Human-Machine Collaboration in Decision-Making

Alexander Hatz

Pforzheim University
Tiefenbronner Straße 65
75175 Pforzheim
hatzalex@hs-pforzheim.de

Jurij Jaklič

University of Ljubljana
Kardeljeva ploščad 17
1000 Ljubljana
jurij.jaklic@ef.uni-lj.si

Frank Morelli

Pforzheim University
Tiefenbronner Straße 65
75175 Pforzheim
frank.morelli@hs-pforzheim.de

KEYWORDS

Machine Learning, Human-Machine Collaboration, Collaborative Intelligence, Success Factors

ABSTRACT

The use of ML-based decision support systems in business-related decision-making processes is a proven approach for companies to increase process performance and quality. To a certain extent, machines are capable of reproducing the cognitive intelligence of humans in specific domains. In order to leverage the resulting potential, synergistic human-machine collaboration (HMC) is becoming increasingly important for companies. However, orchestrating HMC is dependent on a set of framework conditions that determine the success of the collaboration. This study[1] examines the research question of how to utilize the concept of collaborative intelligence (CI) to enhance decision-making processes while using machine learning (ML) -based data prediction. The purpose is to identify success factors in the development, design, and implementation of an ML-based predictive analytics solution to orchestrate HMC in decision-making processes. These success factors state recommendations for companies to fulfil the necessary framework conditions for synergetic HMC orchestration. In total, five success factors were identified that represent a combination of theoretical findings and empirical insights. At the same time, further research needs were uncovered, which point out starting points for future research projects in the field of HMC.

INTRODUCTION

The business environment is changing rapidly, especially with the emergence of innovative technologies as an important influencing factor (Vial, 2019, pp. 118-119). The effect of such technologies is two-folded. On one hand, they embody disruptive forces that challenge companies to expand their existing IT infrastructure and to invest in new information systems to avoid being outpaced by competitors in the long run (Li, Porter, Suominen, 2017, pp. 286-287). On the other hand, they are key for developing new, digital strategies to cope with digital transformation and the challenges it poses. To meet these challenges, automated and scalable business processes must be enriched with data insights and smart technologies (Vial, 2019, p. 122). In this way, the disruptive forces of technology are able to be transformed into potential. Companies that master the digital transformation can emerge as digital pioneers with innovative business processes and permanently change the existing competition on the market in their favor (Jafari-Sadeghi et al., 2021, p. 108).

Machine learning, as a sub-area of artificial intelligence (AI), is an emerging technology that has already disrupted the business environment in the past and will continue to do so in the future (Statista, 2020; Chang, 2020, pp. 99, 110). Due to its versatility and scalability, ML opens up potential in a wide scope of application (Chen & Guestrin, 2016, p. 1). Among other areas, it is used in medicine to diagnose breast cancer, in cybersecurity to detect malware, or in the industry as the basis for business process improvements (Wilson & Daugherty, 2018, pp. 116, 121). Especially in business-related decision-making processes, ML can be used for predictive analytics to forecast outcomes (Nyce, 2007, p. 1). This improves both the flexibility and quality of operational and strategic business decisions to gain a competitive advantage as a company (Kaparthi & Bumblauskas, 2019, p. 660). Since ML solutions are capable of reproducing the cognitive intelligence of humans for abilities related to systematic thinking and pattern recognition, some companies assume that humans are no longer needed in these application areas (Jarrahi, 2018, pp. 577-578; Metcalf, Askay, Rosenberg, 2019, pp. 102-103). A replacement by machines is supposed to be a cost-efficient alternative that achieves the same or even improved performance. However, this approach only leads to short-term success (Kaplan & Haenlein, 2018, p. 24; Malone, 2018; Wilson & Daugherty, 2018, p. 126). The assumption of companies that ML applications are plug-and-play solutions that are implemented once and can solve tasks independently, as humans did before, is a misconception. The data basis of ML-based solutions must be continuously improved, extended, and controlled by humans (Fountaine, McCarthy & Saleh, 2019, p. 64; Ridhawi et al. 2018, pp. 375-376). Furthermore, ML solutions are

[1] The study was conducted in collaboration with SAP SE, a German software development company, and the universities of Ljubljana and Pforzheim.

applications that have been trained for a specific application domain. Outside this scope, the cognitive abilities are not sufficient for adequate problem solving, whereas humans are able to intuitively adapt to changing conditions and find innovative solutions (Kaplan & Haenlein, 2018, p. 16; Malone, 2019, p. 126). Consequently, human intervention is required to maintain the machines performance, which in turn suggests that simply replacing humans with machines is not an appropriate strategy in the long-term. Rather, HMC must be orchestrated, otherwise the desired increase in performance will evaporate (Ridhawi et al., 2018, pp. 375-376; Wilson & Daugherty, 2018). In the field of the CI knowledge base, this problem is addressed and HMC is presented as an alternative outcome. In this way, companies can use the individual strengths of both agents to compensate for the individual weaknesses (Epstein, 2015, pp. 40-41; Wilson & Daugherty, 2018, p. 116).

This paper addresses the research question of how to utilize the concept of CI to enhance decision-making processes while using ML-based data prediction. The purpose is to identify success factors in the development, design, and implementation of an ML-based predictive analytics solution to successfully orchestrate HMC in decision-making processes. The research object is narrowed down to analytical AI systems that are used for the cognitive augmentation of human capabilities. Conversely, this means that industrial robots used for physical augmentation are outside the scope of this work because these types of intelligent machines are usually used separately from humans, which means that no HMC takes place.

As research framework of the paper, a design science research (DSR) approach was used to develop the design artifact. As evaluation method, a case study was implemented within the DSR approach. To collect data from the case study, a multiple sources of evidence collection approach was used.

The first chapter of the paper presents the underlying theoretical knowledge base and is divided into the topics of predictive analytics and CI. Then the developed research design is presented by explaining the used methodology in detail. Based on this, the development and evaluation process of the artifact is presented. Chapters five and six present and critically reflect the research results before the final chapter concludes the paper.

KNOWLEDGE FOUNDATION

Predictive analytics is an established concept that represents the foundation for the development of ML-based predictive analytics solutions. In direct comparison, CI is much less known by name but combines characteristics of research areas such as human-in-the-loop (HITL), explainable artificial intelligence (XAI), and collective intelligence. To define the framework that applies to the design and implementation of the ML-based predictive analytics solution, an interdisciplinary application of both research areas is necessary.

