Responsible AI-based business process management and improvement: observations from financial domain cases

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Abstract: Organizations today seek to improve and adapt their business processes because of an increasingly competitive economy. The use and application of Artificial Intelligence (AI) for business process improvement and management is often discussed and put in place, regardless of its potentially negative impact if AI is implemented in the wrong way, especially around the processing and storing of personal data. We discuss the use of AI for the management and improvement of business processes, especially in the financial domain, and how to ensure responsible AI use in enterprises for this aim. We propose an information system design for responsible and trustworthy business processes, and we envision that businesses will need strong and well-defined control points in their information systems for managing processes and creating associated audits to enforce their principles. We define questions and challenges that companies will need to reflect upon and follow to achieve an application of responsible AI in an enterprise context. We also outline considerations for AI and data protection regulation for companies, while also considering the technical challenges that would need to be solved.

Keywords: Business Processes, Business Process Management (BPM), Responsible AI, Data Science, AI, Enterprise Architecture.

1. Introduction

The fast evolution of business process management systems and architectures has brought about the generation of a vast amount of data coming from business process execution (Weske, 2007). These data can be used to discover or validate knowledge regarding existing processes or to help improve processes and provide flexibility and the possibility for human intervention. A business process is defined as "a collection of tasks executed in a specific order to achieve the business goal" (Weske, 2007 p. 4). This definition suggests that business process management systems track the execution of the process it supports and ensures that the process conforms to a set of restrictions. The application of artificial intelligence (AI) opens the possibility for knowledge workers to obtain new knowledge, and to provide additional flexibility without endangering the correct execution of the business processes itself.

The use of AI in companies is on the rise. The uses of AI are multiple, i.e. the implementation of predictive models to foresee events, or for predictive algorithm design, the development, efficiency, and the deployment of products and services (Waller & Fawcett, 2013; Newman et al., 2016). In business contexts, the application of AI is referred to as artificial intelligence and analytics (AI&A), and it supports the collection, management, analysis, and visualization of large amounts of data. This is something that is of great importance for providing managers, especially in terms of their own operations and business processes, with recommendations and insights (de Medeiros et al., 2020).

The topic of the application of AI to business process management is relevant because organizations that use their business operations data to drive their decisions through AI&A can achieve better performance (Brynjolfsson et al., 2011; Müller et al., 2018). According to Newman et al. (2016), the ability to manage operations with AI has become significant for organizations, therefore also the adoption of the AI&A approaches for this aim is important.

While organizations have understood the power of data analytics for mining and enhancing business processes, there are also great concerns about the use of data for this aim. The power inherent in AI, however, naturally poses certain threats, especially in terms of fairness, trust, and privacy (Eitel-Porter, 2021; Van Der Aalst, 2016). AI projects could deliver erroneous or biased outcomes and thus breach regulation or cause reputational damage to the company. These outcomes can happen for various reasons, like bias in the data, bias encoded in the algorithms, or irresponsible management of both the data and the algorithms (Martin, 2022). Data decisions may be unfair or non-transparent, and confidential data may be shared unintentionally or abused by third parties (van der Aalst et al., 2017). Detection and prevention of bias and discrimination is an important aspect when applying AI, especially for companies, where their brand and compliance with regulations is at stake. For instance, in Europe the General Data Protection Regulation (GDPR) requires transparency and accountability in applications and procedures that involve the processing of personal data.

In the context where business processes and business process management are supported by AI, all business processes should be able to run as intended and preserve the ability to recover and roll back from undesirable and inconsistent outcomes (Dumas et al. 2023). Interactive dashboards and business intelligence interfaces, which aid the execution and adaptation of business processes, and which suggest how to mitigate problems and propose countermeasures, should provide the knowledge operator with options and information regarding the business process at hand and any previously unavailable insights.

To exploit the maximum potential of the use of AI, the business process management system should be able to interact with agents in an optimized manner. Implementing big data-enhanced business processes in companies and organizations whose information systems were not originally designed for structuring and processing big data, or that do not have management structures that enable big data analysis and value creation through the generation of actionable insights, is a big challenge. Moving to data-driven business process management requires both, suitable personnel to apply AI in the first place, a change in the underlying architectures and systems to allow for suitable collection and analysis of big data, and a change in mindset. Data-driven innovation commons are crucial and the design of successful data commons demands analysis of different dimensions of the data economy (Guidi, 2023)

Improvement of business processes can be achieved by providing more and new insights about the execution context and suggestions regarding process-related goals and actions, based on observed situational information. In addition, ideally, also the suggestions should be adapted to the profile and the preferences of the business user, adapt the information provided to the type of user it interacts with, and the contextual situation in which the interaction happens. Improper implementations of AI can bring systematic discrimination and invasions of privacy (European Parliament, 2022), therefore it's important to prevent non-transparent and inaccurate conclusions, and to avoid the negative side effects that data may have in any context (van der Aalst et al., 2017).

