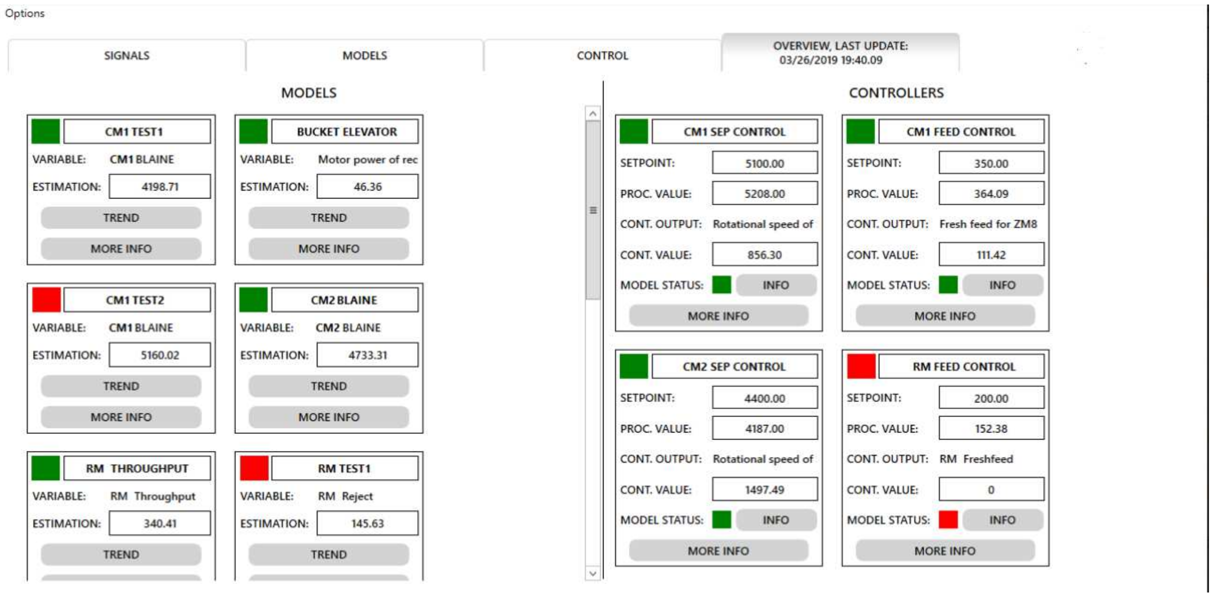
4.3 START OF ARTIFICIAL INTELLIGENCE PROJECT - MAIN MILESTONES AND ROLES

In 2016, the Mannersdorf cement plant received an offer from a supplier to install and test, for an insignificant cost, a new neural network-based ES in order to predict and control cement fineness. The main goal of the project was to improve the cement mill production rate by improving cement uniformity, which would lead to reduced quality targets, and consequently to an increased production rate (normal logic in cement production). The name of the supplier and product will be kept anonymous, to avoid product promotion and biased assessment. The Plant Manager approved the pilot project and defined the project team members, consisting of the Process Manager (at that time, the author of this thesis) and one process engineer. The project started in the beginning of 2017, with the first results in the middle of that year.

4.4 SHORT DESCRIPTION OF THE EXPERT SYSTEM

The new ES is based on the machine learning concept, where artificial neural networks are used to model production processes, and based on those models, a model predictive process control is employed. It comes as an open platform in the sense that the plant can use it to setup and control any production process, but it is in plant's hands to do that. The supplier provides extensive training and creates a control for one of the defined process, as an example of use. The plant team considered the setup process dramatically simplified compare to the ES already installed in the plant. There are three steps to follow to create full process control. First, in the section Model (Figure 11) a mathematical model is created by importing the necessary signals into the ES database. In the same section, training of the model is performed (one push of a button). Finally, the same model is imported into the section Control to be used for Model Predictive Control. The last section is Overview where the user can have an overview of all running processes. There are very few things that the user has to set up, and those are the signal tags, where control output is written, limits for the actuators, and to choose the type of system to control. Also, the user can choose if the dynamics of the system/model created should adapt themselves automatically.

