FAIL NO MORE IN INDUSTRIAL AUTOMATION INVESTMENT!

A novel technology success indicator model

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ABSTRACT

The research question of this study is how company management can make better decisions when deciding on industrial automation investments. The objective of the study is to create a general, global and structured technology success indicator model for companies that evaluate investments in industrial automation. The model takes a comprehensive approach by analysing the company, the technology, and the social environment in question. The model entails a technology readiness index and combinations of success factors that decision makers can utilize. The emphasis is on discrete manufacturing operations. Only the very newest technologies are analysed, with the anticipation that the results will be applicable into the 2020s.

This study describes the needs for a novel technology success indicator model. The current rapidly changing production environment is analysed from the technological perspective in order to build a conceptual foundation for the technology success indicator model. The technology success indicator model is developed and hypotheses to be tested in the empirical stage of the research project are presented.

Key words: Technology success indicator model; technology investment; success factor; robotics; 5G wireless technology; discrete manufacturing

INTRODUCTION

Background

Discrete manufacturing is now facing fundamental changes due to technological development in the field. Consequently, managers more often need to decide whether to invest in automation to improve their company’s performance. Traditional motives for automation investment have been to achieve cost-effective manufacturing processes and automate the processes that can potentially cause danger to employees (Windmark, et al., 2012). The decisions have been trade-offs between the level of automation, labour costs and flexibility. A high level of automation has been considered to require large capital investments in equipment and in control system, but it delivers homogenous product quality and improves productivity. Traditionally, a high level of automation has been considered feasible mainly in a high volume discrete production with a low level of flexibility. Similarly, a low level of automation has been considered to require smaller capital investments in equipment but to cause more labour costs. Manual work is considered to result in quality variations but can typically be considered to be relatively flexible for production changes.

Modern industrial robots used in manufacturing are making a global breakthrough. This phenomenon is called "robotization", and it is a vital part of the industrial evolution. The emergence of fifth-generation mobile network (5G) technology enables wireless, real-time communication between field devices and Edge stations, offering large data download speeds. Robotization together with modern 5G technology and with cloud-based Internet of Things services will make significant improvements to industrial productivity and flexibility and the competitiveness of industrial companies in specified industries. The Internet of Things will transform business processes by providing more accurate and real-time visibility into the flow of materials and products (Lee & Lee, 2015). Augmented reality is entering the industrial environment (Kolberg & Zühlke, 2015).

The nature of traditional work is changing, and man–machine collaboration is a natural step in this development. Robots bring increased productivity to businesses in the manufacturing industry, and so enable continued competitiveness. It seems that market behaviour is driving industries to produce smaller series faster than ever. Market requirements are forcing production lines and robot cells to be easy to use and flexible enough to enable rapid product changes. Products are designed for automated production. In the future, flexible and robotized micro-factories will be born.

Discrete manufacturing and the construction industry are facing game-changing new technologies in terms of the utilization of robots and large 3D printers (Zavadskas, 2010). The traditional reputation of these industries of being labour-oriented and slow-developing businesses is likely to change so that production cells will be movable, production is done by modern robots in collaboration with humans, and all devices communicate wirelessly. Production is becoming more flexible than ever, based on market needs. Robotized production cells are able accommodate to the needs of a large range of different products, as robots are reprogrammable and becoming mobile. Economies of scale still exist in some instances, but new robotized production will enable flexible micro-factories to compete in the market.

The over-all picture of the automation environment in discrete manufacturing is likely to change fundamentally due to the ongoing rapid technological development. Decision makers need to understand the technological benefits and requirements of needed competences in the changing environment.

Managers need new tools to support decision making concerning automation investments.

Theoretical frame and the research gap

The extant literature does not offer an applicable investment model for companies that are engaging in investments in new technologies. Martin (2015) has studied how traditional Key Performance Indicators (KPI) can be used to evaluate automation investments in static production environments. Sanders, Elangeswaran & Wulfsberg (2016), and Kolberg & Zühlke (2015) have investigated automated production from the perspective of optimizing entire value chains. Wagels & Schmitt (2012) have researched self-optimizing production in manufacturing industry. Schuh, Reuter, Haupthvogel & Dölle (2015) in their studies of automation investments have emphasized productivity improvements. Lindström & Winroth (2010) have analysed automation investment as part of manufacturing strategy; and Windmark, Gabrielson, Andersson & Ståhl (2012) have researched different cost models to determine an optimal level of automation.

