Towards Natural Language Processing: An Accounting Case Study

Practitioner Paper

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Abstract

Natural language processing (NLP) helps to extract data from digitized documents. An interesting use case occurred with the International Financial Reporting Standard 16. Following design science research in information systems, the objective of this article is to lay out design guidelines to automate data extraction from physical leasing contracts by applying NLP. Taking a leading international technology group in the areas of specialty glass and glass-ceramics as our case study, we discuss as follows: (1) The data format of the receiving IS is a sine qua non requirement of the project. Thus, set up the NLP process from the end of the project. (2) Evaluate machine readability of the input documents before preprocessing. List most frequent extraction issues in a manual early in the process. (3) Cluster documents regarding their structure and content beforehand. Then, apply a specifically trained ML algorithm for each cluster. (4) A trainer should guide the machine. Use recall and precision as measures. (5) Design an intuitive user interface by offering both parallel windows and a highlighting feature to offer a quick comparison even for complex contract documents. (6) Project iterations are worthwhile until a stable process is achieved.

Keywords: Digital Technologies, Artificial Intelligence, Machine Learning, Natural Language Processing, Accounting: IFRS 16 (new leasing standard)

Introduction

According to a recent survey, seven out of ten companies report minimal gains from their artificial intelligence (AI) initiatives (Ransbotham et al. 2019). *Natural language processing* (NLP) is an AI-based technique that is used for extracting data from digitized documents in order to accomplish human-like processing (Fisher et al. 2016). An interesting use case occurred in the accounting domain with the International Financial Reporting Standard (IFRS) 16. Effective in 2019 (IFRS Foundation 2017), IFRS 16 is a *new leasing standard* which improves financial transparency (Deloitte 2020). Similar challenges apply to lessees reporting under US GAAP (ASC 842). For lessors, the changes are rather small. For lessees, in turn, the situation is changing. They must report most of their operating leases which have been off-balance until now (IFRS Foundation 2017).

Analyzing leased assets requires detailed information from the leasing contracts. As many lessees do not have all information in a digital format yet, it takes a considerable effort to comply with IFRS 16 manually. As IFRS is mandatory for accounts in 144 countries and in the European Union over 28% of all investments are financed by leasing (Morais 2013), the potential market size for an automated solution is huge. Furthermore, leasing is a unstoppable trend in medium-sized company (ABC 2020). Applying NLP to transform physical information into a *digital format* is a promising option. Audit firms and IT providers offer first solutions. We found articles about the impact of IFRS 16 on financial ratios (Morales-Díaz and Zamora-Ramírez 2018), the balance sheet of lessees per se (Joubert 2017) as well as IS outlets about text-based technologies (Chan and Franklin 2011). However, we could not find any article on how to apply NLP for fulfilling the new IFRS 16 standard. A research study should evaluate the feasibility of automating such a data extraction. Hence, the objective of this paper is to lay out design guidelines on how to *automate data extraction from physical leasing contracts by applying NLP*. We answer two research questions (RQ):

- What *process steps* are needed to implement NLP that enables automated data extraction from physical leasing contracts?
- Which are *design guidelines*[1] to apply NLP for IFRS 16 fulfillment?

To create things that serve human purposes (Simon, 1996), we follow Design Science Research (DSR) in IS (Hevner et al. 2004; vom Brocke et al. 2020). The publication schema by Gregor and Hevner (2013) and its application for developing of design guidelines (Vaishnavi and Küchler 2015) gave us direction. We motivate this article in terms of data extraction for IFRS 16 fulfillment by applying NLP (*introduction*). Based on the state of the art, we identify research gaps (*literature review*). To address these gaps, we adopt a case study (*method*). Relevant findings are captured in design guidelines (*artefact description*). Emphasizing iterative "build" and "evaluate" activities (Peffers et al. 2007), we discuss these guidelines with an auditor and a manager from a chemical company (*evaluation*). Comparing the results with prior work and examining how they relate back to this article's objective, we end with a summary, limitations of our work, and avenues for future research (*discussion and conclusion*).

Literature Review

Following Webster and Watson (2002), we started our literature review with a (1) *journal search* focusing on leading IS[2] journals complemented by both proceedings from major IS conferences[3] and leading accounting journals[4]. For our (2) *database search* assessing the outlets, we used ScienceDirect, EBSCOhost, JSTOR, and Google Scholar. We then applied an iterative search process by updating our (3) *search string* whenever we identified new relevant aspects (vom Brocke 2009).