Predictive Analytics

The need to predict outcomes, budgets, demand, or supplies is crucial for surviving in today's highly competitive business environment (Nyce, 2007, p. 1). Data-driven decision-making processes supported by intelligent systems have become an integral part of many industries (Chen & Guestrin, 2016, p. 1). The availability of sufficient data as well as the progress and simplified access to advanced technologies are driving this trend forward (Nyce, 2007, p. 2). As a basis for predictive analytics solutions, AI in the form of ML models enjoys great popularity. The applications are particularly attractive because they are able to process large amounts of data efficiently and recognize complex relationships within the abundance of data. Furthermore, the ML models are scalable and versatile due to their learning ability (Bawack, Wamba & Carillo, 2021, p. 646).

Collaborative Intelligence

Due to the technical progress in the field of AI, a new paradigm within the IS discipline was initiated in the 2000s, focusing on research of cognitive computing systems. In this new paradigm, modern AI systems are characterized by experiential learning rather than repetitively reproducing programmed knowledge. Furthermore, modern AI systems should be able to interact with humans and share tasks as if they were conscious beings themselves (Aleksander, 2004, pp. 24-25; Epstein, 2015, p. 39).

Collaborative intelligence as a school of thought deals with the interaction between humans and machines and considers replacing humans with innovative ML-based solutions to improve business performance as an outdated mindset (Epstein, 2015, p. 40; Wilson & Daugherty, 2018, p. 116). Instead, the integration of such technologies is about orchestrating HMC in a way that the strengths of both agents augment each other. Accordingly, there is no replacement of humans by machines, but a shift in responsibilities and task allocation between both agents. The capabilities gained using ML augment the existing capabilities of the humans, vice versa, humans complement the machines outside its scope of application as controlling agents (Paschen, Wilson & Ferreira ,2020, p. 412; Bawack, Wamba & Carillo, 2021, pp. 646-647; Epstein, 2015, p. 44).

A functioning HMC is subject to certain framework conditions that must be fulfilled in order to be able to use the potential of both agents (Alizadeh et al. 2020, pp. 4-5; Epstein, 2015, p. 40). However, this aspect is often neglected when integrating innovative technologies into existing business processes, so that the AI adoption fails (Wilson & Daugherty, 2018, p. 116). The literature on CI as well as related research areas collective intelligence, XAI, and HITL address this challenge and describe recommendations for action in order to create the necessary framework conditions and carry out HMC orchestration (Arrieta et al. 2020, p. 100; Metcalf et al., 2019, pp. 84-86; Wilkens, 2020, pp. 258, 261-262). In the following, these recommendations are summarized and presented as five Design Principles. In the literature, the term Design Principle is not used in the context of CI. Rather, it is an umbrella term introduced by the authors of this paper in order to be able to cluster individual recommendations for action according to their focus area.

Accuracy for the Applicability of the model – Adequate accuracy of a prediction is a basic prerequisite for the solution to add any value at all in practice (Arrieta et al., 2020, p. 100; Shearer, 2000, p. 15). However, accuracy alone is not sufficient to develop an applicable decision support system (Lossos, Geschwill & Morelli, 2021, pp. 316-317). The trade-off between accuracy and transparency is crucial when it comes to optimizing HMC orchestration (Arrieta et al., 2020, p. 100).

Transparency to achieve acceptance, trust, and interpretability – Transparency comprises the explanatory approaches that are expected to make the decision-making logic and results of an AI solution comprehensible to the user. Consequently, transparency is necessary to counteract the black-box character of AI (Arrieta et al., 2020, p. 83-84; Lossos et al., 2021, p. 305). Especially in the context of decision-making processes, the level of transparency is a decisive criterion on whether an ML solution is used in practice or not (Bohanec, Robnik- Šikonja & Borštnar, 2017, p. 1390). Moreover, the results of Arnold et al. (2006, p. 95) have shown that decision-makers tend to use the recommendations of decision support systems if, in addition to the accuracy of the prediction a cognitive alignment is established. Cognitive alignment is defined as a fit between the decision maker's understanding of the underlying business problem and the decision-making logic of the ML solution (Arnold et al., 2006, p. 94). Consequently, transparency is necessary to establish cognitive alignment, and cognitive alignment is in turn the basic prerequisite for user acceptance and trust in the results of a decision-support system (Epstein, 2015, p. 40, Bohanec et al., 2017, p. 1403). Furthermore, transparency lays the foundation for the interpretability of the results as it provides the explanations for the comprehensibility of the decision-support system (Arrieta et al., 2020, p. 83-84). Gilpin et al. (2019, p. 5) define interpretability as “the ability to explain or to present in understandable terms to a human”. The goal of interpretability in an ML context is to describe the underlying logic of the system in a comprehensible way in order to enable decision-makers to derive the correct business decision (cognitive augmentation) as part of an informed decision-making process (Gilpin et al., 2019, p. 2; Lossos et al., 2021, p. 305). There are various recommendations for action to implement the Design Principles. Among other things, developers should carry out a target-group-oriented design of the artifact, adapted to the expertise of the decision-maker as the addressee of the decision-support system (Harbers, van den Bosch & Meyer, 2010, p. 132). Furthermore, the results of Bohanec et al. (2017) and Lossos et al. (2021) have shown that providing the decision-maker with insights into the development process and decision-making logic of the ML model is a proven way to increase transparency, trust, acceptance, and interpretability. Analogous to Lossos et al., (2021, pp. 312-313) the insights into the solution-finding process can be divided according to three different points in time: Ante-hoc with regard to input data, AI design with regard to solution development, and post-hoc with regard to output data. Moreover, according to Gilpin et al. (2019, p. 9), the supply of metrics is a proven means to obtain trust and acceptance with the user. However, the choice of metrics needs to be adapted to the individual use case and the addressees.

