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Applying Design Science to RPA and AI-Based Systems

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Abstract

The organizational adoption and use of computer systems incorporating artificial intelligence (AI) or robotic process automation (RPA) is increasing. The goals are to streamline business processes and improve their efficiency and effectiveness. However, the adoption and use of these AI technologies can manifest complications in human/system interfaces in diverse parts of the organization. Design science research (DSR) emphasizes the creation of innovative artifacts and computer solutions, keeping user goals at the forefront, and has the potential to avert such downstream system issues. Successful systems must be designed to easily coexist with humans and support the collaboration between human and machine actors. This research study investigates the impact of applying design science methodologies in the implementation of automated systems that incorporate AI or RPA. The interview data is collected and analyzed from an agricultural dairy farm automation case study. The results support the benefits of using DSR methodology and are applicable to any AI-based system design/implementation with human components.

Keywords: Design Science, Systems Analysis, Artificial Intelligence, Robotic Process Automation.

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Applying Design Science to RPA and AI-Based Systems

Biswadip Ghosh

1. INTRODUCTION

The organizational adoption and use of business systems incorporating functionality based on artificial intelligence (AI) and robotic process automation (RPA) is growing. These technologies provide an opportunity to streamline processes and improve efficiency and effectiveness in various industries such as manufacturing, logistics, transportation, defense, and agriculture. RPA is a lightweight automation technology being applied to automation of high volume, routine, and repetitive work, and is particularly well suited to monitoring status coming from control systems, system-to-system integration events and user interface signals. AI is a more sophisticated technology that is applied to more complex scenarios and less well-defined work tasks. In contrast, RPA connects events with automated actions based on conditional statements and is a key interface technology for repetitive responses to routine external triggers.

Studies show that interfaces that connect AI-based systems to human users must provide rapid operational context, transparency, and explain-ability to help the human user better understand the autonomous system's decision making and behavior in real time and adjust as needed (Azafrani & Gupta, 2023). For more complex automation scenarios, popular AI models apply rule-based or case-based reasoning is paired with human judgement to make decisions and execute actions. For example, in autonomous weapons systems, RPA and AI technology is being used together with human decision making to enhance military-civilian interfaces (Froding & Paterson, 2021). In such weapons applications, the human element provides the balance between the need to mitigate the potential for societal harm and the effectiveness of the military mission.

The introduction of RPA and AI vastly changes the roles played by human actors in the workplace. There is greater risk that the use of AI and RPA can result in organizational issues downstream (Staaby et.al., 2021). The typical implementation focus of these technologies is primarily localized optimization, and downstream issues can manifest in other parts of the organization. These issues include automation bias, unforeseen system events, unexpected errors, overdependence on technology causing obsolescence and deskilling of human actors.

Such ramifications increase the need to adopt design science (DSR) methodologies so that automation systems can be designed/implemented to easily coexists with humans and support the collaboration between the two actors – human and machine. Though there is greater interest in the use of RPA and AI technologies in organizations, there is still limited research studies on how process automation and artificial intelligence applications can be best integrated responsibly into business processes that depend heavily on human creativity and input. The systems' design methodology must view the technology and the human actors as a system of systems – a hybrid system - and build on the synergies of interplay of all actors to improve overall outcomes. For example, in a military RPA interface, background data can be collected by the weapons software agent and decisions suggested in rank order to the human to take final action steps to trigger the weapon (Vassilakopoulou et.al., 2023).

Design Science research (DSR) stems from the evaluation of a system from a user-centric lens. The design science methodology for realizing system artifacts consists of iterative implementations, and comprehensive metrics for usage together with measurements for benefit realization. As new system artifacts are planned and/or built, design science research evaluates these artifacts for their use and value and generates possible explanations for changes in the behavior of systems, people, and organizations (Vaishnavi & Kuechler, 2004). This new approach is a response to the increasing complexity of modern technology and modern business and applies the principles of design to specify systems to relate to the way people work. Ideally, design science can be applied to establish common system goals between both actors – automation and human - via interfaces that support transparency, reciprocity, and sustainable interactions (Venable et.al., 2016).