Responsible implementations must ensure the fulfillment of the following principles (van der Aalst et al., 2017)

– Fairness, that is outputs should avoid unfair conclusions even if they are true
– Accuracy, that is the outputs and results should be accurate, and not guesswork
– Confidentiality, that is results should answer questions without revealing secrets
– Transparency, that is outputs should provide an explanation to the final user on how the decision was made, and that explanation is clear and makes sense.

There's the AI ethics guideline for trustworthy AI by an EU Independent High-Level Expert Group on Artificial Intelligence, that highlights the need for AI systems to be human-centric. The new EU regulatory framework applies to products and services relying on AI. Ethics Guidelines for Trustworthy AI advocate for AI technology that is more human-centric and doesn't discriminate, therefore also responsible and trustworthy business processes based on big data should follow these guidelines and behave in compliance with them. New ethics of sharing approaches and principles have been devised by previous literature to with an emphasis on privacy issues (Søe & Mai, 2023), and other works have identified challenges specifically in for the realm of intelligence analysis and have provided suited recommendations for companies on how to tackle them (Blanchard & Taddeo, 2023)

Another important consideration when considering responsible implementations of AI is compliance with regulations that govern the use of AI. In Europe, as mentioned previously, the GDPR was introduced into law in 2018 and has regulated how personal data is treated in organisation not only in Europe but globally, i.e. if the organisation processes personal data of Europeans. The challenge now faced by organisations is how to implement AI that is transparent and accountable when processing personal information.

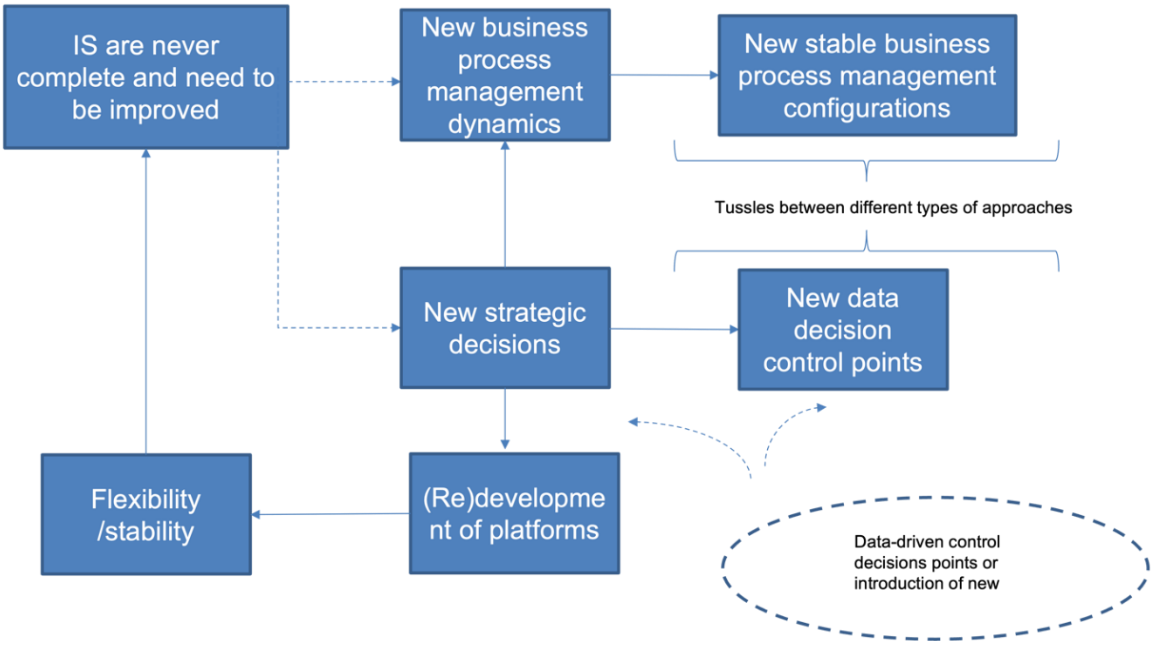
Given all the above, in this article, we first hypothesize and discuss an information system design for implementing responsible and trustworthy business process management and improvement. Next we outline, remaining challenges, research questions, and opportunities for research in the domain. Finally, we outline actors and stakeholders that should work together to answer the outstanding challenges and questions in this domain. We conclude the paper with a short discussion/reflection around outstanding questions and we outline future directions.

2. Information system design for data-driven companies

In order to have a responsible and trustworthy application of AI in a business process context and which is based on big data, there must be adequate tools, methods, and technologies to support such governance and decision-making (Chen et al., 2012). These elements, that is governance frameworks and technologies, should come together, so that responsible AI principles can be applied at each stage of the big data analysis of the business operations context.