Participation to foster organizational learning – Viewing ML solution as a simple tool that takes over the part of the work that humans are unwilling or unable to do is outdated. Instead, machines should be seen as an equal partner that elevates the collaboration to a higher level (Demetis & Lee, 2018, pp. 946-947; Schuetz & Venkatesh, 2020, p. 3). Staging human-machine interaction fosters organizational learning in dealing with ML solutions, which in turn strengthens the performance of both and enables informed decision-making (Ansari, Erol & Sihn, 2018, p. 117; Bohanec et al., 2017, p. 1403). There are different recommendations for action to implement the Design Principle. The basis of a successful collaboration is a dialogue in order to achieve the same understanding and a cognitive alignment of the underlying business problem. Such dialogue can be achieved in HMC by providing information about the underlying business problem (feedforward) and explanations (feedback) that make the ML development and decision-making process more transparent to the user (Arnold et al., 2006, pp. 81, 95; Epstein, 2015, p. 44). Furthermore, Chander et al. (2018) and Langley et al. (2017) describe the backward integration of business users into the ML development process as a way to intensify the interaction between humans and machines. The idea is based on giving the user access to the development process, thereby considering their perspective on the underlying business problem at an early stage to achieve cognitive alignment (Arrieta et al., 2020, p. 87; Chander et al., 2018, p. 4).

Task allocation due to competence transferability – A successful group performance is based on a reasonable allocation of responsibilities based on individual competencies. Thus, the cognitive augmentation of humans by machines is also dependent on the premise that the shared task is divided into sub-tasks, and these are allocated based on the individual competence profiles (Ansari et al. 2018, p. 119). Through technological progress in the field of AI, a transfer of competencies between humans and machines is taking place. AI is able to adapt the cognitive abilities of humans, which promotes the integration of machines into formerly human-centric processes. Humans, in turn, must develop new competencies in an AI environment. This shift requires the adaptation of individual competence profiles and a clear definition of responsibilities based on revised competence profiles (Ansari et al., 2018, pp. 121-122; Wilkens, 2020, pp. 260-262). Based on the competence profiles of humans and machines, specific task pools (human-specific, machine-specific, shared task) should be defined individually adapted to the use case at hand and employed as a basis for task allocation (Ansari et al. 2018, p. 119; Wilkens, 2020, p. 257).

Governance to ensure a regulatory framework – Governance represents the overarching regulatory framework to which all Design Principles should be subject (Lossos et al., 2021, pp. 307-308). In ML-based decision support systems, data security and privacy must be ensured, legal frameworks have to be respected and discrimination against individuals must be avoided (Arrieta et al., 2020, p. 84, European Commission, 2019). Similarly, the implementation of control mechanisms with human oversight is a way to define responsibilities and establish the regulatory framework. Analogous to the HITL concept, interactive human involvement ensures the objectives (European Commission, 2019, pp. 19-20). Furthermore, for in-depth insights, the following frameworks can be recommended in the context of IT governance: COBIT 2019 (ISACA, 2019), the General Data Protection Regulation (GDPR) (Sartor, 2020), or "Assessment List for Trustworthy AI" (European Commission, 2019).

RESEARCH DESIGN

The research design consists of a combination of the DSR methodology and a case study, whereby the case study functions as evaluation method within the DSR framework. By describing the scientific and empirical techniques used, the validity and reliability of the results presented can be questioned critically.

Design Science Research

The DSR framework of Hevner et al. (2004), presented in Figure 1, was used as the overarching research methodology of the study. Design science is an iterative development and evaluation process of a design artifact synthesized from concepts and methodologies of an existing knowledge base (rigor) to solve existing business needs (relevance) of an organization (Hevner et al., 2004, pp. 76-78). The underlying knowledge base refers to the research areas of predictive analytics and CI as well as the related topics of XAI, HITL, and collective intelligence to ensure a holistic perspective. The relevance of the DSR approach is embodied by the business needs of organizations and people facing the challenge of integrating analytic AI artifacts into enterprise infrastructure as part of the digital transformation of decision-making processes (van der Merwe, Gerber, Smuts, 2020, p. 170; Hevner et al. 2004, p. 85).

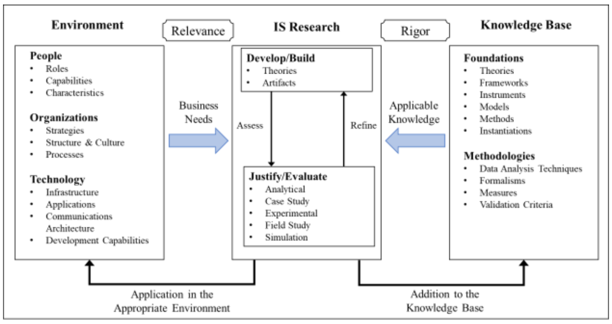

Figure 1: Information Systems Research Framework [Source: Hevner et al., 2004, p. 80.]

As DSR artifact, a prototype of a decision support system in form of a predictive analytics solution was developed, which consists of an ML-based prediction model and a dashboard as an interface for HMC. To implement the iterative design and evaluation loop according to Hevner et al. (2004, p. 85), a case study served as the evaluation method. However, the iterative design and evaluation loop is limited to one cycle. As evidence collection methods of the case study, a mixed method in the form of a triangulation of a survey and semi-structured interviews were conducted. This allows to collect quantitative as well as qualitative insights for the evaluation of the design artifact. To validate the gathered data, a pattern matching approach was carried out. A detailed description of the mixed method evaluation and the pattern matching approach will be given in the presentation of the case study. As a conclusion to the DSR process, the insights gathered in the design and evaluation process serve as research contributions to practice and theory (Baskerville et al., 2018, pp. 367-368; Hevner et al., 2004, pp. 80-81).

Case Study

The case study was created following a critical single case design. According to Yin (2018, p. 46), the use of a clearly defined theoretical foundation is particularly important in single case design to ensure external validity. Therefore, concepts of the research areas presented in the literature review were logically linked to define research propositions. Based on Yin, the research propositions in Table 1 serve to determine the research direction of the research question to ensure that evidence is sought in the right places (2018, pp. 27-28).

Table 1: Research Propositions [source: own work.]

1	CI ensures a focus on the HMC when implementing a predictive analytics solution.
2	The interdisciplinarity of the CI Design Principles ensures a holistic perspective on the basic requirements of an HMC orchestration.
3	The implementation of analytical AI artifacts using the CI Design Principles ensures an informed decision-making process.