Research Goals

The goal of this research is to apply design science methodologies to achieve successful implementation of automated systems, and to evaluate any resulting benefits or failings of such methodology. The research premise is that design science evaluation of automation-human system makes long-term human-machine collaboration more effective and eliminate detrimental downstream issues in these systems. Systems success results from managing functional needs to exploit a mix of human, and automation resources to reduce complexity and uncertainty in business processes, and support a balance between all the actors. Successful systems implement strict division of labor, sustain organizational norms, create cost efficiency, and manage all stakeholders in effective roles (Gottschalk & Solli-Saether, 2005).

2. BACKGROUND

Design Science

Design science emphasizes the creation of innovative artifacts or solutions keeping human actors' goals at the forefront. Such artifacts could be software systems, interfaces, processes, or technologies that constitute components of a solution (Stige, et.al., 2023). The methodology is data driven and user feedback is collected during the design process to finalize system components that are more user-friendly and provide greater implementation success. The design science approach calls for an iterative problem-solving process with empathy and collaboration with the users (Oulasvirta, et.al., 2022). Design Science incorporates a set of principles for creating better system interfaces and human use cases: (i) empathy with users, (ii) a discipline of prototyping, and (iii) a tolerance for rework. In DSR, the process is commonly presented as cyclical with three cycles: design, relevance, and rigor (Hevner, 2007). The application of DSR methodology leads to developing more responsive, flexible information systems.

Design Science Research Phases

The approach of design science evaluation of an RPA and/or AI-based system is done in three phases (Table 1) to find evidence of a successful artifact being realized – (i) proof of concept (POC), (ii) proof of use (POU), and (iii) proof of value (POV). The implementation and deployment of system artifacts with AI and RPA projects are thoroughly researched with the intent of creating a consistent system of components to support the organizational needs. As the system is constructed, the delivered artifacts are checked for relevance (proof of concept) and their value evaluated (proof of value) through data collection via user demonstrations (proof of use). System demonstrations show that the developed artifacts are being successfully applied by the users to the target use cases and business problems. Evaluation of the artifacts involve comparing the objectives of the solution to actual observed results from using the developed artifacts in the demonstrations (Hevner et.al., 2004).

During the "proof of concept" stage of DSR, the examination of the system involves showing that the conceptual system architecture is working in the organization's IT infrastructure to produce aggregated results. Data is collected during the "proof of use" stage (measurement phase) on the use of the new service through a cross-sectional analysis of usage based on system log data. Each time a person invokes a feature, the software logs a time stamp and the details of the user interaction. Finally, in the "proof of value" stage, data is collected to evaluate how the system manifests in benefits for the organization. The end outcome of DSR evaluation shows that the system of components fits the organizational infrastructure, the system is being used by the various users, and there is value in these components to the business.

DSR Phase	System and Organizational Aspects of Methodology	
	Automation Focus	Human Focus
Proof of Concpt (POC)	Architecture and aggregated components all working	No down-stream and up-stream process issues
Proof of Use (POU)	Measure/analyze usage - adapt automation Tech	Support user's thought process and practices
Proof of Value (POV)	Estimate value of automation on productivity	Human/System synergy & interfaces