Different kinds of technology readiness models and technology maturity models exist in the literature. A general technology readiness model aims to assess the functional maturity of a certain technology. A technology Readiness Level (TRL) model introduced by National Aeronautics and Space Administration (NASA) in the mid-1970s and its further developments in 1995, were developed to allow more effective assessment of various technologies and to assist in communicating the status of new technologies under development among organizations (Mankins, 2009). Maturity models are used as an instrument to conceptualize and measure the state of maturity of a company in a certain context, for example, when adopting certain technologies. Both terms - technology readiness models and technology maturity models - are widely applied in research studies and they are not mutually exclusive.

Charalambous, Fletcher & Webb (2017) applied the previously mentioned NASA model in their research focusing on the development of the Human Factors Readiness Level tool in the context of automation investment. This research study pointed out that it is crucial to integrate human resources into the process when implementing industrial human-robot collaboration and automation. Schumacher, Erol & Sihn (2016) have introduced a conceptual model that manufacturing companies can use to assess their Industry 4.0 maturity. The model includes nine dimensions focusing on basic enablers (Products, Customers, Operations, Technology) and organizational aspects (Strategy, Leadership, Governance, Culture, People). The maturity assessment follows a three-step procedure: measuring, determining and representing the company maturity results. The model aims to capture the company's current state of technology maturity. The model gives a static picture of the situation.

The present study will combine the approach of building a technology readiness model and of building a technology maturity model. The study combines applicable parts of both approaches. The present study also aims to develop a model that contrary to the existing models is dynamic. The comprehensive approach and the dynamic nature of the new model offer a novel view to research on automation investment. The research gap stems from the fact that the implications of emerging modern technologies, especially wireless technologies and modern industrial robots, are not well understood.

Objective of the study

The objective of this study is to create a general, global and structured technology success indicator model for companies that are evaluating investments in industrial automation. The model will benefit companies in investment planning, as it will function as a high-level guideline for successful investment. It also provides an understanding of measures to be taken in order to improve productivity, and an understanding of a company’s ability to adapt to technological change. The study focuses on companies in discrete manufacturing.

RESEARCH DESIGN

Sample and data

This study is at its initial stages. A broad literature study and extensive interviews among representatives of company management will be conducted. Case studies will be made among individual companies. Quantitative data from fifty companies will be gathered. The model will be further developed based on the research findings in an iterative process.

Conceptual framework of and variables in the technology success indicator model

The model consists of four dimensions. The dimensions are built on factors describing the characteristics of the technology success indicator model in each level. The conceptual framework underlying the technology success indicator model suggests that a certain readiness level in each dimension needs to be fulfilled in order to move to a higher level. A higher level in the model suggests improved productivity and quality, and improved production flexibility. The developed model is dynamic as it takes into account continuous technological advancement and corresponding human resource competencies. It also provides a guideline to companies in understanding how to improve productivity by adopting new technologies.

Production environment

The production environment is the foundation of production performance, and it has a significant impact on productivity. The production environment dimension describes the development phase of production on the factory floor. At a very basic level, the production is done manually without the external help of any machines. In a semi-automatic environment, humans operate standalone machines or production lines, and affect the production extensively with their own actions. Automatized production represents a further developed environment in which the production is done either by an automatized manipulator line or by a robotized line. Humans perform the production starts and stops, and assist the production line when needed. The production line is typically programmed to inform operators if something unexpected occurs during the production and it is able to stop automatically in such situations. An autonomous environment represents the most developed production environment in this study. In an autonomous environment, the entire production is done fully by machines. Machines communicate with each other in order to optimize the production, and the whole value chain is digitalized.

The production environment part in this research also includes production planning systems. Production planning systems have an impact on overall productivity and the fluency of production due to material, resource and manufacturing planning characteristics. The production environment generally describes the level of automation in production.