The case unit was the fictitious company named Global Bike Incorporated (GBI) which is from the SAP University Alliances. The SAP University Alliance provides a framework of SAP software and learning content used for educational institutes for conducting case studies (SAP, 2021). The GBI represents a medium-sized company operating in the discrete manufacturing sector. In the long run, they are pursuing the business goal of increasing their competitiveness in the market by establishing a bike-sharing business as a second major sales channel. To this end, the management of the GBI aims to develop a predictive analytics solution in the form of a decision support system. The added value of the decision support system is to provide a demand forecast as well as background information and influencing factors of customer behavior for the responsible managers in order to improve the performance of operational and strategic decisions. By implementing CI Design Principles, the specific design of the decision support system is intended to orchestrate HMC to add value to the solution. The data used for the case study originates from a data set of Kaggle, which is based on a real bike-sharing use case (Kaggle, 2022).

To collect data from the case study, a multiple sources of evidence collection approach was used to increase the construct validity and reliability of the results (Yin, 2018, p. 126). For this purpose, the design artifact was tested in a simulation in the form of a usability test (Hevner et al., 2004, p. 80). The results of the usability test were collected through a combination of survey and semi-structured interviews. The triangulation ensured the validity, reliability, and practicality of the collected data (Yin, 2018, pp. 118, 126-128). As guidance, Saunders et al. (2016) and Yin (2018) were used for a scientifically correct methodology. The collected data was analyzed using a pattern matching approach. A theoretical pattern is a hypothesis about what is expected in the observational realm – observed patterns. The pattern matching approach ensures a structured research process that increases the internal validity of the results (Sinkovics, 2018, p. 2; Yin, 2018, pp. 175-178). Based on the findings of Sinkovics (2018), it is up to the researcher to decide in what form and granularity the theoretical patterns for pattern matching are defined. Therefore, the theoretical patterns in Table 2 were derived from the research propositions to establish an alignment between the theoretical knowledge base, research question, and the case study. As part of the derivation process, the scope of the theoretical patterns was delimited to AI in the form of ML and decision processes. This ensures that the theoretical patterns and the observed patterns have the same level of abstraction.

Table 2: Theoretical Patterns [source: own work.]

1	The applicability of a decision-making system is linked not only to accuracy but also to the transparency of the underlying ML model.
2	Achieving cognitive alignment between humans and machines is a precondition for establishing trust and acceptance within the HMC.
3	An interpretable and comprehensible design of a decision-making system determines the added value of cognitive augmentation.
4	The implementation of measures that orchestrate the interaction between humans and machines promotes mutual learning and increases overall performance.
5	The implementation of ML-based solutions in decision-making processes requires an adjustment of existing roles and responsibilities based on the capabilities of the participants.
6	Governance as an overall regulatory framework in dealing with decision-making systems is needed to ensure compliance requirements in HMC.

The data collected from the survey and semi-structured interviews serve as basis for the empirically observed patterns. Together, the theoretical and observed patterns form the counterparts for the pattern-matching approach, which enables the theorizing process of the success factors. A sample of three people, two business users, and one expert user were selected for the data collection. The usability testing with the survey and the semi-structured interview together took about an hour per participant. The observation units were SAP employees representing potential users of a decision support system. When selecting the participants, it was taken care that they had no direct relationship to the research project to minimize the influence of possible bias.

ARTIFACT DEVELOPMENT

Within the case study, the predictive analytics solution was implemented to simulate the orchestration of the HMC. The aim was to create a synergy between humans and machines through a cognitive augmentation of the decision-maker by the machine, in order to enable an informed decision-making process. In the backend, an ML model formed the basis for calculating the demand forecast of the decision support system. The front end was represented by a dashboard that acts as a user interface for decision support.

For the development of the ML model, the methodology of the CRISP-DM process model was followed as a blueprint. Since this is a de-facto standard, the necessary rigor of the DSR approach was also ensured. In the selection of the ML method, special attention was paid to transparency and interpretability in addition to the accuracy of the model. Therefore, several models were compared with each other in order to achieve an optimal trade-off between transparency and performance.

For the development of the dashboard, the recommendations of Few (2006) were followed to ensure a coherent design, an appropriate information density, and an optimal visualization adapted to the specific content. While selecting the content to be visualized, measures were derived from the Design Principles in addition to decision-relevant information. The measures provide information that contextualizes the demand forecast and thus indirectly contribute to decision support by helping the decision-maker to process the information.
The dashboard is divided into several pages. This corresponds to the basic idea of decomposability as a measure to reduce the complexity of the decision support system. The division into logically related subject areas is intended to increase comprehensibility and transparency for the user. Despite the division, the use of links and drill-down options ensures that the content is logically linked. This creates a story flow that makes it easier for the user to process the content provided. Furthermore, each page contains textual explanations that are directly linked to the corresponding key figures or diagrams. In terms of a target group-oriented design, this fosters transparency and increases comprehensibility for better interpretability for both novice and experienced users. For the same purpose, a help button has been implemented to support the use of the dashboard.

Landing Page - It is the user's first point of contact with the predictive analytics solution. The page contains an overview of all other pages of the dashboard including a short description and a link to the corresponding pages.

Decision Support Page - The decision support page serves as the central information base for decision support in controlling and planning dynamic business processes within the bike-sharing business. In Figure 2 a simplified depiction of the dashboard page is provided.

Introductory Sentence		Link Help Page
Forecast	Feature Importance – Explained Variance	
Performance Metrics	Link Calendar Effects	Link Weather Effects

Figure 2: Decision Support Page

On the left half of the page, the demand forecast is displayed which can be used by the decision-maker as decision support to draw conclusions for future demand planning. To show the user that the forecast results are trustworthy and reliable, the ML model performance metrics are visualized directly below the forecast. This is a model-agnostic measure intended to provide transparency post hoc to the model development process. On the right half of the page, the underlying feature importance of the two ML models is visualized by ranking the top ten features per model that explain the largest share of the data variance in the forecast. This post-hoc model-agnostic measure not only helps the decision-maker to gain transparency about the decision logic of the ML model but also contains additional decision-relevant information for the underlying business problem.

Knowledge Foundation Page - To ensure maximum transparency for the decision-maker, the knowledge foundation page provides basic information about the features as well as insights into the data set on which the ML model development is based (see Figure 3). Those ante-hoc feedforward measures allow novice and expert users to gain a holistic understanding of the data set and contextualize the forecast to ensure informed decision-making.