In a first iteration, we used "*IFRS 16"* as our primary search term and looked at titles, abstracts, and keywords that are related to NLP (Table 1). This led to zero hits. We then extended our search to "grey" literature accessible. This led to four hits. However, we still could not find any IFRS 16 literature applying NLP for data extraction. In a second iteration, we added "finance, accounting, documents, and contract" and combined them with "NLP," "automation, information extraction," and text (data) mining." This search led to 150 hits, from which we selected 18 relevant publications as they focus on NLP, automation or IFRS 16. Finally, we conducted a (4) *backward and forward search* with references from these publications. Including these results, we ended up with *35 relevant publications*.

[1] In addition to the four types of DSR artifacts identified by March and Smith (1995) – constructs, models, methods, and instantiations – *design guidelines* (a.k.a. principles) contribute to (design) theories that specify how IS artifacts should be designed based on kernel theories (Vaishnavi and Küchler 2015).
[2] We followed the Association for Information Systems (AIS) and their senior scholars' basket of eight leading IS journals (2020): European Journal of Information Systems; Information Systems Research; Information Systems Journal; Journal of the Association for Information Systems; Journal of Information Technology; Journal of Management Information Systems; Journal of Strategic Information Systems (JSIS); MIS Quarterly.
[3] We followed the AIS list of four leading IS conferences (2020): Americas; European; International; Pacific and Asia Conference on Information Systems.
[4] We took Scimago Journal Rankings with the subject area "Business, Management, and Accounting" and Academic Journal Guide (AJG) with the subject area "Accounting."

For our gap analysis, we structured the relevant publications in three clusters (Fig. 1): (a) Regarding the *NLP methods* we derived three steps from the Knowledge Discovery in Databases (KDD, Fayyad 1996) process model as follows: Information retrieval; information extraction; text (data) mining. The category "others" covers outlets that cannot be allocated to the NLP methods. (b) The cluster "*research approach*" covers empirical and non-empirical research. The first item covers publications that investigate phenomena in the real world (Helfat 2007): Case studies, action research, surveys, and experiments. We subsume all other publications under non-empirical research. (c) The "*contribution type"* allocates our references to DSR in IS or behavioral research (Hevner and Chatterjee 2010). Within DSR in IS, we differ in the four types of artifacts identified by March and Smith (1995): Constructs, models, methods, and instantiations.

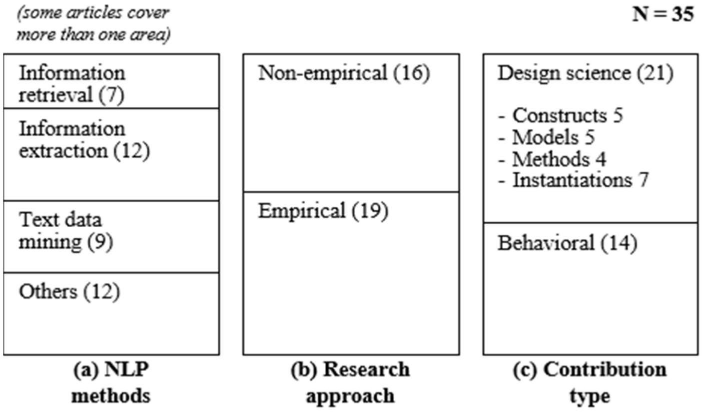

Fig. 1. Literature Systemization.

(a) NLP methods: Ferrari and Esuli (2019) presented a NLP approach across domains and languages. However, for several scenarios the application was unsuccessful in terms of performance. Seven publications focus on *information retrieval*. Another twelve publications cover *information extraction*. For example, Seng and Lai (2010) developed a tool to extract financial data from news, statements, and notes. Nine publications cover *text (data) mining*. Ittoo et al. (2016) analyze the text analytics industry. Ngai and Lee (2016) reviewed applications of text mining in policy making. Esuli et al. (2013) focused on radiology reports. Another twelve publications refer to IFRS 16 or automation in general.