Figure 11. Installed ES - Overview page

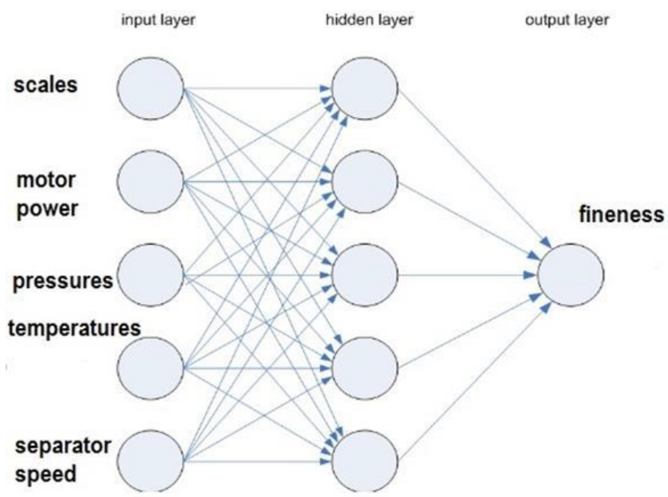


Source: Software interface, used with permission

4.5 CASE ONE – AI FOR CEMENT FINENESS PREDICTION AND CONTROL

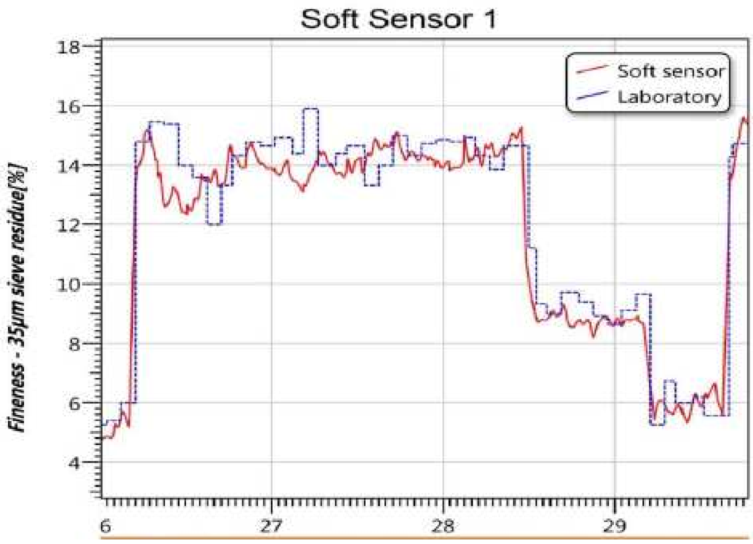
In case of cement fineness prediction, the ES uses process signals as an input to the neural networks. On the other side, hourly laboratory samples and results of cement fineness (how fine the cement is ground) are used as a neural network output (Figure 12).

Figure 12. Neural Network with Input Signals



Then, the neural network is trained and the mathematical process with nonlinear correlation between inputs (process signals) and output (cement fineness) is established. After the process model is created, actual, real-time process signals/data from the production process are used as an input, and the model estimates output/cement fineness according to the learned correlation (Figure 13).

Figure 13. Example of Cement Fineness Prediction



Source: used with permission from software interface

Further, to adjust the actuator and to control the process continuously, the same model is used for so called model predictive control, and in the case of cement grinding, the actuator is the cement mill separator. The outcome is that, instead of receiving quality data hourly, the system receives an estimated value every minute, and acts continuously to prevent higher quality deviations.

4.5.1 Traditional cement control - technology comparison

The type of control described is feed-forward control, and it is only possible if the controlled process is mathematically modeled. Process modeling can be performed in several ways, but this particular ES uses artificial neural networks, a versatile tool used for adaptive control in many industries, and a core process in many modern AI applications. Due to this capability, there is no need for the user to tune any control parameter as the ES does this by itself. On the other hand, most traditional systems are based on feedback control, and it is important to say that the Mannersdorf plant already had this kind of ES installed. Feedback control means that the ES receives measured values from the sensor or measured lab values, acts in steps on the actuator and repeats the process from the beginning, in a closed loop. In the case of cement fineness, the current ES solutions were receiving data from the laboratory at an hourly rate and acting on the cement mill separator only at that moment. The result of this action was received in one hour, when the next lab sample was measured. In addition, the mentioned action on the actuator was defined by using plant experience and IF-THEN logic. Therefore, in order to have reasonable results, the coefficient that defines the action of an actuator, in this case a mill separator, must be tuned. In the newly installed ES, there is no tuning needs as the action is calculated based on a created mathematical model of the controlled process. Further, as the system can estimate cement fineness, the sampling period can be prolonged from an hourly to a 2 or 4-hour sampling rate, which could reduce costs of cement grinding quality control.