Introductory Sentence	Link Help Page
Textual Feature Description	Descriptive Analytics Metrics

Figure 3: Knowledge Foundation Page

For this purpose, the left half of the page defines each feature from the underlying dataset and the right half of the page visualizes a selection of relevant descriptive metrics for the dataset.

In-depth Insights Pages - The two in-depth insights pages provide the user with the opportunity to understand the decision logic of the ML model by showing calendar and weather effects within the dataset that the algorithm uses for prediction (see Figure 4 and 5).

Introductory Sentence	Link Help Page
Number of Customers per Year	Distribution of Customers per Weekday

Figure 4: Calendar Effects Page

Introductory Sentence	Link Help Page
Correlation of Temperature to the Number of Customers	Correlation of Humidity and Wind Speed to the Number of Customers

Figure 5: Weather Effects Page

Particularly as a complement to the visualized feature importance on the decision support page, these ante-hoc insights serve as a way to contextualize and improve the interpretability of the feature importance ranking. Furthermore, these insights act as a cognitive augmentation of the decision-maker by creating a holistic understanding of relevant influencing factors for the underlying business problem.

Machine Learning Decision Making Page - The ML decision-making page serves as a detailed explanation of the decision-making process and the decision logic of the ML model (see Figure 6). Both contribute to the creation of transparency of the ML design, which in turn increases trust and acceptance in the ML model. Furthermore, valuable insights into the underlying business problem can be derived from the decision logic of the ML model.

Introductory Sentence	Link Help Page
Feature Importance – based on F-Score	Visualized Regression Tree

Figure 6: Machine Learning Decision Making Page

As a model-agnostic measure the feature importance based on the F-score is provided on the left half of the page. Again, the visualization form of a ranking of the feature per model is used for this purpose. Compared to the feature importance based on the share of variance explained, the F-score-based feature importance indicates how often a feature is used to split the data across all trees. This should help the user to understand the influence of the metric explanatory variables compared to the categorical variables to understand the decision-making process of the ML model. As a complement to the F-score-based feature importance, the right half of the page includes a complexity-reduced visualization of the regression tree underlying the ML model. The visualization, as a model-specific measure, is intended to help the user make a connection between how the ML model uses the different variables and to generate the results of the forecast.

Evaluation for Continuous Improvement Page - The evaluation for the continuous improvement page serves as a monitoring and data collection mechanism to identify optimization potentials with regard to the orchestration of the HMC when dealing with the predictive analytics solution (see Figure 7).

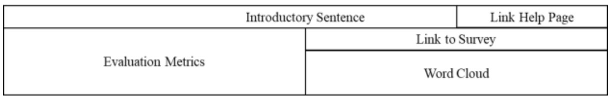

Figure 7: Evaluation for Continuous Improvement Page

Therefore, a link to an online survey is provided in the top right-hand corner of the page. The survey acts as a feedback loop in which users can participate to initiate the desired continuous improvement process and promote mutual learning. On the left side of the page, the evaluation metrics are provided. By answering the questionnaire, five different dimensions are quantitatively assessed, which in their entirety are intended to evaluate the performance of the implemented measures and determine the added value of the dashboard. In addition to the quantitative evaluation via metrics, qualitative insights from the survey are visualized via the word cloud on the lower right side of the page.

Help Page **-** The purpose of the help page is to provide background information on the predictive analytics solution in order to create a transparent knowledge base, which is especially necessary for ML-based solutions to build trust in the solution (see Figure 8).

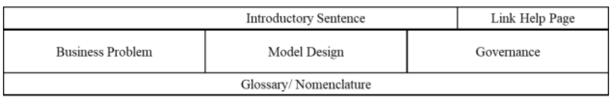

Figure 8: Help Page

Therefore, information about the underlying business problem is provided to make the framework conditions transparent. In addition, key facts of the model design and information on the governance of the predictive analytics solution are stated.

ARTIFACT EVALUATION AND DATA ANALYIS

The two evidence collection methods were carried out separately: As a starting point, each respondent was educated about the underlying business problem for which the DSR artifact was developed within the case study. Afterward, they performed an independent usability test of the decision support systems user interface to gather impressions and experience of using the solution before answering the questions in the survey. Following the survey, each respondent was invited to a semi-structured interview. Complementing the survey with the interviews was providing a deeper understanding of the motivations behind the respondent's answers and allow contextualization results to enrich the quantitative information with qualitative ones.

A descriptive analysis of the survey was conducted at question block and individual question level to draw conclusions for the observed patterns. When analyzing the qualitative data from the semi-structured interviews, a thematic analysis according to Saunders et al. (2016, pp. 579-580) was conducted. This involved looking for patterns within the data that could be used to contextualize the quantitative data from the questionnaire. The same sequence of questions in the questionnaire and the interview implied that there was already a thematic coherence, which simplified the analysis. The findings of the data analysis regarding the subjects' perception of the underlying mechanisms of the CI Design Principles form the basis of the observed patterns. Within the pattern matching approach, these observed patterns were compared with the theoretical patterns.

The pattern matching showed that in most cases there is an agreement between theory and practice. Patterns one, two, three, four, and six could be matched. Pattern five could not be matched because the use case of the case study was without an implementation scenario in a real environment. Due to that fact, no data could be collected for an observed pattern, which does not allow an empirically valid statement about a possible match. Nevertheless, the pattern matching provided valuable insights from theory and practice for the definition of success factors. In addition, future research needs were identified.

DISCUSSION

The present success factor research aimed to identify operational factors that distinguish successful from less successful HMC orchestrations. It builds on the assumption that success or failure can be traced back to central influencing factors that have a decisive impact on HMC orchestrations. Due to the increasing relevance of the integration of AI artifacts in the form of ML-based solutions in decision-making processes and the associated complexity of HMC orchestration, success factors are required to prevent AI adoptions from failing. The success factors were clustered according to a thematic coherence to the individual patterns of the pattern matching approach. In terms of content, they comprise the quintessence of theoretical and practical insights derived from the data analysis.