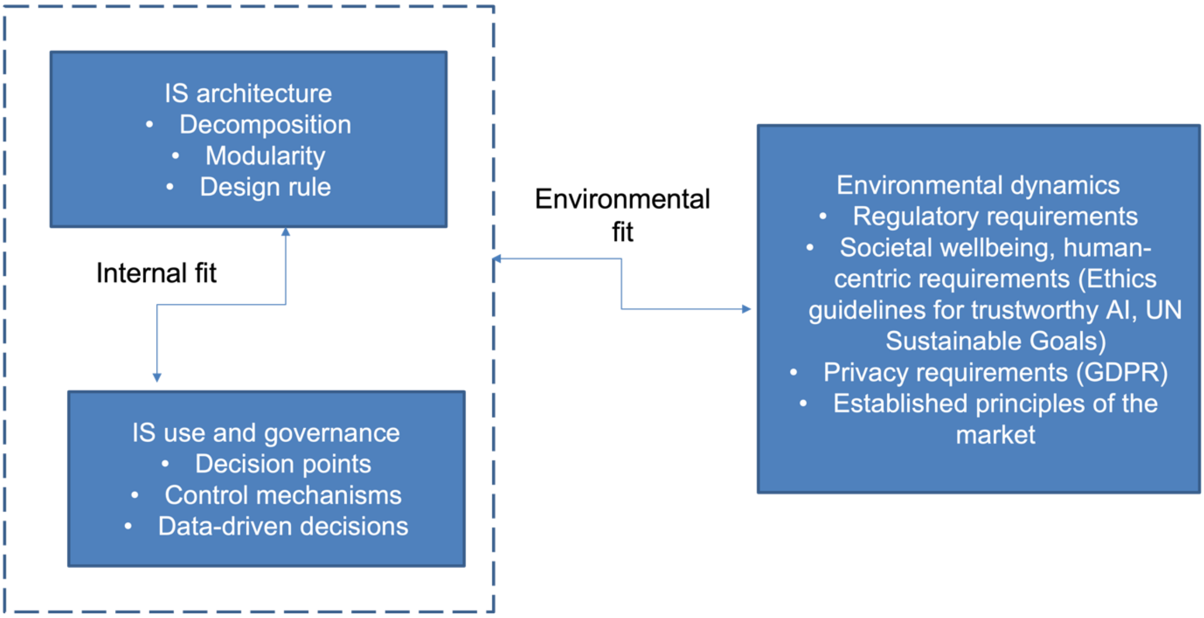
Given the new demands of companies to constantly innovate and stay relevant, research in the domain of information systems (IS) agree that IS are considered as 'never complete' and constantly in need of improvement (Tilson et al., 2010; Tiwana et al., 2010). The development of business process governance, based on big data, requires that sociotechnical constructions are revisited, and new decision points, based on data and observations from outputs of the application of AI methods are introduced. These new strategic decision control points, in return, introduce new stable socio-technical constructions. The new strategic decision points require re-development of the management platforms, and there's a process of flexibility/stability that follows until a new, stable IS configuration is found (Figure 1).

Figure 1. Process of governance of business processes management, with new sociotechnical constructs and decision points decided on big data and application of AI, inspired by Tilson et a l. (2010) (own processing)



The new IS design to support such business process execution, requires that the IS architecture is modular by design, decomposed, and follows simple design rules. The design, in turn, must have a good fit with IS use and governance for business operations, therefore, decision points and control mechanisms, are decided based on data, and the application of AI based on operations data. This IS organization is influenced by the environment in which the company operates and relevant regulatory, societal wellbeing, privacy and security requirements, as well as the established principles of the market in which the company operates (Figure 2). For instance, the GDPR dictates that a privacy-by-design approach be deployed for all IS that process personal data within an organisation.

Figure 2. On one side, IS architecture needs to be modular, allow for easy decomposition, and based on simple design rules, to allow for an easy internal fit with the introduction of new decision points, and control mechanism, or the introduction of data-driven decisions regarding business processes. On the other side, there must be a good environmental fit with regulatory requirements, societal wellbeing values, privacy requirements, and established principles of the market in which the company operates. inspired by Tiwana et al. (2010) (own processing)



Ethical AI governance in businesses foresee that first the company determines, based on existing guidelines, the ethical principles that apply to its own work and to which it will adhere. Preferably there should be an ethical board, that among other important members of the company, consists of ethicists, and approve the strategies then implemented in AI implementations, especially for own company operations. As proposed in our framework, there must be a clearly outlined governance structure, based on data collected and the application of AI, there must be clarity over who is expected to make decisions about which aspects of the business operations, and possible tradeoffs and benefits from the company, as deduced from the AI analysis. Next, such knowledge should be spread across the whole company and all the company members. Finally, there should be strong monitoring and oversight, preferably with metrics, of both, data-driven approaches and governance to yield ethical, responsible, and trustworthy results.

3. Implementing responsible use of big data for companies

3.1 Explainable AI, the problem of output explanation to different stakeholders and for different needs, and the problem of governance

The problem as we outline in this paper lies in the intersection of human-centric AI and enterprise architectures and applications, with a focus on business process management and optimization for businesses. In the previous section, we outlined an IS governance model for business process management, however, various questions and challenges need to be answered before a governance model, enhanced with AI, is put in place in organizations.