Table 1: Design Science Research Phases

Automaton in Agriculture

Agriculture is one of the oldest forms of industry. The industry suffers from low productivity partly due to its underutilization of technology, which has led to recent research into this realm. Many ancient practices remain in use in modern farms, such as around crop rotation and harvesting schedules. A large variation in the adoption of automation technology can be seen in agriculture around the world; and this diversity is related to socio-demographic factors, such as lack of computer skills, age, income, regional culture, values, and experience. Published reports show that deployed technology has made very nominal impact on such ancient agricultural practices (Sood et.al., 2022). The adoption of automation is higher in developed countries than in developing countries. For many years, technology supported minor tasks with minimal automation – such as sensing and measuring soil moisture and detecting crop disease. A greater degree of automation is seen in the current wave of technology deployment in agriculture such as weed control with cameras, robotic harvesting of crops, and proper irrigation of land. Artificial intelligence (AI) and automation continues to complement traditional many labor-intensive work processes. Smart farming using sensors, cameras, drones and IoT devices to empower farmers with data and predictions made from the data are being used to increase productivity and crop yield (Sood et.al., 2022).

Evidence from the agriculture industry suggests that the need to keep the human element central and fully embedded in any automated systems deployment in agricultural smart applications is critical. The AI and RPA based systems supporting agricultural processes must achieve a high degree of automation, while retaining many socio-technical elements in their design. The diversity of natural conditions faced in regional agriculture and the severe impacts of climatic change results in the need for prototyping and evaluation of these smart technology approaches. Therefore, the design and deployment of automation such as AI, RPA, data science and IoT, into agricultural processes, provides the appropriate industry case to study the application of DSR in the design and adaption of AI and RPA based systems.

3. METHODOLOGY

This study uses qualitative research with interpretative methods based on semi-structured interviews. Interpretive research is inductive and does not rely on previous literature or prior empirical evidence. The study develops grounded theory by comparing incidents and connecting emerging concepts in concert with theoretical research. The objective of grounded theory is to generate constructs and discover relationships among the constructs using qualitative data (Eisenhardt, 1989; Strauss & Corbin, 1990). Rather than start with a pre-conceived research model and hypotheses to test, grounded theory uses an inductive approach, which is data driven, and through simultaneous data collection and analysis to discover patterns and concepts underlying the phenomena. This methodology places emphasis on abstracting participants' accounts of experiences and events and relating those to existing literature to explain the phenomena (Strauss & Corbin, 1990). This recursive activity employs theoretical sampling whereby additional data collection builds on the initial findings. This then narrows the scope of the study until theoretical saturation is reached, where no new data changes the emergent constructs. Moreover, this type of methodology explains process, `how' research questions, and context, and provides detailed information for deducing constructs for theory generation and elaboration.

GlobePort Dairy Farm Case Study
GlobePort Dairy Farm is a small niche operation in the agricultural region of Kansas, USA. Owner Bill Clark has owned and operated the farm for many years. Their farm consists of approximately 150 cows who are maintained in a purely natural habitat and with all farm work done with manual labor. These old-style operations of the GlobePort dairy farm had become an operational challenge, due to labor shortages after the COVID pandemic. The strict milking schedules required to run the dairy had begun to wear physically on Bill and his farm workers. Post-COVID, Bill barely had enough time to keep up with the business aspects of the family farm. The frequent absenteeism of the dairy workers forced Bill to consider implementing RPA farm automation using a robotic milker and farm management software to streamline his dairy business. The farm figured that it takes an hour to milk five cows by hand, while 50 cows could be milked in the same time with a milking machine for a 10X efficiency increase through an automated system. But owner Bill Clark was still not sold on the idea of bringing in a robot to do the job normally done by a person, which seemed impersonal and scary. There was also a lot of variation in the response of cows to milking machines - either positively or negatively and human interventions would still be key to address such issues with adoption of farm automation.

4. DATA COLLECTION

Two farm workers, together with the owner, Bill Clark and an IT systems analyst from the farm automation system were interviewed. The generalizability of the findings of a qualitative study are strengthened by including more than one participant's perspective and incorporating theoretical perspectives at multiple levels of analysis into the discussion. Concurrently, the relevant published literature was searched and analyzed to find theoretical support. A grounded theory model of measuring the impact of DSR on the success of AI and RPA based systems is a product of this research study. Although the interviews were open-ended, the following questions guided the theory building:

1. What challenges did you face in adopting the dairy automation system into the farm infrastructure?
2. How were dairy farm operations changed by new human/systems interactions?
3. What were the business benefits of the dairy farm automation system project?