Exposing a first finding, publications addressing information retrieval, extraction, and text (data) mining in the accounting domain simultaneously are underrepresented. To better focus on the KDD process by incorporating different NLP methods, we propose as follows (Sect. 3): (1) Transforming optical characters into a machine-readable digital image, we examined *Optical Character Recognition (OCR)* as a state-of-the-art way in doing so (Chaudhuri 2017). To cluster the contracts by format and contract type, we propose *unsupervised machine learning* (ML, information retrieval). It applies AI procedures to learn a task from a series of examples to perform it more effectively the next time (Simon 1969). In unsupervised learning data is unlabeled as there is no information except the input values for training. The main task of ML is to derive classification rules (Talwar and Kumar 2013). (2) For information extraction, we propose *supervised ML* to capture relevant contract information. (3) We propose *text (data) mining* to identify relationships between the extracted documents.

(b) Research approach: Sixteen publications focus on non-empirical research, whereas nineteen publications are based on empirical research. The latter most often use case studies and action research. Case studies allow researchers to study artifacts in a natural setting (Benbasat 1987; Dul and Hak 2008). We found a case study in the legal domain (Rajbabu et al. 2018) and another one about extracting industrial information (Deokar and Sen 2010). However, no case study proposes guidelines automating the extraction of IFRS 16 contract data. Until now, NLP in terms of IFRS 16 fulfillment is just mentioned in grey literature (Deloitte 2020). Coming to a second finding, we propose *a case study* which provides in-depth information and enables us to learn from practice (Sect. 3).

(c) Contribution type: Fourteen publications contribute to behavioral research. Kloptchenko et al. (2002) combine data mining methods for analyzing quantitative and qualitative data from financial reports to derive a company's performance. Regarding c*onstructs*, KPMG (2020) describes issues with IFRS 16 and specify own solutions. *Models* for document classification (Bui 2016), information extraction, and text (data) mining were proposed as well. Sheikh and Conlon (2012) acknowledge that their model struggles with context-sensitive targets and linguistic pattern variations. Providing an IFRS 16 implementation guide, *methods* were introduced by the IASB (2016). Sen and Deokar (2008) introduce an information extraction framework for analyzing service level agreements. They admit that the quality of the extracted data depends on the quality of the original documents. *Instantiations* differ in data formats. Deokar and Sen (2010) updated IS for the extraction of service level agreements. Oro et al. (2009) address that contracts are typically saved as PDF files. Coming to a third finding, NLP struggles with linguistic patterns and is affected by bad image quality such as handwritings or low DPI rates. Thus, we propose *to explicitly take data quality and format issues into consideration.*

Summarizing all our findings, current data extraction struggles with context sensitive documents and bad document legibility. We did not find a rigorous case study and NLP for IFRS 16 fulfillment is just mentioned in grey literature. So, we propose a new kind of data extraction that automates extraction from physical documents by applying NLP. To do so, we opted for a single case study (Sect. 3).

Method

Following our findings from the literature review (Sect. 2), we opted for a *single case study*. Compared to surveys, case studies provide more in-depth information (esp., internal company data, Benbasat 1987). However, the results obtained are analyzed just in a qualitative manner (Eisenhardt 1989, Sect. 5).

We took a leading international *technology group* in the areas of specialty glass and glass-ceramics as our reference. In 2018, the company had sales of 2.08 bn EUR, 15,500 employees, and reports under the IFRS. From May 2018 to Oct 2019, two researchers (authors of this paper) participated in the IFRS project. The project was organized as follows: *(A) Project set up and NLP solution:* We screened the software market, invited providers, and made our decision based on the following four criteria: Focus on real estate contracts; cover mature learning algorithms; incorporate mature OCR solutions to handle data issues; cover multilingual contracts. *(B) Automated extraction of relevant data from the contract documents:* We applied the KDD process model (Sect. 2, Fig. 2). *(C) Postprocessing the resulting data and loading it into the ERP:* The reference company finally enriched the data table with internal data such as interest rates, developed an interface for the SAP ERP, and loaded the final data table into SAP (not part of the project on hand).

Regarding RQ 1, we compared the status quo in terms of efficient data extraction and better data reliability with the performance of our approach and discussed our results in *manager interviews* (Sect. 5). To arrive at design guidelines (RQ 2), Eisenhardt (1989) gave us direction: (1) We gathered information about the handling of leasing contracts by a *desk research*, crafting observations, and conducting expert interviews (Sect. 4.1-4.5). (2) Crosschecking these results in a *qualitative content analysis*, we finally tweaked the design guidelines by discussing our findings in manager interviews (Sect. 5).