Explainable AI (XAI), for instance, promises to address the explainability problem, that is to enable users to understand the algorithm and parameters it uses to make decisions. The aim of XAI is to provide explanations for the outcome of the AI algorithms and to make these explanations understandable for the final user. The research on XAI has mainly been performed in two directions: visualization of Machine Learning (ML) processes and explainable ML algorithms. These approaches so far have delivered limited results, due to the algorithms' limited capability to explain decisions in humanly understandable ways or rely on abstract visualization methods, which may further increase complexity for final users.

In an organization, there are different kinds of users and stakeholders, and different stakeholders may need different explanations. In addition, not everyone or every role needs or wants an explanation, it may be that the same explanation may be good for more than one role (Langer, M et al., 2021). Therefore, the first question that companies will need to answer in this respect is

1) Which stakeholders need explanations? What kind of explanation does each stakeholder/user need?

Subsequently, there will be the need to test the effectiveness of the explanations generated and how users understand these explanations. There is a need for participatory involvement of all and co-creation of meanings for different users, that is developers of AI solutions and business experts, the need to also teach business users regarding explainability and how to "consume" explanations generated, risks involved, and common ways in which the explanations will be used (Chromik et al, 2021; Felländer et al, 2022). After being provided an explanation, some participants may want or need even more information, on how one can do this efficiently the companies will need to understand by themselves:

2) How can we verify that the explanation is good for the needs of the organization? How can we provide more information for the roles/stakeholders that need such additional information? How can we achieve better alignment of the explanations with the needs of the different stakeholders in the company?

AI algorithms can fail as well, and there are risks concerned with the actions stakeholders usually take or might need to take, so another question is

3) How risky are AI failures for the company?

If users understand how AI works, then they'll understand also preventively what kind of problems may arise for companies, from the application of AI. It may be easier to provide access to people with such knowledge, or to train employees especially on such arguments, although in some particular cases better understanding of the provided results can be achieved only after consultation with AI experts. Therefore, the other two questions to consider for companies are:

4) Do different stakeholders understand the explanations produced by AI?

5) Is it possible to have AI scientists available on the spot to provide explanations to different stakeholders?

Sometimes provided explanations are not the desired ones and may be inadequate, for deciding in the complex world of business. Sometimes the explanation can be of low quality, or too detailed, in different formats, and different kinds of contents, like diagrams, matrices, and logic trees (Wang et al, 2019). Previous research confirms that it's good to visualize data or make a reduction but clear analogies, especially in problem-solving domains, in highly detailed technical explanations are not often favoured, although having cross-disciplinary skills would help the users to feel more secure in the results as they would be able to control the outputs and the data better in their own.

6) What should we do if the provided explanations are too technical?

In the use of AI approaches and data in general it may be better to be sure of the data origin, and the data itself and to see the –input-output demonstration, and therefore understand the biases

6) How will we provide more information about the data origin? In which format?

In a context like this, it is important also for all stakeholders to understand how the system can fail or be misleading.

7) Can we identify a common way in which the system can fail? Can we provide such training to different stakeholders in the company?

Interactive ML is an approach to ML in which algorithms interact with agents (these agents can be humans too) and thus through these interactions they can optimize their behavior (Holzingher, 2016) for a problem like this, the use of interactive ML (iML) is a key as well. It may be the case that the traditional ML approaches might have limited success, in the case of events not available in the training dataset.

The next challenge for the company to solve would be which data should be used for developing such a system. There are privacy-and security-related consequences, as well as, as outlined above, ethical issues that are relevant and important to be considered (Clavell & Peuvrelle, 2020).

In addition, companies need to be compliant with regulations, therefore the system needs to comply with regulations too, especially guidelines coming from the EU regarding the development of human-centric AI systems (European Commission, 2019). There are also existing widgets to use for the development of a fair and non-biased decision-making system (based on e.g., fairness IBM Toolbox and responsible AI widgets) that can make the development of AI solutions easier for companies.

3.2 AI and data protection regulation for companies

Organizations that use AI-based process management and that are located within the European Union or that process the personal data of European citizens need to consider several aspects of compliance with the General Data Protection Regulation (GDPR) to ensure that they are processing personal data lawfully and transparently. Here are some key considerations:

- A lawful basis for processing personal data: Organizations must ensure that they have a lawful basis for processing personal data, as required by the GDPR. This means that they need to identify a valid legal basis for using AI-based technology that involves the processing of personal data. One possible basis could be legitimate interests, but it is important to conduct a thorough analysis of the processing activity to determine the most appropriate legal basis.
- Transparency in processing activities: Organizations must be transparent about their use of AI and the personal data that it processes, which includes providing individuals with clear information about the processing activity, such as the purpose of the processing, the types of personal data being processed, and who will have access to the personal data.
- Data minimization: Organizations must ensure that they only process personal data that is necessary for the specific purpose of the process. This means any collecting and processing of unnecessary personal data that does not serve a purpose is forbidden.
- Accurate and up to date: Organizations must take reasonable steps to ensure the accuracy of the personal data that they process using AI. This includes implementing measures to update, detect and correct errors or inaccuracies in the data.
- Secure transfer and storage: Organizations must take appropriate technical and organizational measures to ensure the security of personal data. This includes implementing access controls, encryption, and other security measures to protect personal data from unauthorized access, use, or disclosure.
- Know, understand and be able to facilitate Data Subject Rights: Organizations must ensure that they comply with the data subject rights outlined in the GDPR, including the right to access, rectification, erasure, restriction of processing, data portability, and objection to processing. Individuals should be able to exercise these rights with respect to the personal data processed by AI-based technology.