Key technologies

The key technologies dimension consists of the technological equipment used in production. Selected technological equipment is in a key role in the technology success indicator model due to its comprehensive role in the production environment. Robots utilized in discrete industries are industrial robots. Industrial robots consist of several types of robots with different designs and technical features. The robots mainly utilized are articulated robots, but several other types exist as well. Collaborative robots, Selective Compliance Assembly Robot Arms (SCARA), picker robots, gantry robots or mobile robots are also utilized in discrete industries. The robot itself needs programming, tools and tool exchangers in order to take part in production. Attention is also paid to the robot and application simulations that enable analysing the production cycle times and work envelopes prior to commissioning.

Control systems control the production equipment. At a very basic level, a human being controls the individual machines. In more developed production systems, automation takes over the human in decision making. Programmable Logic Controllers (PLC) are frequently used to control either a single machine, a production cell or a complete production line. Control can be either centralized or distributed and it follows the program coded by a human in order to execute a desired task or function. In state-of-the-art systems, field equipment is intelligent, and it can make individual decisions based on received data to improve the production output.

Connectivity has traditionally been hardwired in automation. This means that every single input or output (I/O) signal between field devices and control logic have required a physical medium for information exchange. The fifth-generation of mobile networks makes a significant improvement on data download speed thus enabling control, such as PLC functionality, to be executed on an Edge device. In other words, all input and output signals can be transferred from field devices to control a device wirelessly without latency on data delivery. This enables movable field devices, and so increases the degree of freedom in a dynamic production line set-up.

Augmented reality (AR) and Virtual Reality (VR) technologies are entering the industrial environment. Augmented reality means integration of digital information with the user's environment in real time and its first industrial applications are already in use. For example, augmented reality enables digitally guiding the production personnel wearing special augmented reality glasses to receive real time instructions on how to make a product assembly, or on how to recover the production line after a production interruption. Virtual reality technology is a bit more advanced in industrial automation. It is utilized, for example, in production line simulations, and in training. Virtual reality technology plays an important role prior to automation investments. The more detailed the automation environment is simulated, the better its future production output can be predicted.

Platforms, from a technological perspective, require a combination of multiple software and hardware components in a multilayer stack of Internet of Things (IoT) technologies. The stack is usually built of three layers: the thing or device layer, the connectivity layer and the Internet of Things cloud layer. Within the context of Internet of Things, platforms are essentially software products. In an industrial automation environment, the field device software is embedded in the things layer or the device layer. The connectivity layer manages communication between the device and the Internet of Things cloud, and the Internet of Things layer contains analytics and process management, an application platform and the Internet of Things application software. Information security software can be stored in the Internet of Things cloud. (Wortmann & Flüchter, 2015)

Human resources

Depending on the production environment and on the level of automation, the required skills and competences of human resources vary. This is a crucial point to understand when investing in automation that matches the in-house skills or externally available skills and competences with the level of applied technology. The competences are not only important when recruiting new employees but they are something to be taken as a continuous development process to meet a higher level of production and productivity. Human resources in production are also to be acknowledged already in the investment designing phase of automation, especially in brown-field projects, in order to reduce the inertia against new automation and in order to have hands-on, detailed information about the process to be automatized.

Outcome measures

Outcome measures are the results of the selected production environment, key technologies used, and human resources. Manual production can be seen as agile in terms of production changes. Drawbacks are variation of quality and low productivity due to the limitations of human beings. Consistent quality can be improved by adding automation to production, however simultaneously causing a decrease in agility. Automation requires capital investments and, as a result, it improves the level of production output and decreases quality variations. Wireless communication between field devices and Edge devices, and mobile robots that are able to move from a workstation to another, enable unforeseen flexibility and agility in production.

Success factors and a company's ability to adapt to technological changes

General success factors to make successful automation investments are produced as a result of this study. The study not only lists these factors but also models a company's ability to adapt to technological change.

