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The Convergence of Distributed Ledger Technology and Artificial Intelligence: An end-to-end Reference Lending Process for Financial Services

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Abstract

Distributed Ledger Technology (DLT) and Artificial Intelligence (AI) represent two potential disruptive technologies at the top of their hype cycle. Subsequently, questions arise what impact these technologies can have on future business models, especially for service-driven industries like the financial sector. While various assumptions in practice indicate a complementary usage of both DLT and AI to generate new value creation potentials, current literature and research remains scarce. To understand possible synergies for financial services, a segregated perspective on DLT or AI alone is not enough. Therefore, the main objective of this paper is to gain first insights how specific elements of these technologies can be mutually implemented and combined for a potential technological convergence on basis of an end-to-end lending reference process. Building upon the existing body of knowledge and based on Design Science Research, an instantiation of the re-designed process has been created in three iterative cycles. The process prototype demonstrates that DLT and AI are complementary technologies and mostly do not compete against each other with a focus on subsequent synergies. Finally, a comparative overview of the impact on the respective sub-processes has been elaborated to conduct principles for the design and development of future distributed-ledger-based AI applications.

Keywords: Distributed Ledger Technology, Artificial Intelligence, Convergence, Financial Services

1 Introduction

While the idea of Artificial Intelligence (AI) already took shape at the Dartmouth Conference in 1955, Blockchain (BC) and its core concept of Distributed Ledger Technology (DLT) gained first attention more than half a century later in 2009 in form of the Bitcoin protocol (McCarthy et al., 1955; Nakamoto, 2008). Despite this disparity, both AI and DLT provide innovative capabilities for companies in various sectors (Zachariadis et al., 2019; Plastino and Purdy, 2018). In the service-oriented banking industry, various benchmark studies showed a growing adoption rate for these two disruptive technologies (Hileman and Rauchs, 2017; Chui et al, 2018). Where research within the BC domain shifted away from cryptocurrency-related topics, a growing interest for BC as an integrative infrastructure for new application areas can be highlighted (Rossi et al., 2019). Accordingly, scholars assume that highly integrative opportunities are achieved through the convergence of BC, the Internet of Things (IoT), and AI. On that basis, the technologies are catalysing the pace of innovation and enable new solutions in which intelligent processes govern process-related transactions (Hughes et al., 2019; Lampropoulos et al., 2019). Unlike IoT, AI constitutes a more paramount role in reshaping financial services. Machine Learning (ML) applications, e.g., are more than just a productivity enhancer and allow financial institutions to redefine the creation and provision of innovative products (Bahrammirzaee, 2010). Practitioners also believe that the joint usage of BC and AI will have significant business impacts (Panarello et al., 2018). Where DLT-based systems are evolving into an enabling technology for the tracking of ownership of documents, goods or assets, commoditized AI-based services experience high demand and bear tremendous economic potential (Culkin and Das, 2017; Furman and Seamans, 2019).

However, there are no systematic and scientifically sound approaches to foster the common understanding for business leaders where DLT and AI might be used together to support current business processes and how their capabilities may support each other (Salah et al., 2019). Corea (2019) identified that AI is traditionally driven by centralized infrastructures in contrast to DLT's distributed characteristics. Dinh and Thai (2018) also foresee a promising future of smart, decentralized, and secure systems. Prominent cases range, for instance, from innovative data marketplaces to automated platforms for coordination and decision making (Lopes and Alexandre, 2018).

Corresponding academic research remains scarce and the existing knowledge base is strongly limited to grey literature providing limited prescriptive knowledge (Corea, 2019). To address this research gap and gain insights on the potential of both DLT and AI, a process view on a real-world use case within the financial sector is chosen. Driven by substantial inefficiencies in operations, it is assumed that the lending process contains potentials for technology-enabled processes. The creditworthiness analysis e.g. often depends on a manual and time-intensive review process based on various data sources, where technical systems may enable new efficiencies and minimize errors (Zhao et al., 2016). The focus is on three AI-application types due to the versatile applicability of AI from customer front- to settlement back-end within the proposed case (Wang, 2008). By addressing how the convergence of DLT and AI impacts the end-to-end lending process, the paper aims to answer the following questions:

- RQ1: What is the operational impact of both DLT and AI on to the lending process?
- RQ2: Which preliminary principles apply for a process re-design with DLT and AI?

The questions are addressed through an outcome-driven development of new knowledge conducted through an exploratory study on basis of Design Science Research (DSR) (Hevner et al., 2004). In reference to the DSR methodology by Peffers et al. (2007), a conceptual framework is developed to derive process attributes that imply relevant requirements for the usage of DLT and AI. Instantiated on basis of the proposed reference process, potential applicability is demonstrated and discussed. Before a presentation of the solution design takes place, the results are validated through five semi-structured expert interviews with IT experts from the financial industry which are part of a research consortium.

The remainder of the paper is as follows: The next section deals with the research background by highlighting the important aspects of the DLT-AI convergence and its relevance for the financial service domain and the selected reference process. Section 3 elaborates the research design and lays a conceptual grounding for the technology impact analysis. Section 4 consists of the iterative development and artefact instantiation which is followed by the solution design's evaluation in section 5. Section 6 presents and discusses the preliminary design principles. Section 7 contains the conclusion.