In summary, organizations that use AI for process management and/or improvement must ensure that they comply with the GDPR requirements regarding the lawful basis for processing personal data, ensuring transparency, data minimization, data accuracy, technical security, and data subject rights. Added to this, it is essential to conduct a thorough GDPR Data Protection Impact Assessment (DPIA) before implementing any new process or solution that processes personal data. This is to ensure that all necessary safeguards continue to be put in place in the future to protect individuals' personal data.

3.3 Implementing responsible business process management and improvement

As discussed above, implementing business process management, based on AI and big data, requires reflections regarding governance, explainability, and GDPR compliance.

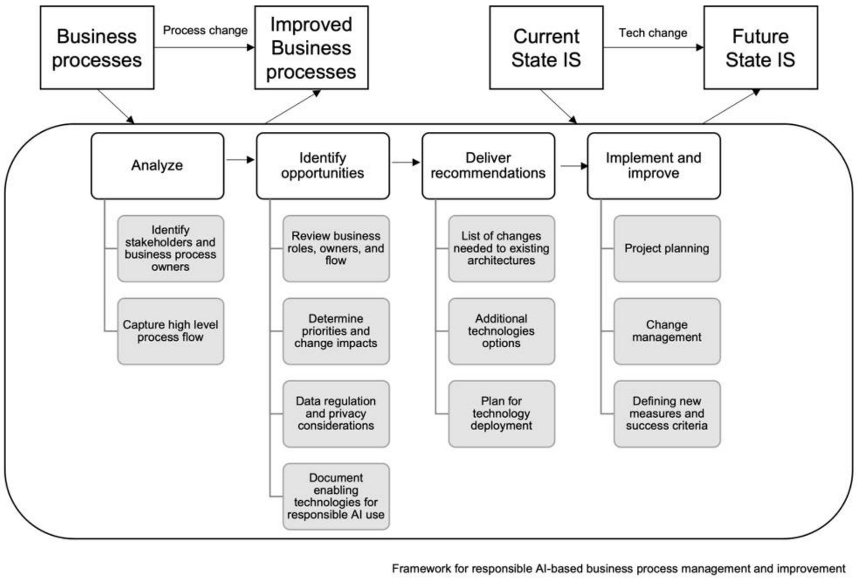
To implement responsible use of AI and responsible business process management and improvement, the companies would need to develop or put in place the following technical skills and competences:

- Ability to develop, analyse, and evaluate methods of artificial intelligence (AI) with regard to trustworthiness and reliability, e.g., when ensuring non-discrimination for their specific context,
- Ability to develop and foremost integrate artificial intelligence methods with their existing information systems
- Ability to quantify uncertainty and define indicators of trustworthy AI for their specific context of work,
- Develop metrics and test data sets to record ethical compliance, so to serve as a 'proof' for ethical and responsible behaviour and track-record.

In addition to the skills above, the companies would need to work on technical implementation of ethics guidelines for trustworthy AI.

Change in the business processes, implies also change on information system level implementation as well. First step of the business process improvement framework, requires that the company identify and document well the correct stakeholders involved and capture high flow of the process. Then, based on the big data analysis, opportunities for improvement are identified, different data privacy considerations have been taken into account when such analysis is performed, and the team working on the business process improvement reflects and checks that the AI implementation has been indeed follows principles of trustworthiness and responsibility, by checking the outputs provided, and if they are in line with the company policies. Based on this, the business process flow and stakeholders involved are reviewed as well, it may be that in the new business process version, new stakeholders would have new roles. Next, recommendations should be delivered on how the business process can be improved, that is the area that will be improved, by implementation of which technology, possibilities for such technology deployment, and role and responsibilities for different actors. Last, a project plan and change management plan should be provided as well as measures of the improved business process. Suitable tools can be built on top of existing enterprise infrastructures to enhance the transition to improved business processes. A new wholistic view is presented in Figure 3.

Figure 3. Framework for responsible AI-based business process management and improvement (own processing)



4. Case studies in the financial domain

With the purpose of this paper being the demonstration of the usefulness of responsible AI and big data based business processes, as well as providing a comprehensive guideline for companies on how to implement these processes, in this section, we analyse two cases coming from the financial industry, namely: the loan application, that is when customers request a loan from the bank and the bank decides whether or not to approve the loan, and the insurance claims process, in which an injury has occurred to the customer, the customer was insured, and now the insurance company has to process the claim and decide whether or not to pay the customer depending on the conditions laid out in the insurance policy. The cases at hand involve an Italian regional/local bank, and an Italian small-to-medium-sized insurance company.