4.5.2 Implementation process and project outcome

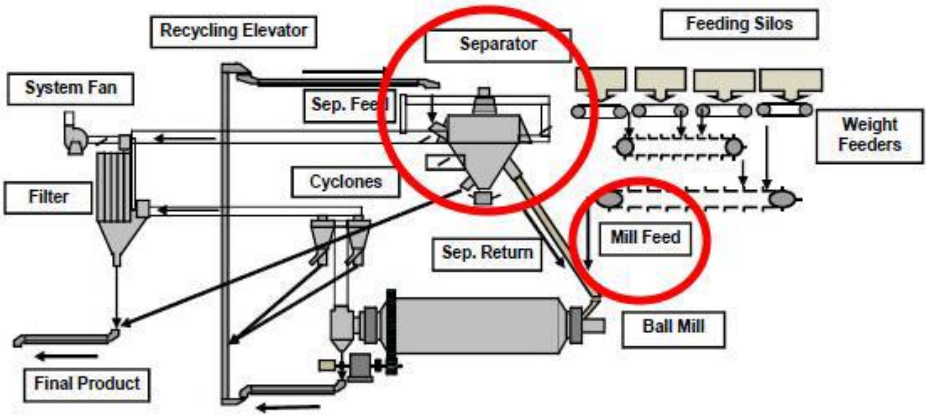
During the project implementation the supplier provided extensive training, as well as developing the first setup of cement fineness prediction and control for one of the cement mills. The first result showed very good correlation between estimated values and the ones received from the lab. Full control of cement fineness started in March of 2017 leading to very good initial results. One of the bigger problems of that time was to establish reliable communication between the industrial servers and software, which lead to long-term stoppages in control. This created some mistrust in the system as the real reasons for system failure were not clear to the end-users, in this case the plant control room operators. The project team had to reestablish trust in the system with extensive communication and reassurance. The reasons for the instability in communication was due to the safety updates frequently done on industrial servers, and a generally outdated configuration. However, reliability was established, and work on further optimization of the ES continued. In addition, the plant operators (end-users) fully accepted the system as it slightly reduced their work in part of the cement mill operation. After analysis, it was found that deviation in cement fineness had been reduced by almost 20%. Having this information, the lab people could reduce target fineness which led to an estimated production increase of 3 %, which would on a yearly basis bring savings in specific power consumption of more than 60,000 €. However, it was difficult to prove these values, and present them to the upper management, as there was conviction that cement fineness target reduction could also come from other factors like improved clinker reactivity (the main component of cement that contributes to strength) or others. This was partially true and required deeper analysis and further use to give a proper estimate. Also, although cement mills output was considered as an important factor, it was also limited by the lack of input material, clinker. Therefore, from the management perspective, the plant bottleneck was rather at the cement kiln side where the clinker is produced, which was partially true. Interestingly to add, there had been several occasions where, due to technical failures in the laboratory, cement was produced based only on estimated data (up to 16 hours of independent run). However, despite this, the quality manager never considered reducing the frequency of cement sampling as an option as this procedure was part of the traditional and established way of production. However, this was not the initial aim of the project, and not the point that could be consider as part of the cost savings. Further, as we mentioned before, there was a very limited number of qualified people who could fully explore the capabilities of the ES, and most of the time they were occupied with the burning issues of daily production. Some tests were done in order to control other processes, but they never led to full installation in the sense of full process control. It is worth mentioning that the supplier provided excellent support with almost instant response in the case of problems or need for software adaptation. Use of the system, precisely cement fineness control continued throughout 2018. Results have been relatively good and very promising, but without huge attention from the management. During this period, the cement recipes changed several times due to the lack of clinker, and other reasons. Consequently, ES effectiveness was blurred by external factors and difficult to measure.

4.6 Case Two – AI for the Raw Mill Control

In December 2018, the plant had significant problems with raw meal production with a reduction in production rate of approximately 15%. The raw meal is used in clinker production as input material for the cement kiln, where clinker formation appears (explained in section 4.2). Loss of raw meal caused a similar reduction of clinker production, and consequently cement production, which has a dramatic financial impact on performance (more than 20,000€/day). There were several reasons for the drop in output, but the major ones are an increase of moisture in the limestone and an increase of foreign bodies in recycled bricks, both components used as input material. The previously installed ES was not able to cope with the multiple changing parameters and its ability for adaptation and tuning to the current situation was very limited. In addition, support from the LH group in this case was limited, with no actual solution provided.

Several actions were implemented in order to improve the situation, however the problem remained unsolved. One of the last, desperate measures was to try the new ES, and control the raw mill feed in order to increase the output. The process of raw meal grinding is very similar to the process of cement grinding (Figure 14.), only in this case intention was to control the feed instead of the separator.

Figure 14. Raw Mill Feed Control



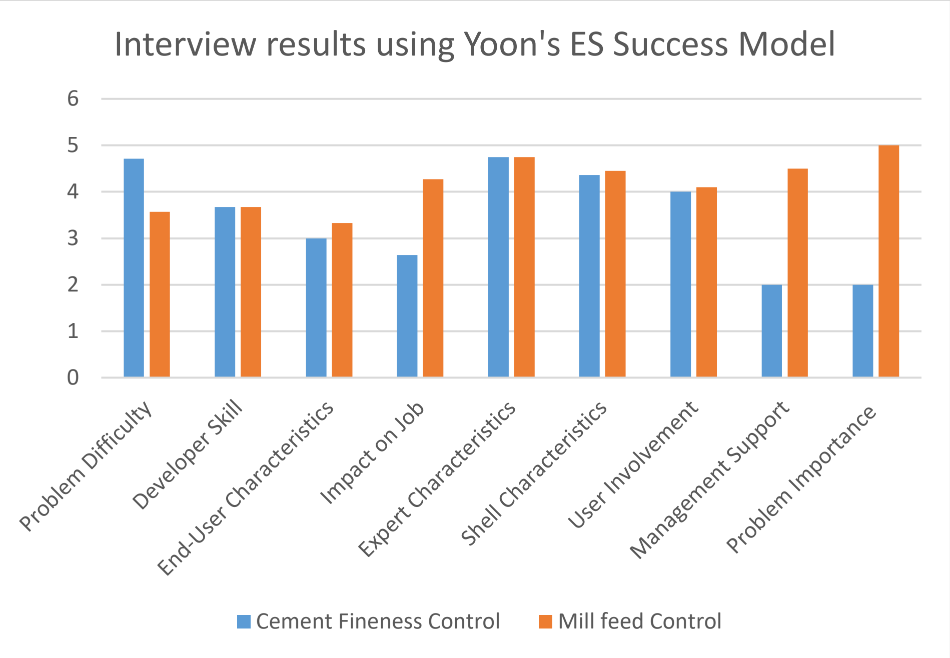
Source: http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0104-66322014000100015

The Plant manager and the rest of the management team supported the decision. The process team, already trained and accustomed to using the new ES, and with the extensive help of the supplier, developed a control logic in less than 8 hours. As we mentioned before, due to the structure of this ES and the way that it operates, it was possible to set up everything off-line and start use without any additional tuning. Immediately after implementation, the output of the mill was increased by 13% on average leading to almost full production rate recovery. In the following days, additional features to the system were implemented (equipment safety features, some operational limits etc...), and since then the system has been fully in operation and became the standard ES in this production area.

