Process-aware Decision Support Model for Integrating Internet of Things Applications using AHP

Christoph Stoiber and Stefan Schönig
University of Regensburg, Germany

Keywords: Internet of Things, Decision Model, Business Process Improvement, Analytical Hierarchy Process.

Abstract: Following the trend of Industry 4.0 and Cyber-Physical Systems (CPS), many industrial companies perform costly projects to integrate Internet of Things (IoT) applications aiming at beneficial business process improvements. However, deciding on the right IoT projects is challenging and often based on unilateral assessments that lack the required profoundness. A suitable method for deciding on specific IoT applications is required that incorporates the desired goals and considers the underlying process details. We therefore propose a structured decision model that considers IoT application clusters, anticipated Business Process Improvement (BPI) goals, and details of the process where the application should be implemented. At first, specific IoT application clusters are developed by conducting an extensive literature review. These clusters are examined regarding several characteristic such as their value proposition or technical aspects. Using this information, an Analytical Hierarchy Process (AHP) model is proposed, that incorporates the main objective, relevant BPI dimensions, and the formulated application clusters. To validate our approach, we applied the model to an actual business process of a leading industrial company.

1 INTRODUCTION

With more than 34 billion IoT devices, the number has more than tripled from 2012 to the year 2018 (Burhan, 2018). And although IoT is anticipated to have massive benefits for companies, a survey of more than 500 business executives revealed, that 90% of organizations are remaining in the proof of concept or even early-stage planning phases for IoT projects (Bosche, 2016). This lack of IoT application maturity can be explained by the complexity of IoT technologies and the extent of included components. This complexity is the reason that adopting IoT technologies is quite different compared to adopting other technologies, which leads to a scarcity of decision models and procedures that support a proper selection of suitable IoT applications (Boos, 2013). This challenge will be addressed within the text at hand, by proposing a structured decision model for selecting IoT applications. To determine an appropriate decision basis, it is necessary to be aware, that most companies highly focus on Business Process Orientation (BPO), as this paradigm resulted in significant positive impacts for adopting enterprises (Willaert, 2007). Therefore, a major part of the value generated by IoT applications is based on Business Process Improvements (BPI) and its core performance measures cost, quality, time, and flexibility (Dumas, 2018). Incorporating the underlying process is increasingly considered as an important preliminary for IoT applications. Janiesch et al. (2017) stated process-aware integration of IoT applications as one of the main challenges for companies initiating IoT projects. In addition, while analyzing existing decision support models, it became apparent, that a decision model must be goal-oriented and incorporate best-practice experiences of already implemented applications to find high acceptance among decision makers in companies (Bradley, 2013). As there have already been hundreds of industry-related and domain-specific IoT applications successfully implemented, they should be analyzed and aggregated to serve as blueprints for further applications. These applications can be allocated into distinct clusters according to their main constituents such as the used technologies, their value propositions, and other attributes described in subsection 2.2. This structured clustering can then be used within a quantitative and goal-oriented model to create a priority for possible IoT projects.

To the best of the authors' knowledge, there has been no research that addressed a structured decision

Stoiber, C. and Schönig, S.
Process-aware Decision Support Model for Integrating Internet of Things Applications using AHP.
DOI: 10.5220/0010400208690876
In *Proceedings of the 23rd International Conference on Enterprise Information Systems (ICEIS 2021) - Volume 1*, pages 869-876
ISBN: 978-989-758-509-8

model for integrating IoT applications, which also considered actual IoT application clusters and anticipated process improvement goals. Existing approaches either focus on on key learnings from other industrial use cases (Bradley, 2013) or suggest frameworks to build up an IoT strategy, which is derived from the company's major business goals (Li, 2012). The work at hand closes this research gap by providing a decision model, that includes two main contributions, *i)* an extensive literature analysis and synthesis of sucessfully implemented IoT applications including a systematic clustering, and *ii)* a decision model based on the Analytical Hierarchy Process (AHP), that supports companies to prioritize relevant application clusters according to their potentials for business process improvement. The model can be used to investigate potential IoT applications for a specific process or a set of related processes. The paper is organized as follows. Section 2 presents the rigorous literature review on IoT applications as well as a clustering. In section 3, the AHP model and its constituents are addressed. After developing an AHP instance for the relevant topic, it is evaluated in section 4, based on an actual process. Section 5 summarizes the contribution and formulates a future research agenda.