2 Research Background

2.1 Distributed Ledger Technology

BC and DLT represent a new form of a decentralized database that ensures the integrity of all kinds of transactions (Catalini and Gans, 2016). But the ability to establish trust among participants without the necessity of a third-party made this innovation a new enabling technology (Swan, 2015). Transactions are often centralized and monitored by additional parties, normally the owner of the network. Accordingly, the central authority validates and verifies transactions. Physical assets e.g. money, inheres security marks and cannot be identically copied, whereas in contrast digitized assets can be easily copied or intercepted. Logically, an intermediate party, e.g. in form of a bank, is needed to operationalize digital payments. Beyond this concept, the process also applies to other digital products, such as software, licenses or music files. Even in our daily life, verification processes through companies or public authorities are necessary and often inevitable. The non-direct negotiation and interaction between two entities is frequently time-consuming, costly and represents, in terms of centralized systems, a potential point of failure (Bertino and Sandhu, 2005). As a replacement of a single authorized ledger which stores the proof that a transaction took place, a shared ledger could replicate its data on countless nodes. Trust in this ledger shifts towards multiple copies and with a reasonable large network ensures safety against corrupted and manipulated information. Consequently, a central authority storing transactional data would not be required anymore. Even so the decentralization of data constitutes a tangible option, an independent mechanism is needed to govern which transactions should be executed and stored. Technical-wise, it must be defined which systemic truth is eventually propagated in the network, the so-called consensus (Mainelli and Milne, 2016). A practical concept to establish trust among unknown participants was implemented in the Bitcoin protocol (Nakamoto, 2008). In fact, it was the first functional solution that enabled a fully public permission-less distributed ledger. The capability to establish trust between unknown parties refers therefore to the immutability of data and relates further to the way how information is structured, generated, and distributed. Consequently, the basic concept relates to four main pillars which unified years of research (Antonopoulos, 2018):

- Peer-to-peer network: The architecture enables the database structure for a distributed ledger
- Transaction logic: Cryptographic methods and digital signatures are used to secure and validate the transactions process between unknown participants
- Immutability of data: The ledger entails consecutive data blocks representing transactions with cryptographically methods stored, interlinked to prior data within a chain
- Consensus mechanism: An algorithm ensures a by all users agreed single true systemic state of the network to synchronize the shared ledger

Although the terms DCT and BC are often used as synonyms in discussions, a shared ledger approach is not always dependent on employing a Blockchain. Recent research shows plenty of distributed database solutions that store an increasing amount of transaction records (Collomb and Sok, 2016). Accordingly, our research focus lies on DLT as the applicable level of abstraction.

2.2 Artificial Intelligence

Besides DLT, AI is another disruptive technology which refers to a vast field of science encompassing not only the computer domain but also psychology, mathematics, linguistics and other areas (Pfeifer and Scheier, 2001). This article views AI as the theory and development of computer systems that perform tasks typically requiring human intelligence such as hearing, speaking or planning (Minsky, 1968; McCarthy, 2007). In other words, algorithms enrich machines or software applications with cognitive functions which enables them to perceive their environment and take actions in the real or virtual world (Russell and Norvig, 2016). A key reason for the emergence and steady development of AI is the exponential increase in available data and computer processing power, making the training of AI algorithms more effective (Westermann, 2018). AI will also enable financial services companies to redefine their work practices, service development and hence customer experience. By letting software applications learn, adapt and improve, AI might be a new production factor and not just a productivity enhancing component or even a cost cutting element (Jubraj et al., 2018).

For the impact analysis, three types of applications with different degrees of AI intensity were chosen. The first and most simple application is Robotic Process Automation (RPA). Even though RPA is not very new in AI, some intelligence is deployed by these robots as they are conducting work which was originally done by humans. RPAs are mostly used for repetitive, monotonous and hence error-prone tasks in banking, e.g. transaction processing, data transfer from and to predefined sources, and simple communication such as standardized responses. RPA is characterized by operational agility, scalability, 24/7 availability, geographical independence and flawlessness if correctly programmed for the specific task (Vishnu et al., 2017). The second AI application type in scope is Cognitive Engagement (CE) which builds on RPA but requires a higher degree of intelligence since CE applications conduct more flexible tasks to analyse actions and to generate insights. This application type includes language processing chatbots and recommendation systems with learning components categorized into supervised or unsupervised learning. While RPAs are mostly used bank-internally, CEs have potential for customer interaction and fulfil tasks like customer support providing increased product or service personalization (Davenport and Ronanki, 2018). The characteristics of RPA also apply to CE, but CE foremost focusses on cognitive tasks which are not repetitive and monotonous by default. In dependence of potential actions and solutions to be taken, CE applications imply a higher level of creativity compared to RPA applications. By drawing a parallel between a CE application and learning students, it can be stated that the application experiences problem-based and limited self-directed learning by the execution of the predefined action(s) (Rotgans and Schmidt, 2011). The third and most complex AI type of the three AI applications in this study is Predictive Analytics (PA). The differentiating characteristic in comparison to CE is the forward-looking prediction component allowing PA applications to anticipate future scenarios based on large structured or unstructured data by analysing relationships and/or patterns of previous events. Bank-relevant PA applications comprise tools for cross selling, churn management, and fraud detection (Eckerson, 2007).

2.3 The End-to-End Lending Process

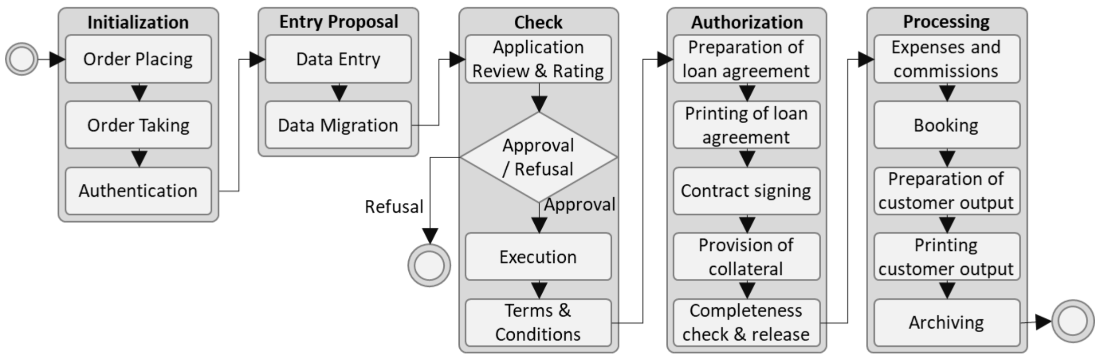

Figure 1. The end-to-end lending process (Alt and Puschmann, 2016)