4.7 Success Factors Assessment - Use of theoretical Model

We will start the analysis by using the model developed by Yoon et al., and the results received from the questionnaire. A set of questions were used to assess each of the measured component in relation to the ES used in the Mannersdorf plant (Appendix B). A summary of results is given in Figure 15.

Figure 15. Interview results Yoon ES Success Model



4.7.1 Problem Difficulty

The graph shows that both problems were considered rather difficult or above average in terms of problem complexity, variable interdependency and expert knowledge required. However, in the case of Cement Fineness, the problem difficulty is higher as the output of the neural network depends on other variables, which are not measured and not an input to the model. In addition, cement fineness results are obtained on an hourly basis, and on the other hand, the model used for the raw mill control uses input and output data at a one-minute rate, so it can easily adapt itself. More research and time are required to improve model output accuracy in Case 1. As we mentioned, the plant organization is very lean. The limited time that plant personal had to spend on setting up the controller had a negative impact on the success of the ES installation. It is worth mentioning that in Case 2, the plant already had an ES controlling the raw mill feed. However, the new ES used different technology, and the problem is still complex from that perspective. However, the experience gained in Case 1 significantly reduced the set-up time needed for Case 2.

4.7.2 Developer Skill

The Developer is the one who captures or possesses the necessary knowledge in the field, communicates with experts and end-users, and uses the ES development tools that are required for the ES to be capable of producing the required output. In the case of the Mannersdorf plant this was the project manager (the author of this thesis), together with two process engineers. The project manager has an educational background in control systems, and vast experience in the process of cement production and control. In addition, the project manager and process engineers showed high commitment to the project due to the new and interesting technology being implemented. Therefore, we rated our selves slightly above average; nevertheless, the rating is the same in both cases, which means it should not be the prevailing factor or reason for the success of the second case. However, a critical factor is that the developer (project leader) forced the use in Case 1 due to a personal interest in the topic, which improved the general knowledge of the team in using the ES, and solved some initial problems, like instability in system communication (mentioned previously in the text).

4.7.3 End-user Characteristics

The end-users of the ES in the cement plant are the control room operators (CROs). They continuously monitor production processes, make corrections in the control and all other activities related to production. They also monitor the ES and its activities, and act in the case of any abnormalities. As mentioned, the plant was already using an ES, and the CROs know in principal the role of an ES. In Case 1, the new ES added additional functionality to the process control and reduced the task performed by CROs. However, they did not have too much work to do in any case as the separator speed for the cement fineness control was changed once an hour, so importance was not so significant. However, in Case 2, without the ES or using the old one, the CROs had to act continuously on the process control to reestablish output, but with little success. Therefore, their expectation of the new ES performance was high, as they needed support in the process control. So, the idea of testing the new ES to control the raw mill was supported by CROs, and good feedback was given during further optimization.

4.7.4 Impact on Job

In rating, we can see a big discrepancy between Case 1 and 2 when it comes to impact on the user's job. Here we specifically mean on one of the developers, a young process engineer. During Case 1 implementation, she acquired a new set of skills, especially when it comes to artificial intelligence, use of neural networks, system control and communication with end-users. As the results of Case 1 implementation were not groundbreaking, there was no significant recognition of her involvement in this project by upper management. There was a danger that her activity, as well as the activities of the project manager and second process engineer would be considered a waste of time. However, as she was in general responsible for the optimization of the raw meal production, she implemented the new ES in control of the raw mill. At that moment, the project manager (the author of this thesis) moved to another position, leaving the young process engineer in the leading role when it came to the new ES implementation. She received much bigger responsibilities, and her contribution to Case 2 implementation has been highly recognized, leading to a change in her role in the organization, with specific developed expertise.

4.7.5 Expert Characteristics

In the questionnaire, Expert Characteristics were highly rated. Support and response of the new ES supplier was exceptional, especially compared to the support that plant had been getting from the LafargeHolcim central corporate team, responsible for the optimization of the already installed ES. The supplier showed good knowledge in several fields like software development, cement production and control system development. A very good and trusting relationship was established, which helped the implementation team to overcome certain difficulties during the implementation process and continued usage of the ES.

4.7.6 Shell Characteristics

In this section, we can notice the above average characteristics of the ES, in both cases very similar. A slight difference is that in Case 2, or raw mill feed control, it seems that the system fits better to the problem as output is changing at a one-minute rate compared to the hourly rate of Case 1, or cement fineness control. This interval is more suitable for the control system design. In general, the ES is very easy to learn, especially compared to the old installed one. The user is able to understand and implement the whole set up by himself after one day of training. This was a much more complicated and time-consuming process in the case of the old ES. Actually, all set up complexities are removed from the user, so even if the user has no prior knowledge of neural networks, AI or control systems, he can still easily setup the system to work in the proper way. As we mentioned, vendor support was excellent, as they eventually needed a reference for their business, meaning good feedback and strong business cases. In addition, the vendor quickly adapted the system to the process specifics, adding new functionalities in less than one day, which was unimaginable in the case of the old ES. To emphasize, this vendor's support has maintained usage of the ES in Case 1, and the easiness to learn of the ES helped to implemented it in Case 2.