Ensure Transparency - To ensure transparency, the solution development process and the decision logic of ML-based solutions must be comprehensible to the decision-maker. A target group-oriented selection of the provided content adapted to the knowledge level of the user is recommended. In general, transparency has a significant influence on all other success factors. Furthermore, each decision-maker needs different components from the solution development process to understand the functionality and decision-making process of the ML-based solution. The selection of the appropriate measures is linked to factors such as the decision maker's individual statistical background knowledge or experience in dealing with ML solutions. At the same time, personal preferences also play a decisive role. Therefore, as a success factor, the target group and its characteristics must be examined in advance of the design of the solution. The division of the components of the ML-based solution into easily digestible building blocks has proven to be a successful measure for reducing complexity. Hereby, it is success-critical that the user can independently link the logical coherence of the individual building blocks by putting them together in a compelling story. When selecting measures, recommended actions include providing the results of descriptive analysis of the data set to provide identified patterns, correlations, or metrics that facilitate a general understanding of the underlying business problem. This makes the solution development process transparent to the decision-maker and allows contextualization of the information. The information needed for this can be generated by following an accepted process model in the ML design process, such as the CRISP-DM model. Besides the visualization of quantitative insights into the decision logic of ML models, the provision of qualitative insights in the form of textual explanations has proven to be useful. The textual explanations are a flexible complement to visualizations or indicators to provide additional information. In particular, enriching model-agnostic and model-specific measures with textual explanations has proven to be best practice in decision support system design.

Foster Trust and Acceptance - The usability of the decision support system depends on whether humans trust the provided information and thus accept the collaboration with the machine. It is in the nature of human beings to question things critically and to check whether they are in line with their understanding and views before they accept them. Therefore, achieving a cognitive alignment between the decision maker's understanding of the underlying business problem and the ML solution finding process is key to success in building trust and acceptance. In this context, ensuring transparency is success critical, because the results of the case study have shown that cognitive alignment builds upon transparency. A transparent design is a prerequisite for the decision-maker to be able to identify and resolve the cause of a possible discrepancy in cognitive alignment. Consequently, from each phase of the solution development (ante-hoc, ML design, post-hoc), holistic information must be provided in order to build trust and acceptance. In particular, the illustration of correlation and interaction effects in the data set through explorative statistical methods combined with insights into the decision logic of the ML solution through a post-hoc analysis have proven to be effective here. Furthermore, the process of cognitive alignment can be accelerated by integrating the decision-maker backward into the development process or by providing contextual information and insights to the developer from the ML design phase.

Enable Interpretability - The added value of a decision support system depends on whether the decision-maker is able to process the results of the decision-support system as well as the provided explanations in order to incorporate it into the decision-making process. Under these conditions, the decision support system fulfills its purpose of serving the decision-maker as cognitive augmentation in the sense of HMC to conduct an informed-decision making process. The results of the case study have shown that shortcomings in the implementation of the success factors of transparency, as well as trust and acceptance, have a negative impact on interpretability. Transparency provides the necessary knowledge base through the target group-oriented provision of information. Establishing a cognitive alignment is crucial for the cognitive augmentation of the decision support system to be trusted and accepted by the user. For achieving interpretability, the explanations regarding the ML decision-making logic are more relevant for cognitive augmentation and conducting an informed decision-making process than insights into the ML development process. The combination of model-agnostic and model-specific measures, as well as the provision of descriptive statistical analysis in the form of influencing factors, correlations, and metrics, provides the necessary transparency concerning interpretability. Moreover, the integration of textual explanations as a complement to the other measures provides the reliability needed to avoid misinterpretations, to ensure that no information is lost and that the correct conclusions can be drawn.

Implement interaction-promoting Design - The use of mechanisms such as feedback and optimization loops ensure that the decision-makers actively engage with decision support systems. This triggers mutual learning processes that improve HMC throughout the organization. The results of the case study have shown that the basis for implementing an interaction-promoting design is the provision of background information about the development process and the functioning of the decision support system. This information enables the decision-maker to actively engage with the solution, expand their individual knowledge level, and identify optimization potential in dealing with the HMC. At the same time, the expanded knowledge also promotes an informed decision-making process, which has a positive effect on the performance of the decision-making process. When implementing a feedback/ optimization loop, it is crucial for success that the underlying communication process between the decision-maker and the developer is transparent, fast, and simple. At the same time, the result must be evaluated and made available transparently so that measures for improvement can be derived.

Providing Governance – A successful HMC orchestration requires an overarching regulatory framework that defines the conditions for collaboration. The case study has shown that the underlying compliance requirements such as data security, data origin, or fairness must be clearly defined and communicated to the decision-maker in an understandable way. Moreover, rules that specify limitations and responsibilities in dealing with decision support systems must be made transparent. Each decision support system has certain limitations that affect the cognitive augmentation of the decision-maker. For example, there are influencing factors that cannot be quantified but must still be considered in the decision-making process. These restrictions need to be pointed out since they have a decisive influence on the quality of the decision support and require the active intervention of the decision-maker. Furthermore, the limitations are included in the definition of areas of responsibility between humans and machines. As another crucial aspect of the regulatory framework, an allocation of responsibilities is necessary to create the basis for HMC. This ensures that subtasks are divided between humans and machines based on their individual strengths.

CRITICAL REFLECTION AND FUTURE RESEARCH

In order to be able to check the applicability of the success factors presented for theory and practice, a critical examination of the external validity of the results must be carried out. For this purpose, the methodological approach is analyzed concerning the collected results. The use of the DSR approach as an overarching research framework has proven to be useful in guaranteeing a scientifically and methodologically recognized approach, which has a positive effect on the external validity of the success factors. Nevertheless, it should be noted that in the sense of the iterative DSR approach, further development and evaluation cycles should follow. In this way, the representativeness of the results can be increased in the long term. The case study as part of the DSR approach has proven to be a useful evaluation method for the present research purpose and research question to generate the necessary data. The single-case design of the case study also achieved the desired effect of being able to test the developed artifact based on the fictitious use case and to demonstrate the relevance of the success factors in the first instance. Only for pattern five, the use case was not suitable. Therefore, case studies with real implementation scenarios should be investigated in future research projects in order to examine the functioning of the measures associated with pattern five. At the same time, further case studies provide the basis for further evaluation cycles of the DSR approach, which would allow the reproducibility of the success factors and the associated mechanisms to be investigated. In this way, the external validity can be further increased. Concerning the evidence collection methods used, the triangulation of survey and interview proved to be ideal for the present research objective. By combining quantitative findings as a snapshot of the usability testing and qualitative in-depth findings on the motivations of the respondents, a comprehensive database was created that could be used for pattern matching as a method of analysis. The pattern matching approach also fulfilled the desired purpose and was able to establish a link between theory and practice in the context of researching critical success factors. Nevertheless, it must be critically noted that the small number of participants must be taken into account, especially with regard to the validity of the quantitative data. Although the findings per subject were rich and varied, there is still potential for improvement to increase the representativeness of the results in the long term. All in all, it can be assumed that the developed research methodology produced valid, reliable, and representative results to answer the research question. However, the research is not yet completed at this point and should be iteratively advanced based on further research projects, analogous to the DSR approach. In particular, involving additional participants in the evidence collection process can improve the validity of the quantitative database, which in turn increases the representativeness of the identified success factors.