The financial service sector is often seen as one of the major industries for early technology adoption for disruptive innovations such as DLT and AI. This phenomenon is not only driven by well-known application areas like cryptocurrencies and AI-based robo advisors, but also by substantial bank process inefficiencies and huge cost base issues. Traditional financial institutions have realized that it is crucial to be on top of these technologies to stay competitive in a globalized economy (Lagarde, 2018; Nofer et al., 2017; Zhao et al., 2016). Credit products constitute one major pillar in the business model of banks, where this paper focuses on the end-to-end lending process. In fact, it (1) contains of interactions between the client advisor, the customer and bank employees, (2) comprises of analytical tasks being part of the decision-making process and (3) represents a case where sensitive information, such as the client's financial situation, are transferred between different parties for a consensus to be found. These aspects ensure a potential applicability of both DLT and AI not only bank-internally but also from a customer viewpoint. It is assumed that the approval of a loan is a manually performed, time- and resource intensive task, where an additional data transfer between different entities and stages increases the susceptibility to errors. The present study is based on a lending reference process by Alt and Puschmann (2016) shown in Figure 1. The reference process consists of an execution as well as a transaction-related and -spanning part where execution contains the following seven process steps: Initialization, entry, checking, authorization, and processing. The seven process steps of the execution part are the research objects of the DLT-AI impact analysis in chapter 4.1.

2.4 Existing Research on the Convergence of DLT and AI

The convergence of technologies is not a new phenomenon and was first put into an academic context by Pennings and Harianto (1992) interpreting the introduction of videotext in financial services as a result of an integration between telecommunication, hardware and software capabilities. Originated from evolutionary biology as a part of life science, the initial concept of convergence describes a tendency of unrelated entities coming together to evolve into one unified instance with new characteristics under similar environmental conditions (Stayton, 2015). This concept found its way into a broader systems perspective more than 20 years ago and was then extended in terms of an interdisciplinary approach in the fields of nanotechnology, biotechnology, information technology and neurosciences to create innovation that would greatly enhance individual and societal performance (Bainbridge, 2004). In todays practice, the concept refers to the integration of two or more different technologies in a single device or system allowing multiple and new tasks to be performed unified as they develop and advance (European Commission, 1997). In case of DLT and AI, it is crucial to understand that their capabilities do not exist in a vacuum and will be intertwined with the development of each other. Accordingly, current literature on DLT-AI convergence remains scarce and takes different views onto the topic: While some scholars solely refer to new innovative services and products which might result, for instance, in deep learning blockchains (Swan, 2018; Rabah, 2018; Corea, 2019), others primarily focus on a more integrative perspective explaining the impact of one another (Singh et al., 2019). One group discusses requirements of AI on BC in the sense of making BCs adaptable to changing environments (Atlam et al., 2018; Rathore et al., 2019). The second group states effects of BC on AI to increase specific features such as the security and trust of AI (Salah et al., 2019; Buch et al., 2019). However, conclusions on current research assume that AI and DLT differ in various ways:

- AI is traditionally driven by centralized infrastructures as opposed to DLT's decentralized and distributed characteristics (Corea, 2019)
- AI is more of a black-box solution (Castelvecchi, 2016) and DLT tends to be more transparent regarding all the transactions processed (Beck et al., 2017)
- AI is often based on probabilistic formulas (Hutter, 2004), while DLT is characterized by a more deterministic logic in terms of smart contracts (Cachin, 2016; Alharby and Moorsel, 2017)

It is argued that the two technologies have opposite characteristics: While DLT has security issues and weaknesses in terms of scalability and efficiency, AI is not always trustworthy, especially in terms of transparency and privacy (Cath, 2018). AI supports people to understand and analyse the massive amount of data but as AI output is stored centralized, it introduces room for abuse and hacking. DLT, in contrast is unable to analyse data decision, but provides a decentralized list of records and may protect AI input or output data which results in enhanced security and faster as well as more transparent operations (Rabah, 2018). Therefore, converging both technologies might create benefits and could enable a process re-design for improved or totally new services (Dinh and Thai, 2018). The convergence of AI and DLT could e.g. overcome the black-box phenomenon especially of deep learning applications by enabling explainable AI. The reasons for explainable AI are manifold and contain justification, verification, control, improvement and learning and could hence solve relevant problems

(Adadi and Berrada, 2018; Samek et al., 2017). As current research on BC and AI convergence remains scarce on one side, a growing interest and relevance of the topic is emphasized by a significant number of grey literature in form of white papers, articles, blogs and reports from non-academic publishers on the other. According to this practitioner's perspective, it can be also stated that both technologies are complementing each other possessing capabilities to solve each other's weaknesses (Dinh and Thai, 2018). The architectural design of DLT includes thousands of parameters and trade-offs between security, performance, and decentralization where AI improves decision making, automates as well as optimize DLT to increase performance and better governance (Pinto, 2018).