4.7.7 User Involvement

User involvement was above average from the beginning of the project, mainly due to the personal interest of the project manager (the author of the thesis) in the field of AI and control systems. During project development, the other two members became increasingly involved as they quickly learned how to use the ES, realizing its potential benefits. In comparison, the corporate central team did the complete installation and setup of the old ES, so user involvement was at a much lower level.

4.7.8 Management Support

In the case of the Management support variable, we can see the biggest difference between Case 2 and Case 1. After the initial success with raw mill control, the management understood the potential benefits and provided all the necessary support for the future project development. However, all support and approval were given only after the benefits became clear.

4.7.9 Problem Importance

In this case, there is an obvious and very strong difference when it comes to the problem importance. One could claim that, in the long-term, ability to predict and control cement fineness in such a way is very important for the LafargeHolcim Group, but in the case of Mannersdorf, this was not considered as such. On the other hand, control of the raw mill shop was an emergency and considered as the highest plant priority, especially in the short term.

4.7.10 Hypothesis testing

We will reflect shortly on hypotheses presented in section 2.3. From the author's perspective, in the case of Mannersdorf plant all hypotheses are confirmed to be valid, except the first one: "*Problem difficulty is positively related to ES success"*. As we mentioned, a more difficult problem requires more resources and more domain knowledge expertise. In a lean organization and in a production environment, focus is usually on production efficiency, and all resources are allocated, and people trained, to deliver high levels of production efficiency and not to perform research activities during their work time. In the case of LafargeHolcim, these activities are usually centrally managed. This point could also explain the lack of initial project support from the plant management team.

4.7.11 Reflection on other IS success models

Here we would like to reflect on an additional construct in the Garrity and Sanders model called Work Life Satisfaction. As explained in section 2.2, this addition to the DeLone &McLean model highlights and evaluates very well a factor that contributes to the general User Satisfaction variable. Table IV in this section gives a set of questions for evaluation, and from the perspective of the project management team, installation of the new ES significantly improved Work Life Satisfaction, especially when it comes to new skills developed and job importance within the organization.

4.8 Summary of critical success factor in ES implementation in the Mannersdorf Plant

After using presented Yoon et al. model for the assessment of Expert System Implementation, we will point out the main success factors critical for the Mannersdorf plant. As primary factors in the case of Mannersdorf, we identified the following:

- Problem Importance
- Developer's skill
- Shell Characteristics

As we explained, the problem solved by using a new ES was one that had a significant impact on the financial performance of the Mannersdorf cement plant. Further, the developer's skills and personal interest (previous education and interest in the topic of AI), was critical in project development. The Developer or project manager (the author of the thesis) had a strong interest to push the project through its main milestones, keep it alive in difficult periods, and help the team members to gain new skills and interest in the topic of AI. Next, we identify shell characteristics as one the critical factors due to the ease-of-use and simplicity of the product. As explained, all complexities and potentially complex features of the software settings have been removed from the user, so no previous knowledge in AI or control system theory was needed to learn to use the ES. This allowed users to quickly gain confidence in the software, continue to use it and finally develop the needed solution in Case 2.

As secondary, but still very critical factors important for successful implementation of the ES we identify the following:

- Expert Characteristic
- User Involvement

In Expert Characteristics, we point out the quick response and domain knowledge of the ES supplier that helped to overcome certain difficulties in installation and maintained usage of the software. Related to this, users were heavily involved in the ES installation and process control development, and this created confidence in the system and most importantly, a sense of self-confidence.

In both Impact on Job and Management Support variables, we see a big difference between Case 1 and Case 2. However, in the specific case of the Mannersdorf plant, we will not place these variables as critical success factors, as the change appeared after the initial successful outcome of the implemented solution. Certainly, those factors helped enormously in further development of the ES, but it is fair to say that success would have come even earlier if there had been strong initial support from the management side.

Finally, we will reflect on the Modified DeLone and McLean IS Success model from section 2, and highlight one of the variables from this model, and that is “Use”, which is interrelated with all other constructs from that model. Indeed, in the case of the Mannersdorf plant initial success in Case 1 extended the use of the ES and allowed users to learn and gain experience in the ES. Further, use of the system allowed for the discovery of potential problems, correcting them along the way and improving ES reliability. This further improved User Satisfaction and Work Life Satisfaction as some new, interesting and modern engineering tasks were introduced into the user's daily routine. Finally, usage of the ES allowed users to discover its potentials and eventually create benefits.

5 Discussion And Conclusion

In the previous section, we have defined five variables as critical for the success of the ES implementation in the Mannersdorf plant. This conclusion represents the personal view of the author of this thesis, supported by exploratory research which gives potential direction for further analysis, and is arrived at based on personal observation of the ES implementation process in the Mannersdorf plant. We could summarize and say that an internally driven initiative, and a simple and effective product that matched important problems, were the main reasons for success. Therefore, it was not a structural process, coordinated from the corporate level and supported from all level of organization. We could be provocative and say that it was almost luck that specific domain-knowledge in the field of AI existed in the plant, together with the personal interest and desire to test new technologies. Certainly, these knowledge and skills do not feature in any job requirements or description for any of the positions in the plant, a situation specific to organizations so heavily oriented towards execution and efficiency. However, we will further elaborate on the conclusions within the framework of the study "Five Management Strategies for Getting the Most From AI" (2017), which summarizes the key success factors of AI projects based on the results of Bughin et al. (2017) before giving recommendations. These factors are:

1. Orientation on growth rather than on cost cutting.

2. Investment in talent, both managerial and technical.

3. Openness to the revision of the company's strategic goals: not only to protect what is already there, but also to design new business models and new products and services.