Data Analysis

The interview scripts were coded using nVivo software. Each interview was transcribed to a separate document and the documents uploaded into the tool. This tool has a sophisticated search engine and features that enable saving search terms and outputting search results for specific terms. Coding in grounded theory has three stages: open coding, selective coding, and theoretical coding. In the open coding phase, the transcripts from the interviews were listed as quotes and analyzed line by line to identify concepts. The key concepts emerged from open coding, and a technique was used for categorizing interview data allowing the major concepts to be identified along with their properties (Table 2). Subsequent theoretical coding was used to relate concepts to other concepts, establishing a model of the perceived phenomena (Figure 1). Analysis continued until no further concepts emerged.

5. RESULTS AND ANALYSIS

The grounded theory approach culminated in a model that sheds light on a fresh theoretical perspective of applying design science to AI and RPA based systems (Figure 1). The theoretical model relates the four concepts found from coding the interview data: Proof of Concept (POC), Proof of Use (POU), Proof of Value (POV) and RPA/AI Systems Success (SS) as illustrated in Figure 1.

Proof of Concept (POC) Phase

The system analyst designed the initial implementation of the farm automation system. Each cow had a special collar that identified the cow as they approached the milking robots. The system tracked the frequency of milking for each cow and did not let the cow "*milk"* if it was not their time. If the system granted permission for the cow to be milked, the system dispensed food for the cow to eat during the milking and a robotic arm proceeded through the milking process. Food is significantly more enjoyable for cows than milking and is often a necessary incentive to distract cows during milking. The system and associated sensors also tracked parameters such as milk conductivity, percentage of milk fat solids, total milk output, bacteria levels, and somatic cell count, which is a measure of white blood cells found in the milk and is an indicator of the cow's health and the safety of the milk product. The system automatically disposed of any milk that was identified as being unsafe. However, initially a large effort was needed to collect data about the herd of cows to configure the system, which seemed to Bill to be not worth the investment. Bill Clark remained skeptical about farm automation,

(1) "*What good would it do to install a bunch of sensors and collect meaningless data anyway"?*

For the previous decade, the Dairy farm has seen increasing operating and maintenance costs as their equipment was getting older and breaking much more often. On several occasions, the farm tested and identified whole unclean batches of milk they couldn't bring to market and had to dump because of high bacteria levels. Farm workers became frustrated, and worker turnover was rising, driven by the COVID pandemic.

(2) "*The old milking systems are very difficult to keep clean."*

In addition, Bill had become so swamped from the early mornings and long days that he was missing important tasks on both the business and operations sides, such as delivering compliance reports, purchasing raw materials, addressing cow healthcare, and procuring feed for the farm.

(3) "*He didn't balance the books regularly and ran out of feed from time to time and had two cows die the previous year from preventable illness*."

The system analyst sold Bill on the savings that he would see with reduced operating costs and the increase in milk production and product quality. Bill was unqualified to process a large set of numbers to understand the cost benefit analysis presented by the systems analysist. He did not have the time to do his own research. Bill confessed,

(4) *"I allowed the system analyst to make many implementation decisions without my input."*

However, the analysist did not think it was important, nor did he know how to manage the operational changes involving both farm workers and the dairy processes, nor consider the intangibles presented by the farm animals, the cows. The system itself was comprised of a network of various sensors, control units and software that automated operations such as feed management, milk product dispatch and accounting. Bill Clark felt deluged with data, when he started receiving the daily system reports, which he did not fully understand.