2 IoT APPLICATION REVIEW

The methodology to survey the state of research is a structured procedure proposed by vom Brocke et al. (2009). The literature search itself was conducted according to the Preferred Items for SLRs and Meta-Analysis (PRISMA) statement, which improves the traceability of the actual search process (Liberati, 2009).

2.1 Literature Search

Figure 1 shows the results of the literature search within a PRISMA flow diagram. The method gradually reduces the number of publications by assessing the eligibility using predefined criteria.

At first the search string *("IoT" OR "CPS") AND ("BPI" OR "Process Improvement" OR "Process Optimi?ation" OR "Process Automation" OR "Application" OR "Process Improvement")* as well as the written-out forms have been formulated. To incorporate and consider preferably all relevant journals and conference proceedings of the research area, ACM Direct Library, AISeL, IEEE Xplore, ScienceDirect, Scopus, and Springer Link have been queried. According to the PRISMA statement, four criteria were defined that a paper needs to achieve to be eligible for this review. The publication must *i)* be a peer-reviewed research paper published in a journal or conference proceeding, *ii)* propose an evaluated solution or real industry application, *iii)* have relevant links to BPI or BPM, and *iv)* be relevant and up to date. As criteria *ii)* and *iii)* are assessed in a rather qualitative manner, criterion *iv)* is defined as a publication date after 2015 and a minimum number of 50 citations. However, if a publication is assessed as highly relevant, the violation of these quantitative criteria is tolerated. A high degree of relevance is given, when a publication was published in a top journal and offers a contribution that cannot be obtained from other eligible publications.

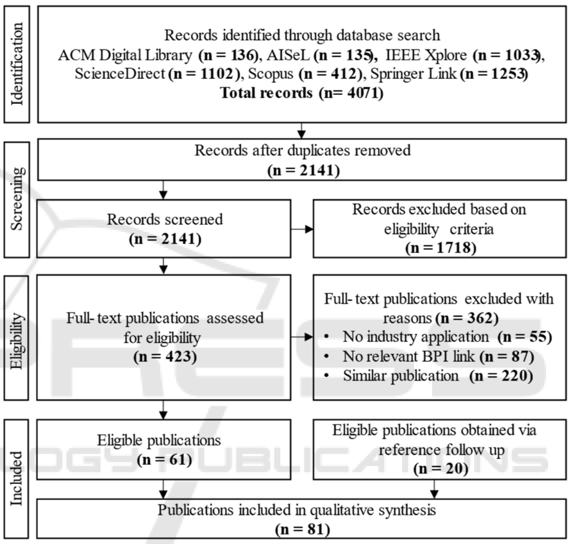

Figure 1: PRISMA Flow Diagram.

Considering criteria *i)* and *iv)*, 1718 records were removed because of a publication date before 2015, low number of citations, or the lack of a peer-review. Eventually, 423 publications were assessed for eligibility based on their abstracts and, if relevant, full texts. Among them, 55 articles did not describe an actual industry solution that can be used for further analysis. Another 87 publications had no specific link to BPI or did not offer any process orientation at all, and 220 articles mentioned a use-case that is remarkably similar to at least another one under consideration. In total, 81 publications were assessed to be eligible including 20 articles obtained from reference follow up.

2.2 Cluster Analysis

After the literature search and selection, a two-step literature analysis framework is applied to derive insights and eventually identify clusters within the set of publications. At first, the publications are categorized in a concept matrix according to Webster and Watson (2002), which gives a first overview of central issues of the contributions. Secondly, a cluster analysis is performed by applying a Multiple Correspondence Analysis (MCA) and a Hierarchical Clustering on Principal Components (HCPC). To categorize all publications according to their main attributes, a concept matrix with five dimensions and 23 subdimensions has been created. The dimensions correspond to concepts for classifying the publications and consist of further subdimensions.