We chose two use cases from the Finance industry as it is a data-rich industry and we believe that it is exactly in this industry that AI holds huge potential to improve organisational operations, while at the same time it can potentially threaten the responsible use of data due to the negligent or incorrect handling of data, i.e. what if a loan application is denied due to bias in the data? Or what if an insurance claim is rejected due to an AI failure to provide correct information to the employees processing the request? The process data is examined from an organizational perspective, which included working closely with managers in each respective company to 1) outline and schematically present the flow of steps involved in these two data intensive business processes/use cases, namely loan requests and insurance claims, and 2) reflect what would be the foreseen benefits if the implementation of these business processes followed the implementation of our responsible AI framework. We then reflect on the output in the subsections below.

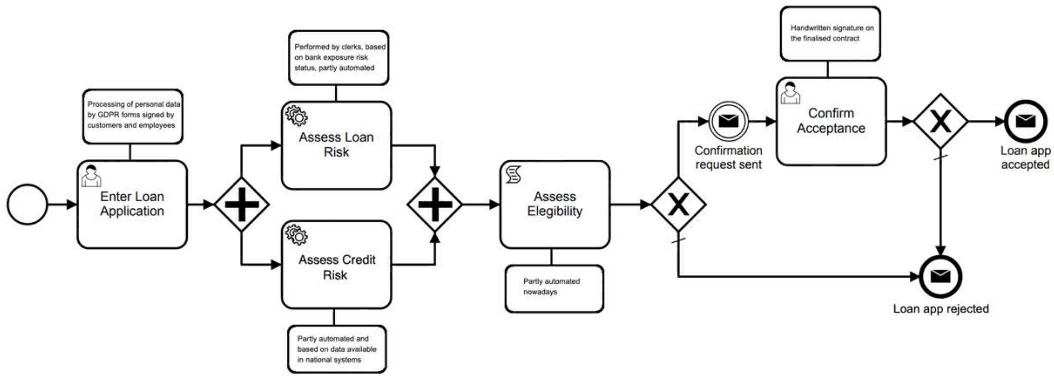
4.1 Use Case 1: Loan Application Process

The loan business process usually consists of the following activities or work steps: submitting a loan application, assessment of the loan application (through loan risk assessment and/or estimation of property value), and approval or rejection of the loan application (Figure 4).

With such huge volumes of data held within these companies, the possibility of objectively assessing such a loan application with the help of AI is quite high. This may significantly improve the assessment of the loan, and make the execution of the business process faster, yet challenges as explained in the previous sections, still arise. For instance, checking a credit score comes from secondary data in the company's possession or perhaps from other financial companies; checking loan risk is based on the history of the user and their overall eligibility in terms of the conditions of the loan matching national or international bank regulations. In this scenario it is important that the use of data is responsible and that the company has assessed in full the risks associated with this kind of implementations of their business processes and has thoroughly followed the steps for responsible implementation and use of AI and data as outlined earlier.

Ultimately, information regarding the loan outcome is communicated to the loan requestor; also communicated may be the next steps to take, in case the loan application has been successful, or a meaningful explanation of why the loan was rejected. Explanations will be easy in all scenarios and this will improve confidence in both employees and customers and increase the level of trust in the company.

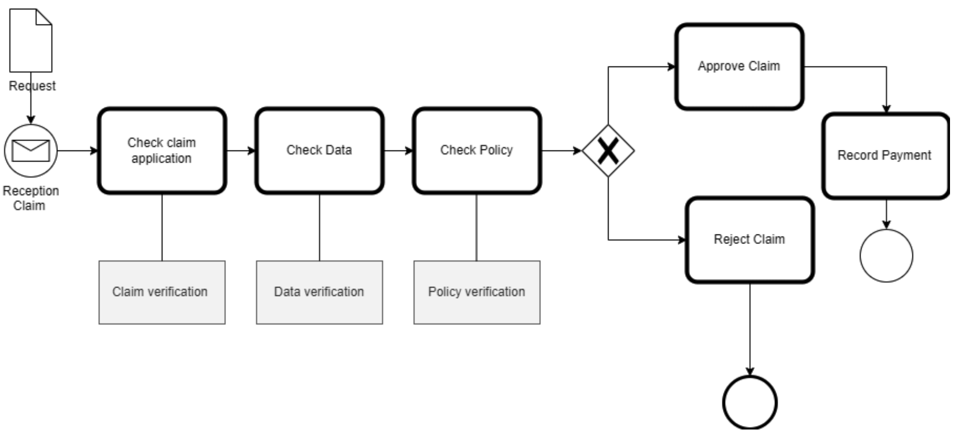
Figure 4. Implementation of the loan request business process in banks and financial companies



4.2 Use Case 2: Insurance Claims Process

Insurance claims involve the following steps: checking claim applications, checking data and policies, approving or rejecting claims, and recording payments (Figure 5).