(5) "*The analysist didn't spend enough time communicating with the farm workers about the changes that would occur after the implementation of the technology and what that means for their daily role."*

A couple of weeks after the initial implementation, Bill was growing concerned that these milking robots were a big waste of time and money; he was growing frustrated. But the systems analysist indicated that the proposed RPA system included various components that would help the farm owner to manage farm operations. Many cows were stressed, and milk production suffered heavily. The dairy workers were confused about their daily work tasks and lost motivation to continue working.

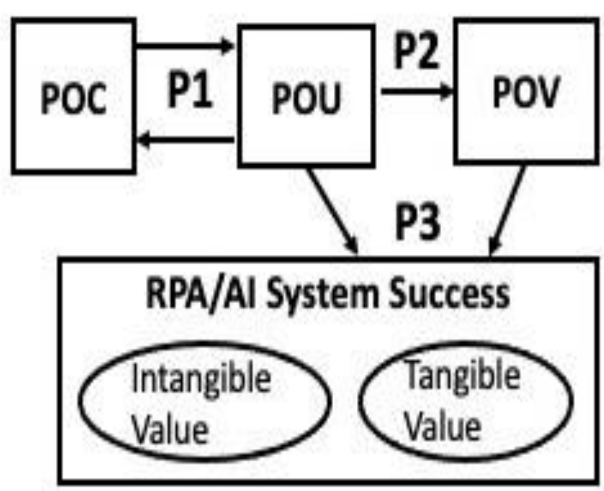

Figure 1: Grounded Theory Model

Proof of Use (POU) Phase

The labor force that Bill employed was far too inconsistent. But the new system allowed that the dairy workers would not have to be held to a strict manual milking schedule. They could instead be freed to do other tasks such as spending extra time with some of the cows if they're sick or need extra attention, maintaining different equipment, or working with the software to generate reports and troubleshoot problems.

(6) *"There were many mornings that at least one employee couldn't make it to the farm because they were sick or on vacation during an extremely busy part of the milking season."*

Bill Clark didn't want to spend a lot of money on hiring and retraining new farm employees, if they were going to be that inconsistent. Workers typically were assigned labor intensive farm work and given very few managerial tasks. Bill Clark also lacked the decision-making data and reporting tools to manage farm resources,

(7) "*Communication with the owner about priorities was lacking which resulted on several occasions in buying too much feed and even forgetting to schedule a shipment to a major milk product distributor".*

Concept	**Concept Attributes**	**Quote**
POC	Develop and Communicate System/Business Strategy	1, 4, 5
	Integrate with IT/IS Infrastructure	10,
	Support Business Process Changes	3, 13
POU	Manage User Interactions with System	7
	Prototype Multiple System Approaches and Usage Paths	8
	Incorporate Feedback from System Usage	9
POV	Measure Usage Behavior - System/Interface Likes Dislikes	12, 13, 14
	Measure Business/Process Impacts	15
	Redefine Systems to Enhance Value	11
SS	Intangible Benefits	12,
	Tangible Benefits	13,14

Table 2. Concept Development and Coding

The initial implementation of the automated

RPA system caused increased anxiety for many cows, who craved daily contact with a known human. System interfaces were analyzed using design science to create further transparency and sustainable communications with the farm workers and to prompt them and allow them to intervene in cow stress management. The metrics from the operational proof-of-concept showed a group of cows experienced higher stress and resulted in a drop in their milk production. An adaptation process was instituted to continue hand milking cows that were under stress. The system analyst revised the system reports,

(8) "*Cows that had stress in the milking station were flagged by the system.*"

Other cows were skittish around the new equipment and did not want to approach the machines. The motion of the robotic arms below them without the human touch made some cows uncomfortable. Teaching the cows to remain calm during the entire process was tiring and took more time than had been anticipated. After a lot of coaxing, some adventurous cows began to explore the new machines and walk around them. However, many cows would kick the robotic arm and became too restless when they entered for their first few milking. Bill didn't have much help because many of the dairy workers quit before there was time to get the robotic milking stations fully operational. The farm workers indicated,

(9) "*We had to coax some cows with soothing pats to make them enter and use the milking stations.*"

The use of the design science approach allowed for additional refinements in the RPA system implementation and supported the emergent needs of the Dairy Farm to develop automation components paired with friendly interfaces for humans and other living actors. Bill and the workers didn't understand how to use the software, and many workers felt threatened that these machines and the "*new-fangled*" software were going to take their jobs. With additional training in the process changes accompanying the system implementation, it became easier for Bill and the farm workers to navigate farm information from the system interfaces.