According to Bloom et al. (2018), IoT systems can be fundamentally divided into four areas of application, maintenance, process control, supply chain, and infrastructure.

Table 1: Concept Matrix.

Reference	Dimensions	Subdimensions	Rel. Freq.
Bloom et al. (2018)	Application Area	Maintenance	13%
		Process Control	58%
		Supply Chain	26%
		Infrastructure	3%
Kortuem et al. (2010)	Smart Thing Type	Process-aware	32%
		Policy-aware	24%
		Activity-aware	45%
Tschofenig et al. (2015)	Communication	Backend-Data Sharing	11%
		Device-to-Gateway	55%
		Device-to-Cloud	34%
		Device-to-Device	11%
Patterson (2017)	Human Involvement	Full Automation	3%
		Action Implementation	21%
		Decision Selection	24%
		Information Analysis	42%
		Information Acquisition	11%
Tai Angus Lai et al. (2018)	Value Creation	Complex Auton. Systems	8%
		Inf. Sharing & Collaboration	34%
		Opt. Resource Consumption	21%
		Automation	45%
		Decision-Making Support	45%
		Situational Awareness	50%
		Tracking and Monitoring	39%

Kortuem et al. (2010) have identified three different types of smart things, that reflect basic design and architectural principles. Activity-aware things understand events and activities, policy-aware things can reflect, whether activities and events are compliant with organizational policies, and process-aware things can place activities and events in the context of processes. IoT systems can consist of small local networks up to global networks, while different network architectures are used. The Internet Architecture Board (IAB) has proposed four possible models, in which IoT devices can be networked (Tschofenig, 2015). Patterson (2017) described another categorization dimension, the type of human involvement to classify the degree of automation. The last dimension represents the type of value creation that is provided by the IoT application. Tai Angus Lai et al. (2018) identified eight different areas of value creation by IoT, which serve as subdimensions for the concept matrix. The 81 eligible publications were then categorized according to at least one subdimension of each dimension. The rightmost column of Table 1 shows the relative frequency of the specific subdimension for all analyzed publications. The MCA has then been used as a preprocessing to transform the categorical binary variables from the concept matrix into continuous ones, that are then used within an HCPC to find distinct clusters in the data set, see Figure 2.

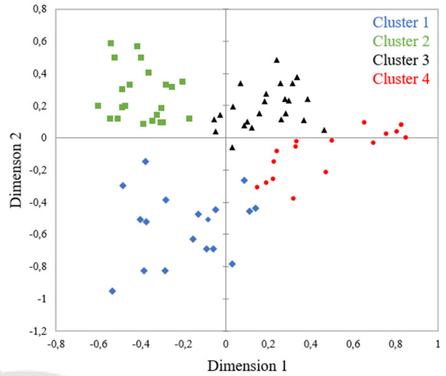

Figure 2: MCA Factor Map.

The data is plotted in a two-dimensional space depending on their similarity to each other. The greater the distance between the individual data points, the more different the items are in relation to the dimensions of the concept matrix.

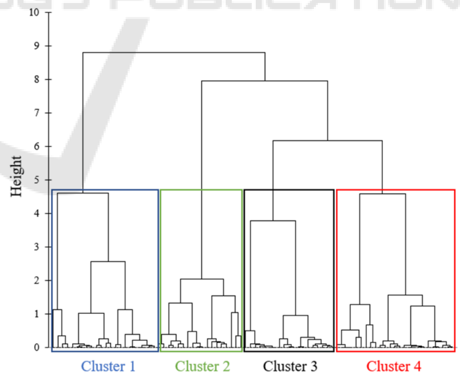

Figure 3: Dendrogram of Cluster Analysis.