Figure 5. Implementation of the insurance claim request business process in insurance companies



In the same vein as the loan approval process, the processing of insurance claims is often automated based on specific rules and the availability of reliable data sources. When a claim is submitted, pay-outs to insured parties may be triggered. It can then be easily paid by accessing verified databases, and intelligent rules that can assist with any potential fraud predictions. The policies within an insurance company might be established as coded, and checked against the provided data, and the company may instantaneously approve or reject any insurance claims submitted, if conditions have/have not been met. This can only be set in place if the company followed rules for responsible implementation of business processes based on big data, if implemented like this the process will promote mutual confidence between the customer and the insurance company for the following reasons: all data is transparently disclosed, and even the smallest contractual deviation leads to compensation to the affected party, however this will only happen if and only if the insurance company has set in place the responsible use of big data for execution of their business processes.

4.3 The need for Responsible AI in the Financial Industry

Responsible AI is crucial in the financial industry for the reasons highlighted in this research. AI systems are often seen as "black boxes" due to their complex nature. Explainable AI (XAI) aims to make these systems more transparent by providing understandable explanations for the outcomes of AI algorithms. This is particularly important in the financial industry where decisions made by AI can have significant financial impacts on individuals and businesses.

In financial organizations, there are various stakeholders, each with different needs. Some stakeholders might need detailed explanations of AI decisions, while others might only need a high-level overview. It is important to identify which stakeholders need explanations and what kind of explanation each stakeholder needs.
Once explanations are provided, it is necessary to test their effectiveness and ensure thar stakeholders understand the explanations. If not, the organization needs to find ways to improve the explanations.
AI systems can fail, and these failures can be risky for the company, especially in the financial industry where decisions about investments are being made. It's important for companies to understand these risks and have plans in place to mitigate them.

Not all stakeholders will have a full understanding of AI. In some cases, it might be necessary to have AI experts available to provide explanations to different stakeholders. This can help ensure that all stakeholders, regardless of their understanding of AI, can make informed decisions based on the outcomes of AI algorithms.
Sometimes, the explanations provided by AI might not be adequate. They might be of low quality, too detailed, or presented in a format that's not helpful for the stakeholder. It's important for companies to continuously evaluate and improve the quality of these explanations.

Responsible AI in the financial industry is ultimately about ensuring transparency, understanding, and accountability in AI decision-making. It's about making sure that all stakeholders can understand and trust the AI systems with which that are interacting. This not only helps to improve decision-making but also helps to build trust in AI systems, which is crucial for their widespread adoption and use (Misheva & Papenbrock, 2022).

There is also little doubt that human-led abuses have contributed to recent economic crises and caused significant adverse societal impacts. On the one hand, if AI is used in inappropriate ways, it has the potential to exacerbate income and wealth inequalities, however, on the other hand, AI can also improve the quality of financial services, like insurance, credit scoring, and fraud detection. From this perspective, financial regulation should be introduced to avoid the dystopian scenarios and encourage the positive scenarios.

5. Discussion and future direction

In this paper, we outlined governance mechanisms for business process management, based on AI, and guidelines for companies, along with two use cases from the financial industry, and a checklist to ensure appropriate implementation of AI-enhanced business processes.

The presented challenges and questions for companies require knowledge and expertise from different domains, and the need to form a team combining a diverse set of needs in order to answer them: data custodians, data curators, and knowledge operators, that would prepare the data coming from different operations for analysis, especially from big data and data coming from different sources of the company; data scientists, that would use the generated data from business process execution to build robust machine learning models that are responsible, trustworthy, and explainable; business managers, that are familiar with the knowledge domain of the company, and existing business processes the company relies upon; regulation authorities, to confirm that the explanations on how the decision was made, are in line with regulation if it is clear and makes sense; ethicists, and company external references regarding ethical criteria in the domain of the company.

The methods for the analysis of data will need to be determined as well. We anticipate that the methods should be mixed and encourage ethical and socially responsible behaviour. Computational social science approaches and computational analytics methods based on machine learning and computational models to contribute to comprehensible AI, taking into account the business processes and business needs should be designed, to accelerate the transition to actionable, responsible, and bias-free insights from big data. There is a need for further research to evaluate the practices regarding knowledge management and data analysis, as well as the gathering, and usage of data in the generic business process management ecosystem of the company, to test the application of relevant existing tools, widgets, and AI and XAI methods to have good quality output. A suited list for XAI approaches

Ultimately, our case studies confirmed our intuition on the importance of the having responsible data-driven decision making in their respective domains, the approach and implementation as outlined in this paper was considered noteworthy by the management of the organizations involved in this research. By reflecting together with the researchers on the predicted behaviour of the business processes, when emphasising the importance of responsible process design, the potential for enhanced performance, elimination of inconsistencies, and better clarity on governance, explainability and more responsible outputs of processes are increased. Such considerations are important for companies not only in the Financial domain but all domains.

There are many possible future directions and problems still to solve.

One of the issues in research like this is deciding which decisions should be fully automated (based on available data) and for which decisions human input shall be needed and why? And how can companies decide on this? A strong argument here is that any AI system that processes personal data should have human oversight to ensure compliance with the GDPR, GDPR auditing, and to avoid any possible negative outcomes such as biases for the individuals linked to the personal data (Mökander, 2023).