CONCLUSION

Companies that want to use the potential of emerging technologies such as AI in the form of ML solutions to their advantage as part of the digital transformation have to deal with AI adoption. More and more situations will occur in which people are compared with machines. Therefore, companies must ask themselves how they want to implement AI in their company. Companies that use these innovations to replace humans with machines will probably experience only a brief performance boost. Instead, companies that manage to achieve synergetic collaboration between humans and machines will gain a long-term competitive advantage by augmenting the strengths of both agents to compensate for their individual weaknesses.

To provide guidance for these companies, the success factors presented in the paper represent heuristic recommendations for action that can be used to create the necessary framework conditions for successful HMC orchestration. The success factors are a combination of theoretical propositions that were confirmed by the usability testing of the developed decision support system and additionally enriched with empirical findings from the case study. The addressees are primarily practitioners who are considering the use of ML solutions in the context of digital transformation and need to orchestrate the HMC. Companies that succeed in achieving synergistic collaboration between humans and machines will gain a long-term competitive advantage by amplifying the strengths of humans and machines to compensate for their individual weaknesses.

Based on the current popularity and number of publications in the field of AI, it can be assumed that the relevance and impact for the business environment will continue to increase. Consequently, within the realm of companies attempting to become an intelligent enterprise, the relevance of a successful HMC orchestration will continuously be reinforced. It remains to be seen how HMC will change when current concepts such as Artificial Super Intelligence are implemented in reality and what implications this will have for the collaboration between humans and machines.

LITERATURE

Alizadeh, F., Esau, M., Stevens, G. & Cassens, L. (2020) eXplainable AI: Take one Step Back, Move Two Steps forward. Workshop on User-Centered Artificial Intelligence (UCAI '20). Retrieved January 30, 2022 from https://dl.gi.de/bitstream/handle/20.500.12116/33513/muc2020-ws-369.pdf?sequence=1&isAllowed=y.

Aleksander, I. (2004). Advances in Intelligent Information Technology: Re-Branding or Progress Towards Conscious Machines? Journal of Information Technology, 19(1), 21-27. Doi.org/10.1057/palgrave.jit.2000001.

Ansari, F., Erol, S. & Sihn, W. (2018). Rethinking Human-Machine Learning in Industry 4.0: How Does the Paradigm Shift Treat the Role of Human Learning? Procedia Manufacturing, 23, 117-122. Doi.org/10.1016/j.promfg.2018.04.003.

Arnold, V., Clark, N., Collier, P. A., Leech, S. A. & Sutton, S. G. (2006). The Differential Dse and Effect of Knowledge-Based System Explanations in Novice and Expert Judgment Decisions. MIS Quarterly, 30(1), 79-97. Doi.org/10.2307/25148718.

Arrieta et al. (2020). Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI. Information Fusion, 58, 82-115. Doi.org/10.1016/j.inffus.2019.12.012.

Baskerville, R., Baiyere, A., Gregor, S., Hevner, A., & Rossi, M. (2018). Design Science Research Contributions: Finding a Balance between Artifact and Theory. Journal of the Association for Information Systems, 19(5), 358-376. Doi:10.17705/1jais.00495.

Bawack, R., Wamba, S. & Carillo, L. (2021). A framework for understanding artificial intelligence research: insights from practice. Journal of Enterprise Information Management, 34(2), 645-678. Doi:10.1108/JEIM-07-2020-0284.

Bohanec, M., Robnik- Šikonja, M. & Borštnar, M. (2017). Decision-making framework with double-loop learning through interpretable black-box machine learning models. Industrial Management & Data Systems, 117(7), 1396-1406. Doi:10.1108/IMDS-09-2016-0409.

Chander, A., Srinivasan, R., Chelian, S., Wang, J. & Uchino, K. (2018). Working with beliefs: AI transparency in the enterprise. Workshops of the ACM Conference on Intelligent User Interfaces. Retrieved January 30, 2022 from http://ceur-ws.org/Vol-2068/exss14.pdf.

Chang, S-H. (2020). Technical trends of artificial intelligence in standard- essential patents. Data Technologies and Applications, 55(1), 97-117. Doi.org/10.1108/DTA-10-2019-0178.

Chen, T. & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 785–794. Doi: 10.1145/2939672.2939785.

Demetis, D. S. & Lee, A. S. (2018). When Humans Using the IT Artifact Becomes IT Using the Human Artifact. Journal of the Association for Information Systems, 19(10), 929-952. Doi: 10.17705/1jais.00513.

Epstein, S. (2015). Wanted: Collaborative intelligence. Artificial Intelligence, 221, 36-45. Doi.org/10.1016/j.artint.2014.12.006.

European Commission (2019). Ethics guidelines for trustworthy AI. Retrieved January 30, 2022 from https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai.

Few, S. (2006). Information Dashboard Design – The Effective Visual Communication of Data. Italy. O'Reilly & Associate.

Fountaine, T., McCarthy, B & Saleh, T. (2019). Building the Ai-Powered Organization. Harvard Business Review, 62-73.

Gilpin et al. (2019). Explaining Explanations: An Overview of Interpretability of Machine Learning. 5th IEEE International Conference on Data Science and Advanced Analytics (DSAA 2018). Turin, Italy: IEEE. Retrieved January 30, 2022 from https://arxiv.org/pdf/1806.00069v3.pdf.

Harbers, M., van den Bosch, K. & Meyer, J.-J. (2010). Design and evaluation of explainable BDI agents. IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, 125–132. Doi:10.1109/WI-IAT.2010.115.

Hevner, A., R., March, S., T., Park, J. & Sudha, R. (2004). Design Science in Information Systems Research. MIS Quarterly, 28(1), 75-100. Doi.org/10.2307/25148625

ISACA (2019). COBIT 2019 Framework: Governance and Management Objectives. Retrieved January 30, 2022 from https://www.isaca.org/bookstore/bookstore-cobit_19-digital/wcb19fgm.