The clusters have been created using the HCPC and are visualized by different colours and data point shapes. The results analysis has shown that optimally four clusters can be formed. Another form of visualizing the HCPC results is the dendrogram shown in Figure 3. Here, the different distributions of each cluster are shown in the form of exactly two branches per level. The higher the tree, the higher is the variance between the included publications.

Based on this analysis, the publications of each cluster have been examined again to investigate similarities and interpret them. The results are described in the following subsections.

2.2.1 Improved Information Exchange

The first cluster comprises 20 applications, in which the IoT systems serve to collect information about the process flow and the process environment. The smart devices used for this cluster are mostly process-aware and connected to the cloud via gateway. The gateway only serves to forward data, while the analysis takes entirely place in the cloud. The IoT devices perform a context-sensitive communication and interaction between several process entities such as machines or employees. Due to the strong involvement of people in the process, the benefits of IoT systems is not automation but improved communication and coordination of information, e.g., by using wearables. Schönig et al. (2020) for example described a production process in a cardboard factory and an improved information exchange and visualization using IoT sensors and smartwatches. Moreover, König et al. (2019) illustrated the training of new employees in a manufacturing company with the help of smart devices.

2.2.2 Tracking and Tracing

Cluster 2 comprises 22 publications including IoT systems for mainly tracking and monitoring solutions using simple activity-aware devices, such as RFID tags. The sensed data is mostly sent to a cloud for further processing and provision of IoT services. One focus is process improvement along the supply chain, in which the continuous tracking of the involved resources is particularly important. Chang et al. (2019) describe a smart container for transporting chemical waste products, so it can independently send transport information to a cloud. Other publications show applications in the manufacturing industry that enable location monitoring of products and machines (Valente, 2017) or unique identification using RFID (Rasmussen, 2019). These applications provide an improved transparency and therefore better process quality, since a permanent traceability is guaranteed.

2.2.3 Faster Reaction to External Influences

Cluster 3 comprises 23 case studies, focussing on identifying environmental factors and responding to changes in a rapid way. The used smart things are mostly policy-aware and can independently detect deviations from predefined process rules. As soon as these rules are violated, the things can trigger signals which cause further reactions. Data processing is often performed using cloud services or edge computing. Ammirato et al. (2019) introduced an IoT application to improve the security measures of a bank. With the help of cameras and hybrid data processing or image analysis in real time, threats can be detected automatically at an early stage to initiate countermeasures. Other applications based in the agricultural industry comprise systems that measure the environmental parameters of fields, such as moisture, and can initiate appropriate actions, if necessary (Celestrini, 2019).

2.2.4 Flexible Automated Systems

The last cluster comprises 16 case studies, which are further scattered on the factor map. These applications include more complex IoT systems than those comprised in the other clusters. Li et al. (2017) describe a completely autonomous system in which the production materials can automatically communicate with the equipment and transporting machines to plan and schedule the production. In the case study of Nikolakis et al. (2020), a set of robots and humans can handle production material and are both connected to a mutual network. By performing the production planning and scheduling in a cloud, the work steps can be planned when a new material arrives, and appropriate instructions can be sent to the robots or smart devices used by human. Also, retrofitting and automating machines can be a major step towards flexible process automation and IoT-guided process execution (Murar, 2014).

3 DESIGNING THE AHP MODEL

3.1 AHP Setup

The AHP has been introduced as a theoretical modelling technique for complex decision making (Saaty, 1990). The user designs a multi-layer decision tree including the main objective, relevant criteria that affect the decision, and possible alternatives. Subsequently, expert surveys are performed to collect numerical data for every model layer. The criteria are pairwise compared against each other regarding their importance for achieving the objective. In the same way, all alternatives are pairwise compared against each other for every single criterion. Consequently, the comparison data is processed to get a priority of importance for each alternative.

3.2 Design of Decision Tree

The first step of the AHP is to design the decision tree by defining the decision problem and its objective, decision criteria, and potential alternatives. In the following, these three layers will be specified for our model instance. The AHP model addressed in this paper focuses on prioritizing potential alternatives that may improve the underlying process. The top layer of the AHP therefore is BPI as the main objective. The second layer consist of respective decision criteria, that influence the degree of objective achievement. Popular Process Performance Measures (PPMs) related to BPI are time, cost, flexibility, and quality (Dumas, 2018).