Artefact Description

The contract data extraction consists of five process steps (Fig. 2). We gathered leasing contracts from the reference company's subsidiaries and loaded them into a database (step 1). After data preprocessing and transformation (step 2), we used NLP methods to retrieve, extract, and analyze the required data such as lease installment, term, and incentives from the documents (steps 3a-c). After validating the identified data fields in the extraction tool (step 4), data were interpreted, evaluated, and returned in two data formats: XLSX and JSON (step 5).

Contract Selection (step 1)

To get a profound *business understanding* of the reference company, we conducted expert interviews with the project manager and an expert from university. We then defined our target *data set* and made the decision that no internal leasing, no short-term, and no low-value contracts had to be included. At the end, 790 leasing contracts from lessors all over the world were in scope. Selection of the contracts was random. However, due to language restrictions (only German, Spanish, or English contracts), we had to reduce the number of relevant contracts to 429. Then, we communicated the objective of the extraction process, data were collected in a *single point of truth database* and analyzed regarding their *attributes* such as lessee name, duration, leased item. Furthermore, we discussed the data format. It not only had to be fully compatible with the receiving ERP system, but it had to be fixed upfront as it determined several project steps before the final data upload. We propose a first design guideline:

Design Guideline 1: *The data format of the receiving IS is a sine qua non requirement. Thus, set up the NLP process from the end of the project.*

Preprocessing and Transformation (step 2)

Next, we performed the data cleaning, preprocessing, and transformation operations which was most time-consuming in comparison to the other process steps (Fig. 2). We analyzed both the physical and digitized contracts regarding their *machine readability*. We categorized the most frequent digital image issues and thought about their consequences for automation. Looking forward, we set up a list of *instructions for later users* on how to reduce the number of potential errors in the extraction process (Table 1). Based on a list of instructions, users should classify documents as not machine readable if they identified too many potential errors. Focusing on maximizing the precision, we propose a second design guideline:

Design Guideline 2: *Evaluate machine readability of the input documents before preprocessing: List most frequent extraction issues in a manual early in the process.*

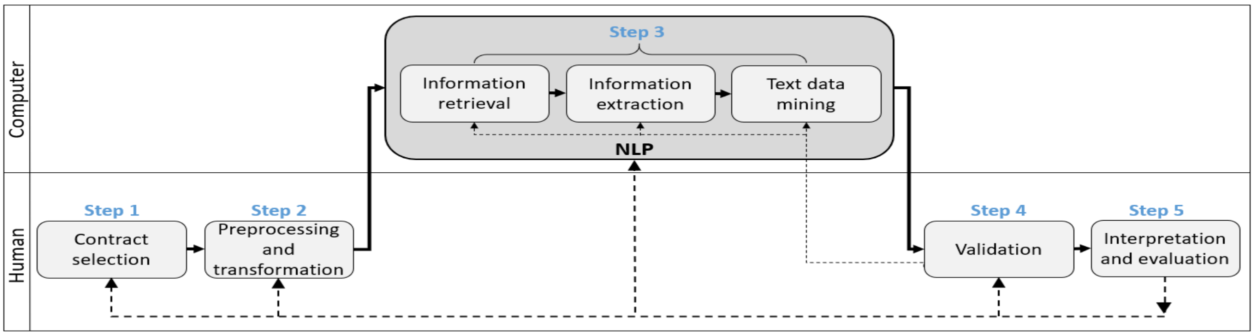

Fig. 2. Contract Data Extraction Process.

Natural Language Processing (step 3)

Different OCR tools can be used to address lack of document quality. After an evaluation, we used the OCR tool of IBM Datacap to convert scanned contracts into machine-encoded text. Then, we inserted the machine-readable text into the ML-module of the NLP tool. In doing so, documents were clustered according to different languages, physical, and digitized contracts, with or without handwriting/low DPI rate complexity. For each of the clusters, we applied an own learning model. Reducing the heterogeneity within such a cluster increased the extraction precision significantly. We propose the following:

Design Guideline 3: *Cluster documents regarding their structure and content beforehand. Then, apply a specifically trained ML algorithm for each cluster.*