Existing research on the convergence of DLT and AI is still somewhat limited. The very low number of journal papers in comparison to its practical relevance identified a research gap to demonstrate how DLT and AI transforms specific structures and processes in practice. Although the convergence of these two innovations has received some attention recently, it can be stated that there are no clear answers yet to assure adopters and to provide a basis for further solutions

3 Conceptualization

3.1 Methodology and Design Cycles

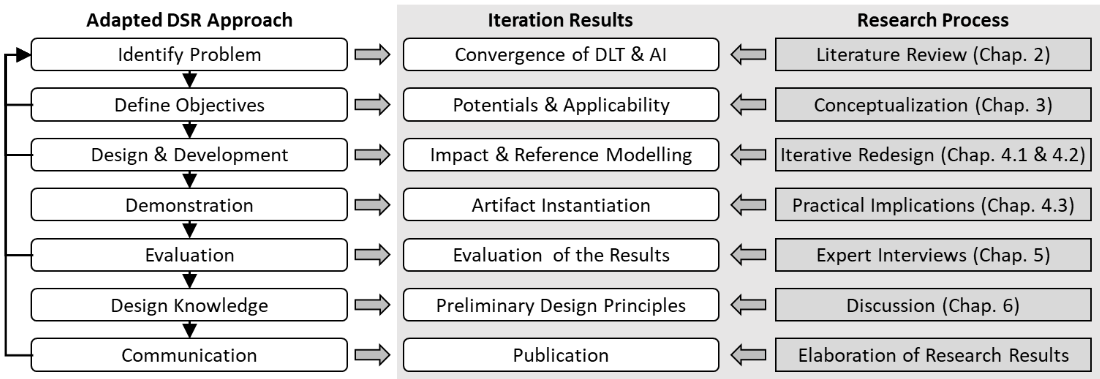

Figure 2. Proposed design cycles and iterative results based on Peffers et al. (2007)

In order to generate new knowledge on DLT-AI convergence, the research gap is addressed through DSR (Hevner et al., 2004). The creation of practical utility through results is one of the core goals (Winter, 2008). Therefore, the objectives are based on an iterative procedure of well-defined steps and refer to an adapted research approach that follows the guidelines of Peffers et al. (2007). On that basis, the rigour and relevance cycles are represented by five phases associated with problem identification and definition, conceptualisation, development, and demonstration (Hevner et al., 2004). Shown in Figure 2, the steps are finalized through the communication of results. The initial cycle is characterized by a literature review to identify relevant process attributes for the conceptualization of an impact assessment framework for DLT and AI. Within an iterative re-design, a conceptual process prototype was developed by not only assessing the potentials separately but rather discussing the convergence of DLT and AI within one scenario through a qualitative analysis and evaluation of five semi-structured interviews. Drawing from these findings, a consolidation of practical assumptions for the design of such systems took place that provides the basis for a discussion anchored in future work.

3.2 Impact Assessment Framework

At the basis of the design cycle lies the need for a systematic framework that analyses the possible impact and assesses the applicability of DLT- and AI-based systems on existing processes. The concept of an impact analysis was developed in the 1960s and represents a traditional method in the field of technology foresight (Weimer-Jehle, 2015). It is considered as an initial component for the development process and provides a first orientation in the design of new technical infrastructures (Gordon, 2009). Impact parameters vary greatly and often rely on the technologies and processes involved.

Therefore, relevant process attributes are derived from the existing body of knowledge and mapped with the potentials of DLT and AI. As a result, Table 1 outlines nine criteria anchored in existing literature which apply for a first qualitative evaluation of DLT- and AI-based optimisation potentials.

DLT & AI related Process Attributes	Impact Analysis Sub-criteria			Process Attribute Description	Selected Literature
Standardization	Inter-changeable	Non-inter-changeable		The existence of established unified rules how a process is performed to be interchangeable	Herwig, 2006 Juhrisch et al., 2007
Automatisation	Fully assisted	Partially assisted	Manual process	The degree to which a process can be performed without further additional human interaction	Bowman, 2015 Otto & Wäsch, 2003
Frequency	Regular	Irregular	Once	The level of how often a task is initiated and repeated within a certain time period	Becker et al., 2010 Luo et al., 2012
Data Variability	Structured	Unstructured		The amount of dispersion in a given dataset and is based on the informational input required	Brahe, 2007 Luo et al., 2012
Data Sensitivity	Sensitive	Non-sensitive		The availability of data that shows susceptibility to unauthorized disclosure, theft, and/ or loss	Heckl et al, 2007 Homann et al., 2004
Media Breaks	One Media Type	Various Media Types		The occurence in information processing regarding medium transfer and transmission	Becker et al., 2010 Homann et al., 2004
Information Type	Analog	Digital	Both	The manifestation of a task being performed in a digital, analog or semi-analog way	Gribbins et al., 2003 Murray et al., 2009
Process Patterns	Input	Processing	Output	The structure of information processing	Curry et al., 2006 Küster et al., 2007
Interaction	Human-Machine	Human-Human	Machine-Machine	The nature of interaction between actors and entities	Brahe, 2007 Schemm et al., 2006

Table 1. Impact assessment framework for DLT and AI

The attribute "standardization" describes the compatibility of process variants, while "automatisation" can be understood as the use of IT to assist in the execution of a business process (Muenstermann and Eckhardt, 2009). Additionally, "frequency" further manifests itself in the repetition of a task in a given amount of time (Becker, 2010). "Data variability" indicates how a data sets varies considering the informational content needed to achieve the desired output of a process (Luo et al., 2012). "Data sensitivity" refers to processed information which must be secured from unauthorized access to ensure the security of the organization (Homann et al., 2004). The usage of various media types leads to "media breaks", e.g. digital workflows that require paper-based documents to carry information during data processing (Becker, 2010). The "information type" describes if information is either processed in an analogous and/or digital manner (Gribbins et al., 2003). Technical requirements are increasing, as various analogous processes reveal. In combination with the attributes "process pattern" and "interaction", a differentiation between AI- and DLT-based applicability takes place. Where the process pattern mainly aims to create an output or allows to input data into a system, infrastructural capabilities are required. Processing, however, is defined as a series of operations to conduct a determined result (Curry et al. 2006). AI-based application types, such as RPA, CE and PA underlie these computational abilities. The "interaction" attribute explains the interplay between entities in the process and adds an additional perspective, where especially human-machine interfaces may allow for additional value creation potentials of AI (Schemm et al., 2006).