4. Relying on a solid digital basis (Data Governance).

5. Initiating, supporting and creating local AI ecosystems.

Certainly, problems that could be solved or areas improved should not be trivial ones, but rather, ones important for the organization and its specific business needs. In the case of the Mannersdorf plant we saw that it was not the potential cost cutting solution that was attractive, it was the one that was related to increasing production output as this was the burning need of this business unit. However, in other business units, and looking at the long term, the cement industry will always strive towards efficient and cost-effective production, so both cost cutting and growth solutions will be attractive and desirable. In any case, as already mentioned at the beginning of the thesis as one of the challenges, an AI strategy with clearly defined benefits must be defined.

Next, looking at the case of Mannersdorf, we believe that structural changes in talent management and skills requirement would be needed for the cement industry to benefit from rising new technologies such as Artificial Intelligence. Looking at the competitive market and overall need for these skills and talents, achieving these changes will certainly not be an easy task, especially for the cement industry as, in general, it is not an attractive workplace for the upcoming generations. However, the cement industry could develop and support an attractive ecosystem and use its strategical advantages to attract experts from the field, or at least extensively work with companies that have specific domain knowledge. The advantages of the industry are its size and complexity, the many unexplored areas where use of AI could be beneficial, a safe testing environment, the high potential impact of new solution and many others. Another option could be, as technology now allows this, to have a centrally located trained expert team that could monitor and control plants all around the globe from one central unit. Many benefits could be derived from this scenario, but many other organizational changes would have to happen before that. This brings us to another point which was also noted as a challenge. This is a cultural change in the sense that the company should open itself, revise its business models and overcome functional silos that constrain end-to-end deployment.

Also, the case of the Mannersdorf plant confirms the significance of having solid and reliable infrastructure when it comes to data collection and usage. Certainly, new types of sensors could add additional information that could be used for better control of production in the cement industry. However, to have effective Data Governance, it is important first to raise awareness of data importance among senior managers, and this will lead to further improvements.

To conclude, we believe that, as in the case of Mannersdorf, it is important to start to use systems available at a local level, specifically in cement plants, develop experience and knowledge and utilize and scale best practices on other production sites. However, this requires new skills and talents, a clear strategy and support coming from the senior management, openness to new business models and data driven governance.

6 BIBLIOGRAPHY

Casey, J., 1989. Picking the right expert system application. AI Expert, September, pp. 44–47.

Bughin, J. and Woetzel, J (2019). Navigating a world of disruption. McKinsey Global Institute. Retrieved from https://www.mckinsey.com/featured-insights/innovation-and-growth/navigating-a-world-of-disruption

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlstrom, P., et al. (2017). Artificial Intelligence. McKinsey Global Institute. Retrieved from https://www.mckinsey.com/~/media/McKinsey/Industries/Advanced%20Electronics/Our%20Insights/How%20artificial%20intelligence%20can%20deliver%20real%20value%20to%20companies/MGI-Artificial-Intelligence-Discussion-paper.ashx

Charalambous, E. Feldmann, R. Richter, G. Schmitz, (2019). AI in production: A game changer for manufacturers with heavy assets. Retrieved from https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/ai-in-production-a-game-changer-for-manufacturers-with-heavy-assets

Davis, FD. (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly 13(3), pp 318–346.

DeLone, WH. and McLean, ER. (1992) Information systems success: the quest for the dependent variable. Information Systems Research 3(1), 60–95.

DeLone, WH. and McLean, ER. (2003) The DeLone and McLean model of information systems success: a ten-year update. Journal of Management Information Systems 19(4),

DeLone, WH. and McLean, ER. (2008) Measuring information systems success: models, dimensions, measures, and interrelationships. European Journal of Information Systems (2008) 17, 236–263

DeLone, WH. and McLean, ER. (2016). Information Systems Success Measurement. Foundations and Trends in Information Systems, vol. 2, no. 1, pp. 1–116.

Barsanti, J.B., 1990. Expert systems: critical success factors for their implementation. Inform. Executive 3 (1), 30–34.

Beckman, T.J., 1991. Selecting expert-system applications. AI Expert, February, pp. 42–48.

Byrd, T.A., 1992. Implementation and use of expert systems in organizations: perceptions of knowledge engineers. J. Manage. Inform. Syst. 8 (4), 97–116.

Byrd, T.A., 1993. Expert systems: in production and operations management: results of a survey. Interfaces 23 (2), 118–129.

Encyclopedia Britannica, 2016. Expert system. Retrieved from https://www.britannica.com/technology/expert-system

Gable, Guy G. and Sedera, Darshana and Chan, Taizan (2008) Re-conceptualizing information system success: the IS-Impact Measurement Model. Journal of the Association for Information Systems, 9(7). pp. 377-408.