(10) *"Information about each cow is stored in the database and the system tracks the frequency of milking for each cow."*

Some cows were also upset when they were refused entry into the milking station because the detected cow had been milked too recently. Bill Clark requested a system adaptation,

(11) *"Even if the system does not let these cow's milk at that time, yet it must dispense some food for the cow to consume."*

If the system grants permission for the cow to be milked, the robotic arm would methodically clean each teat, apply milking cups and begin to gently extract the milk to minimize infections. The system and associated sensors also tracked parameters such as milk conductivity, percentage of milk fat solids, total milk output and bacteria levels and somatic cell count. The system was configured to automatically dispose of any milk that has been identified as being unsafe.

Proof of Value (POV) Phase

When milking was complete, the robotic arm would proceed to remove each milking cup and apply anti-bacterial spray to the udder before opening the gate and letting the cow move out of the stall. The consensus among the workers was that,

(12) "The *automated system has freed up a lot of time during the day."*

Yet, the dairy workers that stayed were having trouble with their new roles. They were no longer tasked with milking the cows and were now responsible to set parameters in the software and try to interpret what all of the new reports were telling them. The data taken in from the system was stored on a local computer on the farm that processed the data from the dairy's daily operations. The farm management system also included a software package and associated applications that delivered information supporting the farmer's decision-making process and giving them control to troubleshoot problems and reset various equipment remotely. Workers were impressed by the system features,

(13) "*The system allowed management of the overall herd on the farm, as well as give the ability to handle individual cows based on health and feeding trends.*"

The RPA system and the farm management software was only part of the information system, and that the technology's importance was found in the information it harvested, processed, and served to the farmer for the purpose of making intelligent business decisions, so that he could then focus on potential new business strategies inspired by the information that was collected. Bill Clark said that he liked the regulatory interfaces and automated compliance reporting,

(14) *"The system generated necessary reports for veterinarians and food regulatory bodies and the information was easily sent to regulators."*

Research Propositions

After an initial drop in milk production, eight weeks after the robotic milking stations were installed, the farm management system was starting to work, and the quality and quantity of milk production was rising. The DSR methodology prompted an evaluation of the initial RPA implementation and the collected usage data, and feedback allowed the systems analysist to adjust the implementation to improve business impacts supporting the first research proposition, P1:

P1: The installed system artifacts (POC) boost usage (POU), which supports adaptation of the system artifacts (POC).

The result of the RPA system adaptation and redefinition was driving additional system usage. This manifested in greater operational impact creating more business value (POV). This supports a second research proposition, P2:

P2: Increased System Usage (POU) supports greater business value (POV).

The DSR process supported all farm stakeholders and drove the redefinition and transformation of workers' roles.

(15) *"The automated system improved farm operational efficiency thru better information flow, increased quality and quantity of milk produced."*

The data confirms how the system brought about the posited operational cost improvements, improved milk production quantity and quality, and established prudent automation.

P3: System Usage (POU) and business value (POV), together drive system success (SS).

6. CONCLUSIONS

This case illustrates the impact of applying DSR methodology on an AI/RPA-based farm automation system. The initial system implementation created operational changes for the farm owner and workers – both positive and negative. The DSR approach allowed the RPA system to be adapted to the unique organizational environment of the dairy farm through the onsite definition and management of the IT systems allowing farm resources to be exploited to reduce complexity and uncertainty in business/farm operational tasks. DSR prompted the collection of user feedback that drove these system adaptations. The net effect of the DSR methodology led to improved human-system interactions, effective information flow, and efficient farm management.