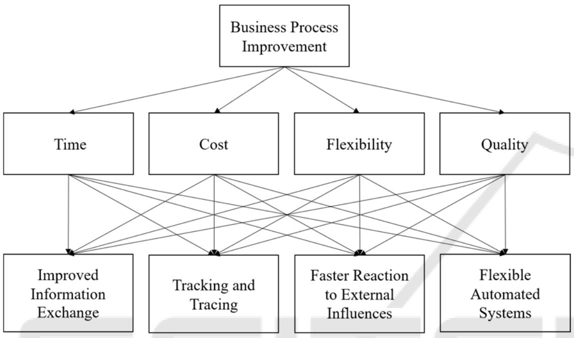

Figure 4: AHP Decision Tree.

Thus, these four components are forming the second layer of the AHP model. The third layer represents possible alternatives to achieve the decision criteria and therefore eventually the main objective. In this case, the identified IoT application clusters are used as relevant decision alternatives, as they are representing aggregated manifestations of IoT implementations. The complete AHP including all layers is shown in Figure 4.

3.3 Data Collection

After designing the decision tree, data needs to be collected by conducting a survey questionnaire for experts and decision makers. This survey consists of two parts, a pairwise comparison of the decision criteria and a pairwise comparison of all alternatives. The criteria must be evaluated in pairs to determine the relative importance between them and their relative weight to the main objective. Analog, the alternatives must be evaluated in pairs to determine the relative importance between them and their relative weight to the decision criteria. The participants need to indicate the relative importance according to a 9-point comparison scale, with increasing importance by increasing numbers. Filling the comparison matrices, the diagonal cells always contain number 1 as they represent the cell value against itself. For a squared comparison matrix with rows i and columns j, each matrix element $a_{i,j}$ has a reciprocal value $a_{j,i}$.

After conducting the survey, a three-step procedure is performed on each matrix including *(i)* gradually squaring the matrices, *(ii)* calculating the eigenvector, and *iii)* repeating step *i)* and *ii)* until the calculated relative weights differ only slightly between two runs. The deviations between the calculated weights decrease with increasing potency, so that an approximation to the actual relative weights is made progressively.

3.4 Results Calculation

At first, criteria weight scores W_C are calculated, which represent the relative importance of the criteria and are mathematically described by the eigenvector. According to subsection 3.3, it is obtained by normalizing the row totals of the squared matrix. The normalization is done by dividing each value by the total column sum. Secondly, the local weight scores of the alternatives W_L are calculated for every criterion. Here, the weight scores W_L represent the relative importance of the different alternatives for the specific criterion. Finally, the global weight of every alternative W_G is determined by multiplying the matrix consisting of all local weights W_L with the vector of the criteria weights W_C. The vector W_G describes the relative importance of all alternatives regarding their importance for achieving the main objective. As the pairwise comparisons need to be consistent respectively transitive, a consistency test must be performed for every matrix to ensure data quality. To do so, the principal eigenvalue λ must be calculated (Saaty, 1990). For a completely consistent matrix, λ is:

$$\lambda = \frac{1}{n}\sum_{i}^{n} x_i \text{ with } x_i = \frac{\sum_{j-1}^{n} a_{j,i}\, EV_j}{EV_i} \quad (1)$$

In this case, n is the order of the matrix and EV represents the eigenvector. Subsequently, the consistency index CI and consistency ratio CR can be calculated:

$$CR = \frac{CI}{R_n} \text{ with } CI = \frac{\lambda - n}{n - 1} \quad (2)$$

The CR and CI are based on the idea, that with perfect consistency of the pair comparisons, to the one maximum eigenvalue λ, which is equal to the dimension n of the matrix, an associated eigenvector EV exists. To decide, if a specific matrix can still be accepted, the consistency ratio CR is calculated. R_n in this formula refers to the so-called random index, which is formed from randomly determined reciprocal matrices. The random index R_n is dependent of the matrix order and can be taken from respective tables that have been created based on empirical tests, e.g., by Saaty (1990). For an exemplary matrix of order four, the corresponding R_n would be 0.89. A decision matrix is sufficiently consistent if CR < 0.1. Before the results can be calculated, all inconsistent matrices need to be dropped. The remaining matrices of the participants are then aggregated via geometric mean to ensure reciprocity.