Jafari-Sadeghi, V. ,Garcia-Perez, A., Candelo, E. & Couturier, J. (2021). Exploring the impact of digital transformation on technology entrepreneurship and technological market expansion: The role of technology readiness, exploration and exploitation. Journal of Business Research, 124, 100-111. Doi.org/10.1016/j.jbusres.2020.11.020.

Jarrahi, M. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61, 577-586. Doi.org/10.1016/j.bushor.2018.03.007.

Kaggle (2022). Bike-Sharing in Washington D.C. Dataset. Retrieved January 30, 2022 from

https://www.kaggle.com/marklvl/bike-sharing-dataset?select=Readme.txt.
Kaparthi, S. & Bumblauskas, D. (2020). Designing predictive maintenance systems using decision tree-based machine learning techniques. International Journal of Quality & Realiability Management, 37(4), 659-696. Doi.org/10.1108/IJQRM-04-2019-0131.
Kaplan, A. & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Business Horizons, 62, 15-25. Doi.org/10.1016/j.bushor.2018.08.004.
Langley, P., Meadows, B., Sridharan, M. & Choi, D. (2017). Explainable agency for intelligent autonomous systems. AAAI Conference on Artificial Intelligence, 4762–4763. Retrieved January 30, 2022 from http://www.isle.org/~langley/papers/agency.iaai17.pdf.
Li, M., Porter, A., & Suominen, A. (2017). Insights into relationships between disruptive technology/innovation and emerging technology: A bibliometric perspective. Technological Forecasting & Social Change, 129, 285-296. Doi.org/10.1016/j.techfore.2017.09.032.
Lossos C., Geschwill, S. & Morelli, F. (2021). Offenheit durch XAI bei ML-unterstützten Entscheidungen. Ein Baustein zur Optimierung von Entscheidungen im Unternehmen? HMD, 58, 303-320. Doi.org/10.1365/s40702-021-00707-1.
Malone, T. (2018). How Human-Computer 'Superminds' Are Redefining the Future of Work. Retrieved January 30, 2022 from https://sloanreview.mit.edu/article/how-human-computer-superminds-are-redefining-the-future-of-work/.
Malone, T. (2019, January). Published interview conducted by Guszcza, J. & Schwartz J. Superminds: How humans and machines can work together. Deloitte Review, 24, 121-131. Retrieved January 30, 2022 from https://www2.deloitte.com/us/en/insights/focus/technology-and-the-future-of-work/human-and-machine-collaboration.html.
Metcalf, L., Askay, D. A. & Rosenberg, L. B. (2019). Keeping Humans in the Loop: Pooling Knowledge through Artificial Swarm Intelligence to Improve Business Decision Making. California Management Review, 61(4), 84-109. Doi.org/10.1177/0008125619862256.
Nyce, C. (2007). PREDICTIVE ANALYTICS WHITEPAPER. American Institute for CPCU/Insurance Institute of America. Retrieved January 30, 2022 from http://www.the-digital-insurer.com/wp-content/uploads/2013/12/78-Predictive-Modeling-White-Paper.pdf.
Paschen, J., Wilson, M. & Ferreira, J., (2020). Collaborative intelligence: How human and artifical intelligence create value along the B2B sales funnel. Business Horizons, 63, 403-414. Doi.org/10.1016/j.bushor.2020.01.003.
Ridhawi, I., Otoum, S., Aloqaily, M. & Boukerche, A. (2018). Generalizing AI: Challenges and Opportunities for Plug and Play AI Solutions. IEEE Network, 35(1), 372-379. Doi.org/10.1109/MNET.011.2000371.
SAP. (2021). SAP University Alliances. Retrieved January 30, 2022 from https://www.sap.com/about/company/innovation/next-gen-innovation-platform/university-alliances.html.
Sartor, G. (2020) The impact of the General Data Protection Regulation (GDPR) on artificial intelligence. Retrieved January 30, 2022 from https://www.europarl.europa.eu/RegData/etudes/STUD/2020/641530/EPRS_STU(2020)641530_EN.pdf.
Saunders, M., Lewis, P., & Thornhill, A. (2016). Research Methods for Business Students (7th ed.). Harlow, England: Pearson Education Limited.
Schuetz, S. & Venkatesh, V. (2020). Research perspectives: the rise of human machines: how cognitive computing systems challenge assumptions of user-system interaction. Journal of the Association for Information Systems, 21(2), 1-43. Retrieved January 30, 2022 from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3680306.
Shearer, C. (2000). The CRISP-DM Model: The New Blueprint for Data Mining. Journal of Data Warehosuing, 5 (4), 13-22. Retrieved January 30, 2022 from https://mineracaodedados.files.wordpress.com/2012/04/the-crisp-dm-model-the-new-blueprint-for-data-mining-shearer-colin.pdf.
Sinkovics, N. (2018). Pattern matching in qualitative analysis. In Catherine Cassell, Ann Cunliffe, & G. Grandy (Eds.), The SAGE Handbook of Qualitative Business and Management Research Methods (2, 468-485). Thousand Oaks, US: Sage Publications Ltd.
Statista (2020). Adoption rate of emerging technologies in organizations worldwide as of 2020, by scale. Retrieved January 30, 2022 from https://www.statista.com/statistics/661164/worldwide-cio-survey-operational-priorities/.
Van der Merwe A., Gerber A., Smuts H. (2020) Guidelines for Conducting Design Science Research in Information Systems. In: Tait B., Kroeze J., Gruner S. (eds) ICT Education. SACLA 2019. Communications in Computer and Information Science, 1136. Springer, Cham. Doi.org/10.1007/978-3-030-35629-3_11
Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118-144. Doi.org/10.1016/j.jsis.2019.01.003.
Wilkens, U. (2020). Artificial intelligence in the workplace – A double-edged sword. The International Journal of Information and Learning Technolog, 37(5), 253-265. Doi.org/10.1108/IJILT-02-2020-0022.
Wilson, H. J. & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. Harvard Business Review. 96(4), 114-123.
Yin, R. K. (2018). Case Study Research and Applications: Design and Methods (6th ed.). Thousand Oaks, California: SAGE Publications.