Future Implications

The implementation of RPA and AI based systems have greater unknowns due to the complex human interfaces and organizational changes needed in conjunction with system adoption. The DSR methodology emphasizes the collection of user feedback, usage data, and insights about user behaviors to adapt the system for business/organizational success. A greater degree of innovation and process efficiency is possible by using an experimental approach, such as DSR, to come up with the eventual system solution. The promising results of the DSR approach call for its further use in Information Systems (IS) practice. Additionally, the practical elements of the application of DSR methodology provide opportunities for further empirical evaluation of DSR in future IS research.

7. REFERENCES

Azafrani, R., & Gupta, A. (2023). Bridging the civilian-military divide in responsible AI principles and practices. *Ethics and Information Technology*, 25, 27. https://doi.org/10.1007/s10676-023-09693-y

Eisenhardt, K.M. (1989). Building Theories from case study research. *Academy of Management Review*, 14(4), 532-550. https://doi.org/10.2307/258557

Froding B., & Paterson, M. (2021). Friendly AI. *Ethics and Information Technology*, 23, 207-214. ttps://doi.org/10.1007/s10676-020-09556-w

Gottschalk, P., & Solli-Saether, H. (2005). Critical Success Factors from IT Outsourcing Theories: an Empirical study. *Industrial Management and Data Systems*, 105(6), 685-702.

https://doi.org/10.1108/02635570510606941

Hevner, A.R. (2007). A three cycle view of design science research. *Scandinavian Journal of Information Systems*, 19(2), 87-92.

Hevner, A.R., March, S.T., Park, J. & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, 28(1), pp. 75-105. https://doi.org/10.2307/25148625

Oulasvirta, J.A., Dayama, N.A., Shiripour, M. John, M., & Karrenbauer, A. (2022). Combinatorial optimization of graphical user interface designs. *Proceedings of the IEEE*, 108(3), 434-464.

Sood, A., Sharma, R.K., & Bhardwaj, A.K. (2022). Artificial intelligence research in agriculture: a review. *Online Information Review,* 46(6), 1054-1075. https://doi.org/10.1108/oir-10-2020-0448

Staaby, A., Hansen, K., & Gronli, T. (2021). Autotmation of routine work: a case study of employees' experiences of work meaningfulness. 54th HICSS, Maui, HI, 156-165.

Strauss, A., & Corbin, J. (1990), Basics of Qualitative Research: Grounded Theory Procedures and Techniques. Sage, Newbury Park, California.

Stige, A., Zamani, E.D., Mikalef, P., & Zhu, Y. (2023). Artificial intelligence (AI) for user experience (UX) design: a systematic literature review and future research agenda. *Information Technology and People*, https://doi-org.aurarialibrary.idm.oclc.org/10.1108/ITP-07-2022-0519

Vaishnavi, V., & W. Kuechler, W. (2004). Design sceince research in information systems. AISNET, AIS, Altanta, GA.2004., http://desrist.org/desrist/content/design-science-research-in-information-system.pdf.

Vassilakopoulou, P., Haug, A., Salvesen, L.M., & Pappas, I.O. (2023). Developing human/AI interactions for chat-based customer services: lessons learned from the Norwegian government, *European Journal of Information Systems* 32(1), 10-22. https://doi.org/10.1080/0960085x.2022.2096490

Venable, J. Pries-Heje, J., & Baskerville, R. (2016). FEDS: a framework for evaluaiton in design science research. *European Journal of Information Systems,* 25(1), 77-89. https://doi.org/10.1057/ejis.2014.36

Zhai, Z., Martinez, J.F., Beltran V., & Martinez, N.L. (2020). Decision support systems for agiculture 4.0: survey and challegnes, *Computers and Electronics in Agriculture* (170), doi:10.1016/j.compag.2020.105256.