For information extraction, we combined different supervised ML algorithms. The NLP tool was already trained with around 16.000 leasing contracts. We decided to do *batch learning* and monitor the learning progress to *intervene in the learning progress when necessary*. Learning took place as follows: (1) The training team defined entities and relations, (2) created rules of most obvious relations, (3) matched entities to their occurrence in the contract, and (4) loaded the rules and output parameters into the training model. Then, labeled examples were used to adjust the algorithms. Measured with *recall and precision,* the training was repeated until an acceptable extraction quality was reached. Yet, with 70% recall measuring the fraction of positive examples over the total amount of examples in the data set (Fürnkranz et al. 2012), and nearly 100% precision, measuring what fraction of the detected examples is positive (Murphy 2012), we beat the manual extraction effort by a factor of five. Then, we applied text (data) mining techniques to identify relations between the main contract and its attachments and relating extracted entities to each other. Combining best of both, we propose a fourth design guideline:

Design Guideline 4: *A trainer should guide the machine. Use recall and precision as measures.*

	Data Quality Issues	Consequence	User instructions
Physical document quality	Bleached out physical contracts	May provoke faulty character recognition	• Repair document damage beforehand
	Forms are filled in or corrected by hand	OCR is not able to interpret the manual editions	• Ensure that contracts are complete
	Document damages, e.g., bent edges, cracks	May provoke faulty character recognition	• Never punch contracts
	Missing contract pages	Missing data attributes	• Treat documents carefully
	Contract includes a lot of shadings	OCR struggles to recognize shaded characters	• Ensure that there is no digital version of the document
	Bilingual contracts	System struggles to detect parts of the contract	• Documents must be placed straight on top of the scanner; no text should be hidden
Digital image quality	Low dots per inch (DPI) rate, faulty scanning	May provoke faulty character recognition	• Clear your documents of all obstructions, scan documents > 300 DPI
	Irrelevant text materials are attached	Dilute pattern with irrelevant information	• Scan relevant text materials • Prefer digitalized documents
	Documents stored with meaningless names	Documents cannot be identified as belonging together	• Store with meaningful names

Table 1. List of Data Quality Issues, Consequences, and Instructions for Users (Excerpt).

Validation (step 4)

Due to the complexity of the real estate contracts, we noticed a significant manual validation effort to ensure reliable data. Especially in contracts with more than 40 pages, users spend up to one hour validating the results of the NLP tool for a single contract. Therefore, we implemented three features to reduce manual validation effort: (1) A *parallel view* of extracted information on the one side and the original document on the other. (2) A *highlighting feature* displaying where in the document the required information was detected. (3) A third feature monitors the *user edits* enabling other persons to track what information was detected by the system and what was edited by the user. We propose a fifth design guideline:

Design Guideline 5: *Design an intuitive user interface by offering both parallel windows and a highlighting feature to offer a quick comparison even for complex contract documents.*

Interpretation and Evaluation (step 5)

Finally, we evaluated the previous steps. We went through our process with a sample of contracts from our database. Whenever we detected significant improvements, we returned to one of the previous steps. After each iteration, we matched the output data model with the data model of the ERP system. In doing so, we increased the compatibility of the output data model as we derived a list of missing data fields. Some data fields such as company codes could not be extracted from the contracts and needed to be added afterwards. Important adaptations to the process model were triggered. We propose a sixth and final design guideline:

Design Guideline 6: *Project iterations are worthwhile until a stable process is achieved.*

Evaluation

Evaluating the *relevance* of artifacts is a major activity in DSR in IS (Venable 2016). Gregor and Hevner (2013) propose several dimensions such as validity, utility, quality, and efficacy. Following RQ 2 we organized *interviews* with (a) an auditor accompanying clients along their IFRS 16 fulfillment and (b) a manager from a chemical company using another extraction tool.

Our first design guideline regarding the *data model* (Sect. 4.1) received full support by the auditor. He experienced various issues with clients in the definition of comprehensive data models. Hence, he stated that KKD is a good concept structuring data extraction. Furthermore, a deep business understanding at the beginning of the project is crucial. His perspective is that an audit firm may help with its process understanding and up-to-date information about the IFRS compliance requirements. For example, IFRS 16 makes exceptions for *low-value assets*. However, the value of an asset is not always known and 5k US$ stated in the IASB conclusion is just an orientation. As a company must justify why a leased item has a low value, this should be aligned with the auditor. Regarding process efficiency, the manager from the chemical company argued that contracts for automotive and IT equipment were already available in a digital format. So, there was no use case for an IFRS 16 project for these leasing contracts. However, data extraction of the more complex real estate contracts is the issue in focus. Furthermore, he agreed that defining the data output format accurately in the beginning of the project helps to make it more efficient.