To ensure a systematic quantification of technological suitability on basis of the proposed reference process with its sub-tasks, the following logic is applied during the impact assessment. A correlation scale determines the technological impact for each sub-criterion in relation to DLT, RPA, CE and PA (Figure 3). While, for example, a manual task has a high potential for optimization through RPA, DLT is rather less suitable due to required interfaces. This allocation between process attributes and technological characteristics took place during the five expert interviews, resulting in indicative correlations between each of the sub-criteria and the technologies corresponding to a high, medium or low optimization potential. The higher the sum of correlations of the selected sub-criteria per technology, the higher the overall impact potential on the analysed task. In case some attributes are not identifiable, a minimum number needs to be addressed. Otherwise, no impact is assumed. As a detailed description of this semi-quantitative approach would go beyond the objectives of this work, Figure 3 gives an indication where and to what extent DLT and the AI application types correlate with the sub-criteria.

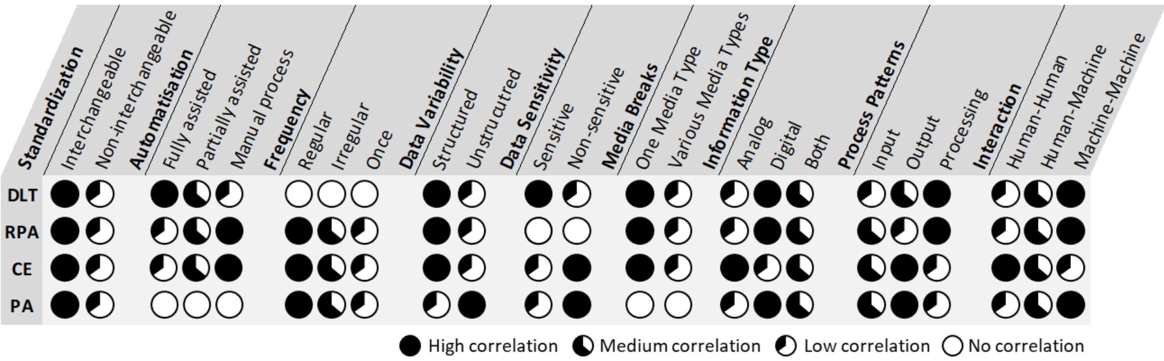

Figure 3. Indicative correlation of optimization potentials between sub-criteria and technologies

4 Iterative Development

4.1 Impact Analysis

Using the predefined relations between process attributes and technological characteristics, the impact assessment framework allows a more differentiated analysis of subtasks. The reference lending process by Alt and Puschmann (2016) consists of seven process steps and twenty-five sub-processes. The impact analysis focusses on the first five process steps being considered the execution phase which is the most visible service part for bank customers. Each of the seventeen sub-tasks in scope is comparatively analysed regarding the status quo shown in Figure 4, where process cost, time and risk optimisation potentials for DLT and the three AI application types RPA, CE and PA are highlighted. The goal is to elaborate preliminary principles for the combination of DLT and RPA, CE and PA, respectively.

A high-level analysis of the overall findings shows that nine sub-processes are affected by DLT, four by RPA, five by CE and four by PA. Highlighting the impact of both DLT and AI, in accordance to each of the three AI application types, a first conclusion indicates an obvious complementary impact on the subtasks of the reference lending process. More specifically DLT-AI convergence occurs between consecutive sub-processes by assigning one sub-process to either one of the two technologies. Following this, it is referred to a so-called between-task convergence based on subsequent technological capabilities. Still, six sub-processes are further identified in which both DLT and at least one of the AI application types constitute an impact, namely on sub-processes (2), (3), (4), (7), (12) and (17). In contrast, this configuration implies a convergence of DLT and AI within-tasks describing closed actions within the same sub-process as an integration into one another. In four of six cases both DLT and RPA have a medium impact on the respective sub-process, particularly on (3) authentication, (4) data entry, (12) completeness check and credit release and (17) archiving. All three have in common that mainly structured data for several purposes within highly interchangeable, partially assisted, human-machine tasks is processed. Given the mentioned process attributes, these cases constitute similarities between DLT and RPA applications. Sub-process (2) order-taking is impacted by DLT because the task is to a high degree interchangeable and within the context conducted on a regular basis. The task is mostly impacted by CE and minimal by PA due to unstructured data, irregular frequency, input process patterns and a high degree of standardization. CE applications further represent a potential, since the sub-process is still partly carried out analogously. Followingly, (2) shows that DLT and AI complement each other within the same task if it comes to highly interchangeable tasks which are based on different data types and sources. Sub-process (4) data entry, in contrast, is minimally affected by DLT caused by high data sensitivity and medium impacted by RPA and CE due to medium data variability. The impact of both technologies within the same sub-process is mainly driven by the medium degree of standardization and a potential media break between paper-based process initialization. Besides of that, high data sensitivity bears potential for DLT if the CE and RPA applications can fall back on the DLT's storage capabilities. Therefore, this case demonstrates the within-task convergence of DLT and AI in tasks where data sensitivity is high, and which require nearly real-time responses (RPA) or insight and recommendations (CE). Interestingly, DLT, CE and PA all have a medium impact on the sub-process (7) approval. Again, a medium degree of standardization and a high data sensitivity manifest the impact of both DLT and AI technologies. For DLT, this is additionally because of potential media breaks to (6) application review and rating. CE and PA applications, in contrast, have an impact due to the partially automatization and medium to high frequency of the task. PA creates also value due to both structured and unstructured data enabling the recognition of hidden patterns. Besides of the beforementioned findings, it is observed that media breaks play a crucial role in the six sub-processes which indicate a within-task convergence of DLT and at least one AI application type. Namely, (2) order-taking, (3) authentication, (4) data entry (7) approval or refusal and (17) archiving are cases which are parallelly impacted by both technologies. From our viewpoint, this is because DLT is an infrastructure which stores, transfers and verifies information while RPA and CE receive and transform sensor-based information and save them on the DLT. In other words, AI transforms real-world perception into machine-readable data and DLT operates digitally according to the input from AI-based applications. Hence, sub-processes (2), (3), (4), (7) and (17) decompose into two subsequent, sequential tasks in which the first is carried out by an AI application and the second by DLT.