Table 1: Variables in the technology success indicator model

Dimension	Variable	Values of variable
Production environment	Production type	Manual, semi-automatic, automatic, autonomous production
	Production planning system	Manufacturing Resource Planning, Enterprise Resource Planning, Manufacturing Execution System
	Level of automation	Low, moderate, high
Key technologies	Robots	Articulated,

		collaborative, Selective Compliance Assembly Robot Arm, picker, gantry, mobile robots
	Control system	Centralized, distributed, Programmable Control Logic, Personal Computer, field devices
	Connectivity	Hard wired, wireless
	Assisting technologies	Augmented Reality, Virtual Reality
	Platforms	Open, closed, open to internal users, open to the public
Human resources	Education level (In-house employees). Operator, Programmable Logic Controller and robot programmer, maintenance person, designer, simulation model builder, electrical engineer, operations manager, production manager	No education, primary school, vocational examination, matriculation examination, bachelor degree, master degree, postgraduate degree
	Relevant work experience in years (In-house employees). Operator, Programmable Logic Controller and robot programmer, maintenance person, designer, simulation model builder, operations manager, production manager	0, 1, 2, 5, 10, 15 or more years
	Education level (System integrator). Mechanical designer, Programmable Logic Controller and robot programmer, electrical designer, commissioning technician, system designer, simulation model builder, IT architect	No education, primary school, vocational examination, matriculation examination, bachelor’s degree, master’s degree, postgraduate degree
	Relevant work experience in years (System integrator). Mechanical designer, Programmable	0, 1, 2, 5, 10, 15 or more years

	Logic Controller and robot programmer, electrical designer, commissioning technician, system designer, simulation model builder, IT architect	
	Personnel competence development	Disorganized, organized
	Change management process	Disorganized, organized
	Management role in the automation investment process	No involvement, weak, moderate, strong
Outcome measures	Production quality	Instable, stable
	Productivity	Decreased, constant, increase
	Production agility	Decreased, constant, increase

The concept of the technology success indicator model

The technology success indicator model is illustrated in figure 1 below. The model produces a technology readiness index that is a combination of two major factors: the success factors for automation investment and a company's ability to adapt to technological change. The success factors define the potential investments and technological readiness level planned to be used in production. The ability to adapt to technological change factor describes how well a company can utilize new technologies. The technology success indicator model describes how well a company can benefit from the potential of the technology that the company plans to invest into.

The model has four dimensions: Production Environment, Key Technologies, Human Resources and Outcome Measures. The idea is that a company needs to fulfil certain requirements specific to a certain readiness level in order to move to a higher level. The higher the level is, the higher the company's technology readiness index and potential productivity. The model considers a company's ability to adapt to technological change as a latent factor that is present in its every dimension and affects the overall success in automation investment. The number of the levels is dynamic, and it can be extended if new technologies are introduced. This study will define the readiness levels and their corresponding success factors in each dimension for specified technologies, and will quantify measures for a company's ability to adapt to technological change.