4 EVALUATION

4.1 Process Description

To evaluate the proposed decision support model, it has been applied to an actual business process of an industrial company. Together with an interdisciplinary group of employees, a specific process has been selected, that does not yet contain any IoT technology and comprises several different entities and interfaces that offer a wide range of possible IoT use cases.

The underlying process is the processing of customer material which is applied for materials that are owned by the customers itself. The process involves four organisational entities, the ERP system, conveyors, and two types of operators, manufacturers and quality assurers. To start the process, a purchase order from a customer, that includes customer material, needs to be received by the ERP system. Fitting customer material is searched in the ERP database. If there is no suitable material from that customer in the warehouse, the purchase order is declined, and the process ends with a request for material to the customer. Having found matching material, a retrieval order is sent to the conveyor system to transport the material to the respective workplace. Simultaneously, an information message is sent to the manufacturers about the imminent arrival. In some plants there are multiple manufacturers wherefore the group needs to first clarify, who will perform the task. As soon as the responsible manufacturer has arrived at the workplace and prepared the machines, the material is processed automatically. After an estimated processing time, the manufacturer is checking the progress. Subsequently, the machines are stopped, and the materials are transported back to the warehouse. The quality assurer gets a notification to analyse the processed material whereupon he moves to the workplace and analyzes the parameters according to the purchase order details. If the analysis results are satisfying, the release order is sent to the ERP system. In case of a failed analysis, rework must be performed.

4.2 Applying the AHP Decision Model

4.2.1 Data Collection

The questionnaire was conducted from July 13th to July 17th, 2020 with an interdisciplinary group of 15 employees of different positions. To cover persons with process knowledge and experiences with IoT technology, the group comprised four project engineers, five process optimizers, three project managers, and three foremen of the specific production area. All employees have knowledge about the process itself as well as experiences with IoT technology acquired at previous projects. They understand the basic value propositions of IoT technology and have insights into potential BPI options for the respective process. The questionnaire consisted of three different steps. At first, the process owner described all process steps and details in a joint workshop to ensure that everybody has the same understanding of general process issues and possible areas of improvement. Secondly, another workshop has been undertaken to discuss general IoT value propositions and possible applications in depth. Furthermore, the literature review of section 2 including the defined clusters and the comprised publications were reviewed to identify first adaption possibilities. Finally, the group had 24 hours to perform the pairwise comparisons. After analyzing the pairwise comparison matrices, two of them turned out to be invalid due to CR values above the rigorous threshold of 0.1.

4.2.2 Results Calculation

According to the structured procedure of section 3, the criteria weights W_C, local weights of alternatives W_L for all criteria, and global weights of alternatives W_G were calculated. Table 2 shows the already squared comparison matrix for the decision criteria. At first, the sum of all row values is added to a total of 108.67. To obtain the eigenvector respectively criteria weights W_C, each row sum is divided by the total 108.67. A corresponding calculation was performed for the alternative matrices for each criterion to get the local alternative weights W_L.

Table 2: Squared Comparison Matrix of Criteria.

	Time	Cost	Flexibility	Quality	∑	W_C
Time	4.50	19.5	9.82	23.00	57.82	0.53
Cost	1.07	3.99	2.41	5.91	13.38	0.12
Flexibility	2.15	9.00	4.49	12.5	28.14	0.26
Quality	0.78	3.30	1.26	4.00	9.34	0.09
				Total	108.67	1

Eventually, the resulting matrix containing all vectors W_L for all criteria was multiplied with the vector W_C. Table 3 illustrates all vectors including the resulting global weight vector W_G and the final alternative priorities.