Our second design guideline about *data cleaning, preprocessing, and transformation* proposes to evaluate machine readability of input documents before scaling and to give users concrete instructions for handling extraction issues (Sect. 4.2). The auditor emphasized continuity in handling extraction issues. The manager from the chemical group learned the same lesson and regarding process efficiency he proposed workshops to explain instructions and train the users in person – not sending just an email with the manual. When outsourcing data cleaning, preprocessing, and transformation, he added, be thorough due to the strong correlation of data quality and the NLP performance.

Our third design guideline aims to reduce the *heterogeneity of documents*. The auditor strongly agreed as his firm itself recognized the demand for more specific learning models and, in doing so, drive data reliability. He argued, no car contract includes reinstatement obligations while almost every real estate contract do. After pre-clustering contracts and applying appropriate learning models the precision and recall increased significantly.

The fourth design guideline motivates a *combined learning mode*. The auditor outlined that the batch-learning approach was a key learning to his company and recommended to always include a manual quality assurance step before updating the learning model. The manager from the chemical company focused on the amount of training data. His team needed at least 400 contracts of similar type to reach a solid extraction precision for each contract type.

The fifth design guideline proposes an *intuitive frontend*. Both interviewees emphasized a parallel view to compare the original document and the extracted data. The auditor stated that this feature reduced the need for manual quality improvement by a factor of three. The employee from the chemical company highlighted the frontend in terms of data reliability. Before transparency features were implemented, we were losing track jumping between the extraction data fields and the PDF document.

The sixth design guideline proposes an *approach with iterations* until a stable process and data model are achieved. This guideline received a mixed feedback. The auditor underlined its importance. He suggested to take one to five percent of the total number of contracts for the first iterations. The manager of the chemical company disagreed with the need for continuously updating the target data model. It should be defined in the first iteration. However, finally we agreed that the target data model must be detailed in the first iteration, however, an adjustment is needed for compatibility.

Discussion and conclusion

Fulfilling the new IFRS 16 standard and taking a single case study as our reference, the objective of this paper was to lay out process steps (RQ 1) and design guidelines (RQ 2) for automating data extraction from physical leasing documents by applying NLP. With 70% recall and nearly 100% precision, we beat the manual data extraction by a factor of five.

For practice, our design guidelines should help companies to enhance their IFRS 16 fulfillment. They can improve existing manual approaches or act as a guide for developing new approaches. We propose that NLP should cover use cases even beyond Finance such as supplier and customer master contracts for a business partner database. However, when physical documents vary in image quality, NLP just works semi-automated and needs human interaction. Here, we laid out the importance of smart frontends (design guideline #5). For *research purposes*, the article on hand is a rigorous approach to tackle IFRS 16 fulfillment by applying NLP. It is based on a literature review (Sect. 2) and a well-documented artefact design (Sect. 4). Until now, NLP for IFRS 16 fulfillment was just mentioned in grey literature (Deloitte 2020). Focusing on the "build and evaluate" process, our design guidelines are more tangible than Esuli et al. (2013) and we focused more on data quality which others mention as their limitation such as Kloptchenko 2002.

However, our research reveals avenues for future research. Due to the use of a case study and just prototyping NLP in the reference company, the cost reduction was not calculated exactly. Nevertheless, considering a reduction of manual effort by a factor of five, IT Managers can evaluate the relevance of the topic on hand based on their number of relevant contracts, IT (hardware, software), and labor costs. Our selection of contracts does not claim representativeness and, thus, needs to be adopted individually in other companies. Furthermore, we will scale our prototype and expect further insights on NLP. "Our data extraction approach faces limitations (design guidelines 1, 2). Increasing the extraction performance, *handwriting* could not be recognized although advanced recognition tools are already available. Thus, we will focus on both better exploiting the technical opportunities and optimizing human involvement. Another research study could evaluate the feasibility of NLP for other types of contract documents. Additionally, the design of the underlaying infrastructure for scaling our solution is interesting. Last, but not least, measuring success of digital technologies should be reworked beyond technology acceptance (TAM) or IS success models. We propose a more balanced approach which we call *triple "e" value circle*. It accommodates the value of digital technologies threefold by efficiency, effectiveness, and experience (Mayer et al. 2021).

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