Another important step would be to understand and distinguish functions that should be carried out by AI-empowered systems, and functions that should be performed entirely by humans, and study their order in each context, to understand how intelligent functions can best support human actions, and vice versa. How to assess trustworthy AI implementation in practice is another challenge (Vetter, 2023).

Another challenge is how to put together such knowledge and adequate visualizations for insights generated from data and the process itself. The recurring challenge is the relationship between data and processes. State-of-the-art approaches like UML still have different diagrams covering different aspects, that is, class models for data, activity diagrams for processes, yet there are no suited visualizations that combine data, business intelligence insights, and business process representations. Petri nets fully integrate both but are difficult to use for complex designs of information systems.

Further research in the domain is timely.

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References

Brynjolfsson, E., Hitt, L. M. & Kim, H. H. (2011), 'Strength in numbers: How does data-driven decision-making affect firm performance?', Available at SSRN 1819486 .

Blanchard, A., & Taddeo, M. (2023). The Ethics of Artificial Intelligence for Intelligence Analysis: a Review of the Key Challenges with Recommendations. Digital Society, 2(1), 12

Chen, H., Chiang, R. H. & Storey, V. C. (2012), 'Business intelligence and analytics: From big data to big impact', MIS quarterly pp. 1165–1188.

Chromik, M., Eiband, M., Buchner, F., Krüger, A., & Butz, A. (2021, April). I think i get your point, AI! the illusion of explanatory depth in explainable AI. In *26th International Conference on Intelligent User Interfaces* (pp. 307-317).

Clavell, G. G., & Peuvrelle, V. (2020). Ethical Issues in Big Data Analytics for Time Critical Mobility Forecasting. In Big Data Analytics for Time-Critical Mobility Forecasting

de Medeiros, M. M., Hoppen, N. & Maçada, A. C. G. (2020), 'Data science for business: benefits, challenges and opportunities', The Bottom Line .

Dumas, M., Fournier, F., Limonad, L., Marrella, A., Montali, M., Rehse, J. R., ... & Weber, I. (2023). AI-augmented business process management systems: a research manifesto. ACM Transactions on Management Information Systems, 14(1), 1-19.

Eitel-Porter, R. (2021), 'Beyond the promise: implementing ethical ai', AI and Ethics 1(1), 73–80.

European Commission (2019). High-level expert group on Artificial Intelligence, Ethics Guidelines for Trustworthy AI, European Commission

Felländer, A., Rebane, J., Larsson, S., Wiggberg, M., & Heintz, F. (2022). Achieving a data-driven risk assessment methodology for ethical AI. Digital Society, 1(2), 13.

Guidi, S. (2023). Innovation Commons for the Data Economy. Digital Society, 2(2), 31.

Holzinger, A. (2016). Interactive machine learning for health informatics: when do we need the human-in-the-loop?. Brain Informatics, 3(2), 119-131

Langer, M et al. (2021). What do we want from Explainable Artificial Intelligence (XAI)?–A stakeholder perspective on XAI and a conceptual model guiding interdisciplinary XAI research. Artificial Intelligence, 296, 103473

Martin, K. (2022), Algorithmic bias and corporate responsibility: How companies hide behind the false veil of the technological imperative, in 'Ethics of data and analytics', Auerbach Publications, pp. 36–50.

Misheva, B. H., & Papenbrock, J. (2022). Editorial: Explainable, Trustworthy, and Responsible AI for the Financial Service Industry. Frontiers in Artificial Intelligence, 5.

Mökander, J. (2023). Auditing of AI: Legal, Ethical and Technical Approaches. Digital Society, 2(3), 49.

Müller, O., Fay, M. & Vom Brocke, J. (2018), 'The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics', Journal of Management Information Systems 35(2), 488–509.

Newman, R., Chang, V., Walters, R. J. & Wills, G. B. (2016), 'Model and experimental development for business data science', International Journal of Information Management 36(4), 607–617.

Søe, S. O., & Mai, J. E. (2023). The Ethics of Sharing: Privacy, Data, and Common Goods. Digital Society, 2(2), 28

Tilson, D., Lyytinen, K. & Sørensen, C. (2010), 'Research commentary—digital infrastructures: The missing is research agenda', Information systems research 21(4), 748–759.

Tiwana, A., Konsynski, B. & Bush, A. A. (2010), 'Research commen-tary—platform evolution: Coevolution of platform architecture, governance, and environmental dynamics', Information systems research 21(4), 675–687.

Van Der Aalst, W. (2016), Process mining: data science in action, Vol. 2, Springer.

van der Aalst, W. M., Bichler, M. & Heinzl, A. (2017), 'Responsible data science'. Waller, M. A. & Fawcett, S. E. (2013), 'Data science, predictive analytics, and big data: a revolution that will transform supply chain design and management'.

Vetter, D.et al. (2023). Lessons learned from assessing trustworthy AI in practice. Digital Society, 2(3), 35.

Weske, M. (2007), Business process management architectures, Springer.

Wang, D., Yang, Q., Abdul, A., & Lim, B. Y. (2019, May). Designing theory-driven user-centric explainable AI. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1-15).