Process step	No.	Sub-process	DLT	RPA	CE	PA
Initia-lization	1	Placing of order	-	-	Middle	Middle
	2	Order taking	Low	-	Middle	Low
	3	Authentication	Middle	Middle	Low	-
Entry	4	Data entry	Low	Middle	Middle	-
	5	Data migration	Middle	-	-	-
Check	6	Application review & rating	-	-	-	Middle
	7	Approval or Refusal	Middle	-	Middle	Middle
Authorization	8	Preparation of loan agreement	-	High	-	-
	9	Printing of loan agreement	-	Middle	-	-
	10	Contract signing	Middle	-	-	-
	11	Provision of collateral	High	-	-	-
	12	Completness check/ credit release	Middle	Middle	-	-
Processing	13	Expenses and commissions	-	Middle	-	-
	14	Booking	-	High	-	-
	15	Preparation of customer output	-	High	-	-
	16	Printing customer output	-	Middle	-	-
	17	Archiving	High	Middle	-	-

Figure 4. DLT- and AI-based impact analysis on the end-to-end lending process

4.2 Potential Convergence

Within the next iteration a deeper exploration of the potential convergence between the technologies is conducted to identify additional traits for a first initial process re-design. Whereas the impact of DLT and each AI application type are assessed from an isolated perspective on sub-processes in chapter 4.1, a comprehensive analysis from an end-to-end viewpoint is required to discuss new combinations and features (Davenport & Short 1990). Following three scenarios of (I) DLT and RPA, (II) DLT and CE as well as (III) DLT and PA, the main results are presented in the following.

As RPA automates especially manual, repetitive tasks, integrative potentials with DLT are highlighted for four applications areas in scenario (I). Within order taking, both the customer identification and authentication process can be automated based on “if-then” actions. Whether data is directly stored or accessed on a decentralized infrastructure, information can be referenced by predefined entities in respective DLT networks. Where the data entry process securely relies on various decentralised sources to perform RPA based operations, such as data access, collection or writing, subsequent processes, such as data migration can become obsolete. According to the processing phase, RPA can also initiate the preparation, printing and postprocessing of documents when certain conditions are met. The combination indicates value creation in terms of cost and time-saving potentials if the RPA application supports the DLT to convert data types or represent data. Evaluating a potential integration of DLT and CE, such as recommendation chatbots, in the second scenario (II), three areas for applicability have been identified. Generally, CE can be implemented in all processes that require virtual assistance in form of human-to-human and human-to-machine communication. Beside the assistance of chatbots within an omnichannel approach, it can further serve as an interface during order taking and authentication to feed customer data directly into a DLT system. During entry and processing, it supports also employees for internal processing of required information. Furthermore, chatbots could explain credit decisions based on trusted information saved on a DLT to customers. A convergence ensures transparency, reduces variable costs and time and increases the reliability for the customer. In scenario (III), DLT's decentralized and immutable capabilities enable explainable and robust AI decisions through PA. Incoming customer requests can be analysed to anticipate customers' needs and forecast the demand based on a vast amount of secure and reliable data leading to a tailored customer approach. PA may also recognize data patterns, where a convergence with DLT for approval or refusal of credit loans makes sense. The optimized process results in faster, more reliable, less risky processing of the credit application, as DLT provides an automated enforcement for the issuance of the loan. The security-by-design features of the DLT allow for credit release digitalization based on a digital signature.

4.3 Solution Design

The impact analysis results allow to describe a solution design where a convergence of DLT and all three AI application types RPA, CE and PA is demonstrated and discussed. Following the seventeen sub-processes in scope and starting with (1) placing of the order, customers initiate the process by either face-to-face, via phone, or mobile banking platform. Depending on that, the interaction for (1) order-placing differs: (1.1) As a CE chatbot takes the order during direct customer interaction on the internet banking platform, incoming data is analysed, and a pre-review of the financing request is undertaken and temporary saved on the DLT. If the pre-review is positive, the analysed order data is translated into customized products which are offered the client through the CE chatbot. If the pre-review is negative, further information on the customer are required. In case the pre-review is finally negative, the process is closed, and the conversation data deleted from the DLT. (1.2) If the order is placed through a client advisor, the CE chatbot in combination with the DLT capabilities supports the bank employee and improves product customization. If the pre-review is finally successful and the customer accepts the recommended product, (2) order taking is initiated by adding the information of the chosen product to the DLT through a predefined smart contract logic. The subsequent (3) authentication is fully automated. A DLT-based digital identity ensures data sovereignty and reinforces an RPA application to carry out the identification without room for human error. Having stored all relevant information on the DLT from the beginning of the process makes (4) data entry and (5) data migration redundant. Thus, the DLT transaction capabilities enable a scalable infrastructure solution with low variable maintenance costs. Additional information could be directly sourced, accessed and processed through a network. Nevertheless, it is crucial to actively coordinate involved parties to understand which data is directly accessible to whom. For the lending process, related entities, such as land registry offices, architects or construction companies, could be involved. This would enable an efficient transfer of ownership for real estate property and minimize the bank's risk in construction financing if e.g. the architect could directly document the construction progress on which the pay-out plan depends. PA creates substantial upside potential within (6) application review and rating based on increased data consistency and reliability through a DLT. More precisely, PA helps to recognize patterns for creditworthiness leading to a cost- and risk reduction with increasing processing speed. Relying on a credit officer during (7) approval or refusal and the insights provided by the PA in the previous step, a decision on the financing project is taken and added to the DLT. Sub-process (8) preparation of the loan agreement represents a strong DLT use case in terms of information post-processing which is crucial for AI applications. A seamless conversion of data sets as a design feature of DLT is a clear advantage in comparison to a traditional database. However, after a contractual obligation is set up by an RPA application, the smart contract takes over a decisive role. Step (9) printing of loan agreement becomes redundant since relevant informational flows are tracked by the DLT to trigger a scripted print command during application review (Maurer, 2016). The build-in authentication through a private and public key pair facilitates (10) contract signing, where customers sign and access the DLT in real-time. The value transfer capabilities also offer an alternative to a conventional (11) provisioning of collaterals using a digital currency or a tokenized bankable asset. With additional conditions implemented in the DLT smart contract logic, the sub-process (12) completeness check and credit release automatically initiates the transfer of ownership which subsequently triggers an RPA application on behalf of the smart contract to conduct (13) expenses and determination of commissions and (14) the booking that are both predefined by RPA scripts. (15) The preparation as well as the (16) printing of customer output becomes obsolete as all relevant data is accessible through the decentralized infrastructure. All contract-relevant information is archived on the DLT where clients access the data (17) archiving in a consistent, chronological and temper resistant database. Figure 5 shows a simplified process re-design with relevant high-level component interactions based on the three-tier architecture.