Table 3: AHP Results.

		Local Weights W_L			
Criteria	Criteria Weight W_C	IE	TT	RI	FS
Time	0.53	0.18	0.33	0.06	0.43
Cost	0.12	0.18	0.34	0.32	0.16
Flexibility	0.26	0.24	0.24	0.13	0.40
Quality	0.09	0.14	0.26	0.14	0.47
Global Weight W_G		0.19	0.30	0.11	0.39
Priority		3	2	4	1

The results show that time is the most important criteria with a weight score of 0.53, followed by flexibility (0.26), cost (0.12), and quality (0.09). The alternative flexible automation systems (FS) reached the highest weight for the criteria time (0.43), flexibility (0.40), and quality (0.47). Tracking and tracing (TT) was evaluated as the most relevant alternative for criterion cost with a weight of 0.34. With a score of 0.39, flexible automation systems is the top priority alternative followed by tracking and tracing scoring 0.30 on the second priority rank. Priority 3 is improved information exchange with a global weight score of 0.19, followed by faster reaction to external influences with a score of 0.11.

4.3 Interpretation and Evaluation

The results of the AHP model have been discussed with the participants in a subsequent workshop. The most favoured decision criterion was time, which stems from several process issues. Firstly, the lead time is suffering from non-transparent transportation and production times. The manufacturer is not aware of the actual transport status and often arrives too early or too late at the designated workplace. Secondly, the production time is not calculated in detail causing loops for checking the processing progress. In addition, the quality assurer is obligated to move to the workplace for analyzing the processing results, which leads to a high time consumption. Tracking the transport orders enables improved data transparency and new possibilities for just-in-time production scheduling. The manufacturers could get better information about the arrival times of materials and therefore obtain improved workflows. Retrofitting machines could help manufacturers as well as quality assurers to simplify their tasks and reduce time consumption. Sensors with connectivity capabilities will lead to reduced loops for progress checking and manufacturers could get relevant information wireless on their wearables. On this basis, the process owners decided on further investigating the IoT project ideas “location monitoring of materials” and “machine retrofitting towards connectivity”.

After discussing the results of the AHP, the participants were asked to evaluate the model itself. They should assess its main structure, feasibility, and efficacy in a qualitative manner. All employees highlighted the reasonable setup of the model, that incorporates the underlying process, main BPI goals, and actual application cluster. Three participants resumed, that more clusters would lead to more specific results. Two employees mentioned that technical suggestions for IoT applications would be beneficial. Regarding feasibility, the employees described the procedure including the initial workshops and the pairwise-comparisons as rather easy to perform. However, the data analysis and results calculation of the AHP are quite complex and need to be done by experts. Altogether, the decision model was assessed as highly effective for analyzing the process and finding suitable IoT applications.

5 CONCLUSION

The proposed decision support model tackles the challenge of integrating IoT applications in processes based on best-practice application clusters and goal-orientation. By providing an extensive literature review and clustering, the main application characteristics of industrial IoT applications have been formulated. Based on this information, a structured AHP can be applied to an underlying process or a set of processes to create priorities for application categories that fit best to achieve the main objective. The work contributes to researchers, as it paves the way for further extensions of the AHP and future research regarding process-aware IoT selection models. It also contributes to practical users, as it can be applied to concrete decision challenges. The decision support model has been evaluated using an actual process. The results and final discussion proved the utility of the model and led to further follow up with the identified application possibilities. Future research could extend the model by providing more application clusters and abstracting them to IoT improvement patterns which describe the alternatives in a more formal way. A limitation of the model is its unclear generalizability, as it has only been applied to one process instance.

REFERENCES

Ammirato, S., Sofo, F., et al., 2019. The potential of IoT in redesigning the bank branch protection system. *BPMJ, 25(7).*

Bloom, G., Alsulami, B., et al., 2018. Design patterns for the industrial Internet of Things. *In 14th IEEE International Workshop on Factory Communication Systems (WFCS).* IEEE.