Guimaraes T, Yoon Y, O'Neal Q (1997) Exploring the factors associated with expert systems success. GESTÃO & PRODUÇÃO v.4, n.1, p. 8-36, abr. 1997

Fishbein M and Ajzen I (1975) Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. Addison-Wesley, Reading.

Guimaraes, T., Igbaria, M., Lu, M., 1992. Determinants of DSS success: an integrated model. Decision Sci. 23 (2), 409–430.

Harmon, P., Maus, R., Morrisey, W., 1988. Expert Systems Tools and Applications. Wiley, New York, NY.

Hayes-Roth, F., Jacobstein, N., 1994. The state of knowledge-based systems. Commun. ACM 37 (3), 27–39.

Heo, J., and Han, I. "Performance Measures of Information Systems (IS) in Evolving Computing Environments: An Empirical Investigation," Information & Management (1:4), 2002, pp. 1-14.

Ignizio, J.P., 1991. Introduction to Expert Systems. McGraw-Hill, New York, NY.

JIH, W.J.K.: "Comparing Knowledge-Based and Transaction Processing Systems Development," Journal of Systems Management, May 1990, pp. 23-28

Keyes, J., 1989b. Why Expert Systems Fail. AI Expert, November, pp. 50–53.

King, J. L., and Rodriguez, J. I. "Cost Benefit Analysis in Information Systems Development and Operations," Computing Surveys (10:1), 1978, pp. 19-34.

Kim, C., Yoon, Y., 1992. Selection of a good expert system shell for instructional purposes in business.Inform. Manage., forthcoming.

Kim, Y. J., Garrity J.E., Sanders G.E., 1996. Success Measures of Information Systems, pp.1 -2; Source: https://www.researchgate.net/publication/262369059

Laudon, K.C. and Laudon, J.P. Management Information Systems, (2nd edition), Macmillan, 1988. https://en.wikipedia.org/wiki/Information_system

Leavitt, H. J. (1964). Applied organization change in industry:structural, technical, and human approaches, In New Perspectivesin Organizational Research, pp. 55–71. Chichester: Wiley.

Leonard-Barton, D., 1987. The case for integrative innovation: an expert system at Digital. Sloan Manage. Rev. 29 (1), 7–19.

Leonard-Barton, D., Deschamps, I., 1988. Managerial influence in the implementation of new technology. Manage. Sci. 34 (10), 1252–1265.

Liang, P.L., 1986. Critical success factors of decision support systems: an experimental study. Database, Winter, pp. 3–15.

Liebowitz, J., 1989. Problem selection for expert systems development. In: Liebowitz, J., De Salvo, D.A. (Eds.), Structuring Expert Systems. Prentice-Hall, Englewood Cliffs, NJ, pp. 1–24.

Liebowitz, J., 1991. Institutionalizing Expert Systems: A Handbook for Managers. Prentice-Hall, Englewood Cliffs, NJ.

Liebowitz, J., 1993. The need for better educating prospective knowledge engineers on knowledge acquisition. J. Comput. Inform. Syst., Fall, pp. 37–40.

Leetham, D., 2015. The Cement Manufacturing Process. https://www.thermofisher.com/blog/mining/the-cement-manufacturing-process/

Lu, M., Guimaraes, T., 1988. A guide to selecting expert systems applications. Syst. Dev. Manage., 32-03-20, December 1988, pp. 1–11. Reprinted in J. Inform. Syst. Manage., Spring 1989, pp. 8–15. Reprinted in Expert Syst., Summer 1989.

Manyika, J., Bughin, J., 2018. The promise and challenge of the age of artificial intelligence. McKinsey Global Institute. Retrieved from https://www.mckinsey.com/featured-insights/artificial-intelligence/the-promise-and-challenge-of-the-age-of-artificial-intelligence

Matlin, G. "What Is the Value of Investment in Information Systems?" MIS Quarterly (3:3), 1979, pp. 5-34.

Mason, R. O. "Measuring Information Output: a Communication Systems Approach," Information & Management (1:5), 1978, pp. 219-234.

McCaffrey, R. 2018. How artificial intelligence will change the building industry. Global Cement Magazine. Retrieved from http://www.globalcement.com/magazine/the-last-word/1090-how-artificial-intelligence-will-change-the-building-industry),

Medsker, L., Liebowitz, J., 1994. Design and Development of Expert Systems and Neural Networks. Macmillan, New York, NY.

Mumford, E., MacDonald, W.B., 1989. XSEL's Progress: the Continuing Journey of an Expert System. Wiley, Chichester.

Myers, B. L., Kappelman, L. A., and Prybutok, V. R. A Comprehensive Model for Assessing the Quality and Productivity of the Information Systems Function: Toward a Theory for Information Systems Assessment, Idea Group Publishing, Hershey, PA, 1997.

MIT Sloan Management Review, Five Management Strategies for Getting the Most from AI. (2017, September 19). MIT Sloan Management Review, pp. 1–6. Retrieved from https://sloanreview.mit.edu/article/five-management-strategies-for-getting-themost-from-ai/

O'Neal, Q., 1990. Planning and managing successful KBS applications. Presented at IAKE.

Plant, R.T., Salinas, J.P., 1994. Expert systems shell benchmarks: the missing comparison factor. Information Manage. 27, 89–101.

Pitt Lf, Watson RT and Kavan CB (1995) Service quality: a measure of information systems effectiveness. MIS Quarterly 19(2), 173–187.