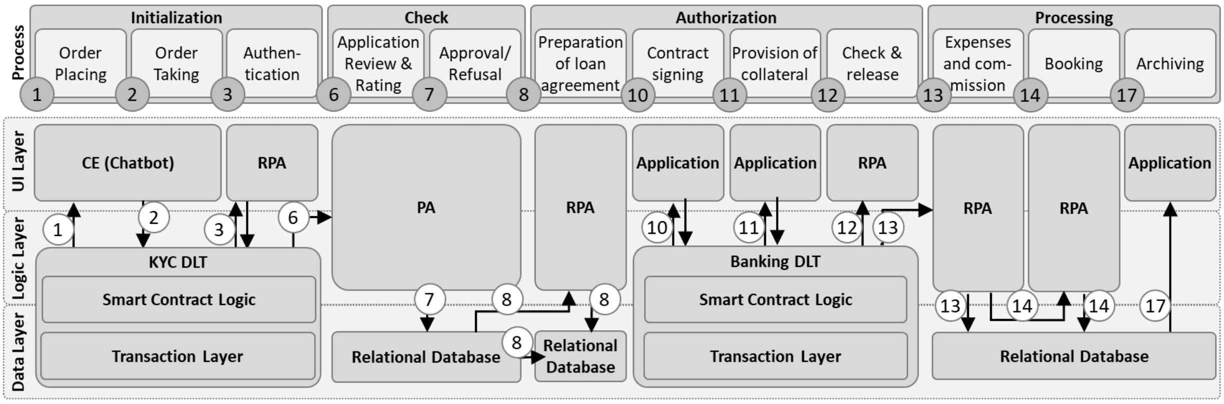

Figure 5. *DLT- and AI-based solution design*

5 Evaluation

Based on five semi-structured interviews with business architects and practitioners in IT administration and process modelling within the financial service domain, a final reflection on both the as-is and the solution design was conducted. The results indicated that almost every single sub-process suffers at least from one pain point and leaves room for technology-enabled improvements. The reference process is time-intensive and inefficient, especially data handling, loan approval and the review of applicants' financial information. In fact, a correlation can be drawn between manual activities and the throughput of many sub-processes leading to higher fixed as well as variable costs. According to the solution design, a strong consent was given in the complementary abilities of DLT and AI highlighting that the technologies interact and converge mostly in a between-task manner. This convergence leads to a double-sided reinforcement, where some sub-processes are impacted by DLT and others by one or more of the AI-applications types RPA, CE and PA. A general opinion that was extracted from the evaluation is that DLT enables a consistent data storage for a reliable processing through AI. This is correct, but a very high-level analysis and gets clearer when focussing on a concrete example that was emphasised in the expert interviews: The application review is a matter of AI, and afterward, the output is stored on a DLT. The more process-relevant and sensitive the data, the higher the impact of DLT. Therefore, DLT alone hast no impact on the application review and rating, but the output generated by AI needs to be stored and partly transferred and provided for the next sub-process. Besides that, the experts underlined the complementary character of the technologies, and hence also follow the finding that between-task convergence reveals massive value creation potential. It is also mentioned by the experts that DLT focuses mostly on the contractual part. AI assists primarily in bargaining, decision making, product offering and specifying contract terms. The interviews also revealed that DLT and AI operate within three different layers according to so-called client–server architectures in which presentation, processual logic, as well as system and data management are separated from a functional perspective (Eckerson, 1995). DLT is located between the system and the logic layer and therefore data-oriented with some logic involved which can be seen in smart contracts. AI, depending on the specific application, is located between the presentation (e.g. CE chatbots) and the logic layer (PA and RPA applications). Following this structure, DLT supports primarily back-office processes, while AI typically supports front office activities serving as an interface for customer interaction. New value potentials are mainly caused through the seamless integration of automated processing on basis of decentralized information sharing. Applying DLT as a spanning infrastructure resolving how data is transferred and handled in the logic layer, modularity within the presentation layer comes by design. Based on a standardized communication protocol, different AI-applications can communicate directly with one DLT layer that reduces overall system maintenance and cuts complexity. This new way of information handling prevents media breaks to release the credit much faster and more transparently.