Bosche, A., Crawford, D., et al., 2016. How Providers Can Succeed in the Internet of Things. *Bain&Company, https://www.bain.com/insights/how-providers-can succeed-in-the-internet-of-things.*

Boos, D., Guenter, H., Grote, G., Kinder, K., 2013. Controllable accountabilities: the internet of things and its challenges for organisations. *Behav. Inform. Technol., 32.*

Bradley, J., Barbier, J., Handler, D., 2013. Embracing the Internet of Everything To Capture Your Share of $14.4 Trillion. *Cisco White Paper.*

Vom Brocke, J., Niehaves, A., et al., 2009. Reconstructing the giant: On the importance of rigour in documenting the literature search process. In *17th European Conference on Information Systems, ECIS.*

Burhan, M., Rehman, R., Khan, B., Kim, B., 2018. IoT elements, layered architectures and security issues: A comprehensive survey. *Sensors, 18(9).*

Celestrini, J., Rocha, R., et al., 2019. An architecture and its tools for integrating IoT and BPMN in agriculture scenarios. In *34th ACM/SIGAPP Symposium on Applied Computing.* ACM.

Chang, W., Su, J., et al., 2019. iCAP: An IoT-based Intelligent Liquid Waste Barrels Monitoring System. In *11th Computer Science and Electronic Engineering (CEEC).* IEEE.

Dumas, M., Rosa, M., Medling, J., Reijers, H., 2018. Fundamentals of Business Process Management (ed.). Springer. Berlin, Heidelberg.

Janiesch, C., Koschmider, A., et al., 2017. The internet-of-things meets business process management: Mutual benefits and challenges. *IEEE Trans. Syst. Man Cybern. Syst., 6(4).*

König, U., Röglinger, M., Urbach, N., 2019. Industrie 4.0 in kleinen und mittleren Unternehmen – Welche Potenziale lassen sich mit smarten Geräten in der Produktion heben? *HMD, 56(6).*

Kortuem, G., Kawsar, F., et al., 2010. Smart objects as building blocks for the Internet of things. *Internet Comput., 14(1).*

Li, Y., Hou, M., Liu, H., Liu, Y., 2012. Towards a theoretical framework of strategic decision, supporting capability and information sharing under the context of internet of things. *J. Inf. Technol. Manag., 13(4).*

Liberati, A., Altman, D., et al., 2009. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions: explanation and elaboration. *BMJ.*

Murar, M., Brad, S., 2014. Monitoring and controlling of smart equipments using android compatible devices towards IoT applications and services in manufacturing industry. In *2014 IEEE International Conference on Automation, Quality and Testing*. Robotics.

Patterson, R., 2017. Intuitive Cognition and Models of Human-Automation Interaction. *Hum. Factors, 59(1).*

Rasmussen, N., Beliatis, M., 2019. IoT based digitalization and servitization of construction equipment in concrete industry. In *GIoTS*. IEEE.

Saaty, T., 1990. How to make a decision: The analytic hierarchy process. *Eur. J. Oper. Res., 48(1)*.

Schönig. S., Ackermann, L., Jablonski, S., Ermer, A., 2020. IoT meets BPM: a bidirectional communication architecture for IoT-aware process execution. *Softw. Syst.Model., 19*.

Tai Angus Lai, C., Jackson, P., Jiang, W., 2018. Designing Service Business Models for the Internet of Things: Aspects from Manufacturing Firms. *AJMSE, 3(2).*

Tschofenig, H., Arkko, J., et al., 2015. Architectural Considerations in Smart Object Networking. *Internet Architecture Board (IAB).*

Valente, F., Neto, A., 2017. Intelligent steel inventory tracking with iot / RFID. In *RFID-TA*. IEEE.

Webster, J., Watson, R., 2002. Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly, 26 (2).*

Willaert, P., den Bergh, J., Willems, J., Deschoolmester, D., 2007. The process-oriented organisation: A holistic view developing a framework for business process orientation maturity. In *5th International Conference on Business Process Management,* ACM.