Prerau, D.S., 1990. Developing and Managing Expert Systems. Addison-Wesley Publishing, Reading, MA

Rolefson, J. F. "The DP Check-Up," Journal of System Management (29:11), 1978, pp. 38-48.

Sedera D, Gable G and Chan T (2004) A factor and structural equation analysis of the enterprise systems success measurement model. In Proceedings of the Twenty-Fifth International Conference on Information Systems (Appelgate L, Galliers R and Degross JI, Eds), p 449, Association for Information Systems, Washington, DC, USA.

Slagle, J.R., Wick, M.R., 1988. A method for evaluating candidate expert system applications. AI Mag., pp. 44–53.

Shannon, C. E., and Weaver, W. The Mathematical Theory of Communication, University of Illinois Press, Urbana, IL, 1949.

Smith, D.L., 1988. Implementing real world expert systems. AI Expert 3 (2), 51–57.

Tsang, E., 1993. Business process reengineering and why it requires business event analysis. CASE Trends, March, pp. 8–15.

Turban, E., 1992a. Expert Systems and Applied Artificial Intelligence. MacMillan, New York, NY.

Turban, E., 1992b. Why expert systems succeed and fail. In: Turban, E., Liebowitz (Eds.), Managing Expert Systems, pp. 2–13.

Tyran, C.K., George, J.F., 1993. The implementation of expert systems: a survey of successful implementation. Database, Winter, pp. 5–15.

Vedder, R.G., 1989. PC-based expert system shells: some desirable and less desirable characteristics. ExpertSyst. 6 (1), 28–42.

Vedder, R.G., Fortin, M.G., Lemmermann, S.A., Johnson, R.N., 1989. Five PC-based expert systems for business reference: an evaluation. Inform. Technol. Libraries, March, pp. 42–54.

Waterman, D.A., 1986. A Guide to Expert System. Addison-Wesley Publishing, Reading, MA.

Will, R.P., McQuaig, M.K., Hardway, D.E., 1994. Identifying long-term success issues of expert systems. Expert Sys. Appl. 7 _2., 272–279.

Yoon, Y., Guimaraes, T., 1995. Assessing expert systems impact on end-users' jobs. J. Manage. Inform. Syst., Fall, forthcoming.

Yoon, Y., Guimaraes, T., O'Neal, Q., 1995. Exploring the factors associated with expert systems success. MISQ. 19 (1), 83–106.

Yoon Y., Guimaraes, T., Clevenson, A., 1998. Exploring expert system success factors for business process reengineering. J. Eng. Technol. Manage. 15 (1998). 179–199

APPENDIX A QUESTIONNAIRE FOR YOON'S ES SUCCESS MODEL

Hypothesis Number	Independent variable	Measure Component Items	Cement Fineness Control	Mill feed Control
		1 - very low, 2- below average, 3 - average, 4 - above average, 5 - very high		
H1	Problem Difficulty	Problem size (# of variables)	5	4
		Complexity	5	4
		Variable Interdependence	5	4
		Expertise needed	5	5
		Input uncertainty	4	1
		Instability of domain	4	3
		Degeee of problem Structure	5	4
		AVG	4.71	3.57
H2	Developer Skill	People - communication and interpersonal skills	4	4
		Models - ability to formulate and solve models	4	4
		Systems - ability to view and define a situation as a system-specifying components	4	4
		Computers Skills	3	3
		Organizational skills	4	4
		Society skills - ability to articulate and defend a personal position on important issues	3	3
		AVG	3.67	3.67
H3	End-User Characteristics	Positive Attitude on ES	3	3
		Expectations	3	4
		Computer/AI knowledge	3	3
		AVG	3.00	3.33
H4	Impact on Job	Increase importance of users job	2	5
		Decrease amount of work required	3	3
		Decrease accuracy demanded	3	3
		Increase skills needed	4	5
		Increase job appeal	3	5
		Increase feedback on job performance	2	5
		Increase freedom in how to do job	2	4
		Increase opportunity for advancement	2	4
		Increase job security	2	4
		Increase relationship with peers	3	4
		Increase in job satisfaction	3	5
		AVG	2.64	4.27

H5	Expert Characteristics	Communication skills	4	4
		Cooperation	5	5
		Availability	5	5
		Computers/AI background	5	5
		AVG	4.75	4.75
H6	Shell Characteristics	Flexibility in knowledge representation & inference engine	4	4
		Developer interface	4	4
		End-User interface	4	4
		System interface	4	4
		Portability (different platforms)	4	4
		Easy to use	5	5
		Easy to learn	5	5
		Training & vendor support	5	5
		Response time	5	5
		Appropriate to problem	4	5
		Flexibility in knowledge representation	4	4
		AVG	4.36	4.45
H7	User Involvement	Initiating the project	5	5
		Establishing project objective	4	4
		Determining user requirements	4	4
		Determining ways to meet requirements	5	5
		Identifying sources of data/information	5	5
		Outlining information flow	4	4
		Developing input forms/screens	3	3
		Developing output forms/screens	3	3
		Determining systems availability/access	3	3
		Initiating the project	4	5
		AVG	4	4.1
H8	Management Support	Understanding ES potential benefits	2	5
		Management encouragement to use ES	1	5
		Have necessary help/resources	2	5
		Management interest in end-user satisfaction	3	3
		AVG	2	4.5