6 Discussion

6.1 Preliminary principles for the convergence of DLT and AI

Since the predominant between-task convergences within the reference process are not surprising based on the literature analysed in chapter 2.4, the four preliminary AI-DLT convergence principles are mainly derived from the within-task convergence analysed in chapter 4.1:

(1) A high degree of data sensitivity generally fosters the DLT-AI convergence

High within-task data sensitivity seems to support the convergence of DLT and CE or PA, because CE and PA can deliver valuable insights and predictions based on sensitive data saved on the DLT. Besides of that, the processing of sensitive data between tasks fits the trust-creating, transparent capabilities of both DLT and RPA. Hence, DLT-AI combinations could be the solution to strict data privacy regulations in customer-related processes and the sharing of sensitive data within consortia or even with third parties. The characteristics of DLT manifest to be a game changer for all three AI application types by providing consistent, reliable and secure data which enables robust insights and predictions by AI while maintaining high privacy standards and making decisions explainable (Corea, 2019).

(2) Media breaks within and between tasks support DLT-RPA and DLT-CE convergence

Media breaks between tasks are a signal for the convergence of DLT and non-predicting AI application types like RPA and CE. This is mainly because media breaks result in problems such as loss of information and information inconsistency. While the first problem can be solved by the architectural characteristics of DLT, the latter can be tackled by RPA or CE application types which first conduct intelligent analysis on both data sets and are able to combine them purposefully. Media breaks also play a crucial role in distinguishing between- and within-task DLT-AI convergence.

(3) A high degree of standardization and low data variability encourage DLT-RPA convergence

Both DLT and RPA are strongly dependent on highly standardized tasks as they operate more efficiently in harmonized processes as both require a high degree specification according to the task and are hence inflexible to implement. Therefore, DLT and RPA favor a low data variability reducing fixed costs as less requirements need to be considered. Also, a high frequency is advantageous for decreasing variable costs for performing a process. Besides of that, both technologies create transparency for the processing of sensitive data.

(4) A high degree of standardization and data variability favours DLT-CE and DLT-PA convergence

In contrast to the DLT-RPA convergence, a high data variability fosters the convergence of DLT with both CE and PA. This is because the trustworthy capabilities of DLT allow for the explainability of actions taken and predictions or decisions made by CE and PA. Therefore, a high degree of standardization is not contrary to the cognitive capabilities of CE and PA but enables their robustness and support their trustworthiness while applying a variety of data. This underlines that information systems generally require standardized processes to unfold their effects (Afflerbach et al., 2016).

6.2 Limitations and further research

The present study abstractly analyzes the impact of three AI application types and a generally defined DLT solution on the lending reference process by Alt and Puschmann (2016). Hence, the first and foremost important limitation of the present research is that the research objective is a reference process meaning that it is the overlap of differing lending processes a research consortium agreed on, process steps as well as sub-processes can vary in other financial institutions. Second, the application types are chosen to reflect the different stages of complexity and development in AI. Such as DLT, the AI application types are described in a general manner for an analysis on a conceptional level. Since the analysis does not comprise any specific AI or DLT solution, the results of the impact analysis only provide an indication which cannot replace a study based on real-world applications and processes. Third, the present study is not containing a detailed description of the impact assessment as the focus is to develop preliminary principles for a process re-design with DLT and AI based on the example of a reference process. The application of the impact framework will be addressed in an additional publication. The present impact analysis e.g. sheds light on media breaks and data sensitivity and proposes well-fitting cases for DLT-AI convergence which could be subject to further research. This is closely connected to the question if the convergence of both could potentially interconnect privacy regulations such as GDPR with machine or deep learning and foster trust on AI-based decision-making. Another open research question is the integration of DLT interfaces – should DLT-based sub-processes such as contract signing take place in a separate, web-based interface or will they be integrated into a general user interface for customer interaction? Generally, the concept of between- and within-task DLT-AI convergence needs to be evaluated with different tasks, processes and even within different service sectors than the financial industry. Another research question arising from the present study's findings is, to which extent the convergence of DLT and AI supports the way to decentralized autonomous services and organizations as proposed by Swan (2015) and implemented by Jentzsch et al. (2016).

7 Conclusion

Since the present article is the first attempt to analyse the impact of a DLT-AI convergence on a concrete service process, the findings and implications are manifold. Nevertheless, the four elaborated preliminary principles on the convergence of DLT and AI should be understood as high-level position statements for the use of both technologies in the service sector, especially the financial industry. They give practitioners orientation in finding DLT-AI use cases within existing processes and hence contribute to the research of Dinh and Thai (2018). Generally, the characteristics and the evaluated impacts of DLT and AI on the lending process underline complementary treatment as described by Salah et al. (2019). Besides of that, convergence of both technologies can occur in a between- or within-task manner which specifies the DLT-AI convergence study by Singh et al. (2019). Generally, a high degree of data sensitivity and media breaks within and between tasks fuels DLT-AI convergence as these process characteristics address the strengths of both technologies in different ways. Media breaks seem to play a crucial role in distinguishing between- and within-task convergences. Furthermore, structured data and highly standardized tasks foster DLT-RPA convergence as RPA neither fits unstructured data nor non-interchangeable tasks. The AI application types CE and PA, in contrast, potentially converge best with DLT if tasks are standardized but entail higher data variability. Although the findings of the present study imply that DLT and AI are best suited for between-task usage, the results of the impact analysis also emphasize that within-task convergence between DLT and AI exists. On top of that, the integrative capabilities make five out of the seventeen sub-processes of the lending process obsolete. In fact, it has been shown that the convergence of both technologies is a further step to intelligent service automation. Sub-processes get much more integrated using both, DLT and AI, which leads to less manual tasks and higher efficiency within the lending process. The convergence of both technologies can furthermore encourage convergence of services and companies in or even across markets as in the case of the information and communication technology industries (Lei, 2000; Borés et al., 2001). Therefore, the convergence of DLT and AI could support the interconnection and service creation of companies and facilitate the raise of technology-enabled business ecosystems.

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