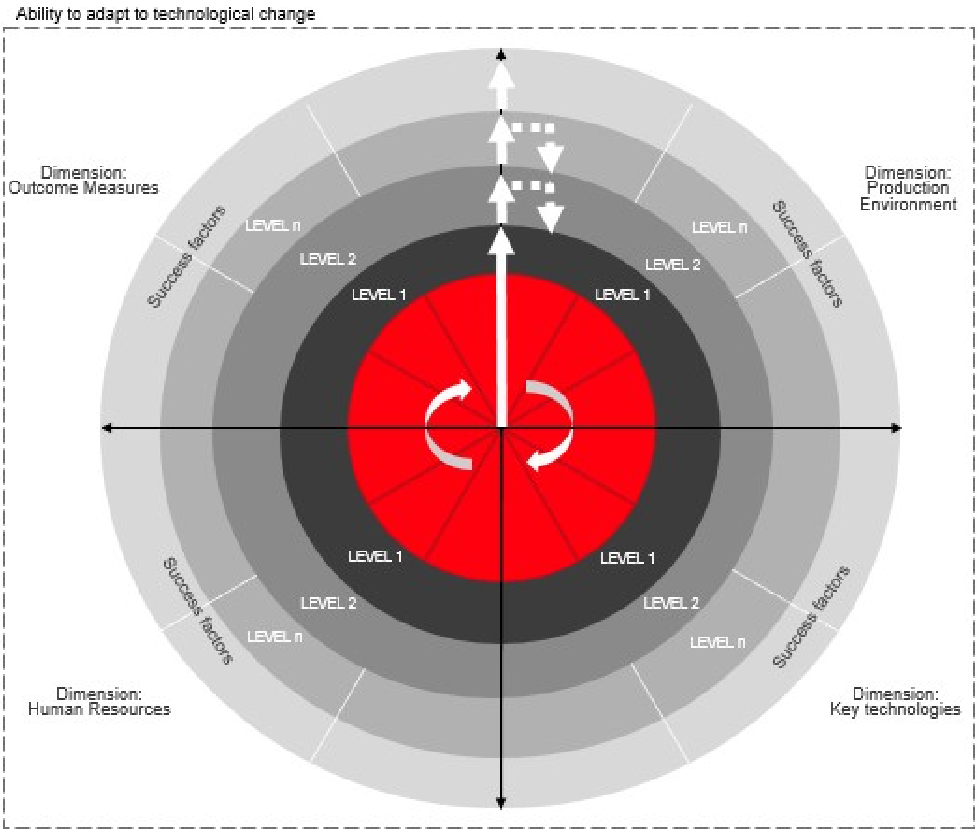

Figure 1: Underlying concept of the technology success indicator model.

The model structure allows weight changes between the dimensions. The bigger the weight of a certain dimension is within a certain level, the more significant that dimension is in the model. The relative weights between the different dimensions can be different between the levels. The model also acknowledges the possibility that not all dimensions have exactly the same importance in the technology readiness index. The model structure allows disruptive technologies to enter the market. These technologies have the potential to make significant improvements on productivity as such. The model's technology readiness index is not derived only based on one dimension and that is why the model also works in situations in which for example disruptive technologies are in use. Disruptive technologies only together with sufficient ability to adapt to technological change enable a company to make a leap over more than one level in the model.

The technology success indicator model is dynamic. A company's technology readiness index can vary over time. The model suggests that a company can reap the full benefit of an automation investment only if it has an efficient automation investment process and a well-structured process for adapting to technological change.

The empirical part of this study will provide values for the technology success indicator model. The relative weights of the success factors will be defined. A company's ability to adapt to the technological change factor will be quantified and the number of readiness levels will be defined. The technology success indicator model will be tested with case companies.

Hypotheses

The hypotheses to be tested in the empirical stage of the study are presented below.

Hypothesis 1: Companies that invest in automation improve productivity.

Hypothesis 2: Companies that have a higher level of automation are more successful in competition.

Hypothesis 3: Companies that are continuously developing their employees are better at adapting to new technologies.

Hypothesis 4: A company's ability to adapt to technological changes improves competitiveness.

Hypothesis 5: The higher the company's technology readiness level is, the higher their productivity.

Hypothesis 6: The higher the number of robots in production is, the higher company's productivity.

Implications of the technology success indicator model

This study will make a balanced contribution to both company management and to the academia. The results of the study will help company management in investment planning, as it would function as a high-level guideline for successful investment. Risks that are inherent to technology investments will be reduced, possibilities to gain competitive advantage will be enhanced, and the potential to reach higher productivity due to an automation investment will be increased.

The lack of a comprehensive quantitative investment model for technology forms a clear research gap. This present study offers access to the leading companies that are deploying automation and robotics, and so offers a unique population to be researched. The findings deliver information on novel technologies to the academia from an investment perspective.

CONCLUSION

This study has described the rapid technological development in discrete manufacturing and has introduced the need for a novel technology success indicator model that can be used when making successful automation investments with 2020s technologies. The introduced model presents the technology readiness index that is a unique outcome of technological success factors and a latent factor describing a company's ability to adapt to technological change. The introduced model is dynamic and extendable. The variables in the technology success indicator model have been introduced. Hypotheses to be tested in the empirical stage of the study have been presented. The introduced model helps company managers to make better automation investments, and the academia to better analyse automation investments.

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