Systematic identification of opportunities to apply Artificial Intelligence to increase efficiency of business processes: a literature review and case study

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During the preparation of this work, the author used ChatGPT, Claude and Google Gemini in order to enhance grammar and word selection. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

ABSTRACT
Artificial Intelligence (AI) is an emerging technology attributed to have the potential to radically impact current business practices. The technology's most reported business value is its ability to improve the efficiency of business processes (BPs) which it enables through automating or augmenting tasks. Organisations indicate to be interested in adoption, but struggle to realize the technology's potential in practice. A specific identified problem is the lack understanding of where AI can be applied in organisations. Previous studies adopt Business Process Management (BPM) methodology to address this issue. This paper recognizes a shortcoming of this approach related to AI: BPM lacks adequate methodology to evaluate technology for implementation. Therefore, in order to provide a more robust and systematic method to evaluate BPs for AI implementation, the theoretical basis of this paper consists of BPM complemented with Task-Technology Fit (TTF) theory. TTF is used to match AI technologies with the type of task it can support. This study adopts a Design Science Research methodology to design an artifact, namely a five-step framework organisations can use to systematically identify opportunities to apply AI to increase efficiency of BPs. This framework is applied in practice in the form of a case study at a data consultancy start-up. There it was shown that the framework results in an overview of the tasks in the different BPs with the most suitable AI technology. This overview is evaluated to be useful in the process of identifying opportunities to apply AI. It was, however, also found that the framework relies on subjective judgement and does not result in concrete AI solutions but rather provides a basis, in the form of an overview, that supports identifying opportunities for AI technologies.

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1. INTRODUCTION

Artificial Intelligence (AI) is an emerging technology expected to radically impact contemporary business practices (Lee et al., 2023). Most companies view successful adoption as a source of competitive advantage (Enholm et al., 2022), which explains why 92% of organisations in a recent survey by McKinsey plan to increase their investments in the technology (Mayer et al., 2025). The business value these companies are primarily seeking is AI's potential to significantly increase the efficiency of business processes (BPs). By offering opportunities to automate and augment tasks, AI enables BPs to be completed in less time, with fewer resources and possibly also more accurately, resulting in an increase of efficiency (Enholm et al., 2022). Empirical research at the firm level has shown a significant positive influence of AI adoption on productivity (Yang, 2022; Czarnitzki et al., 2023; Marioni et al., 2024). Examples of contemporary applications powered by AI are automatic fraud detection of financial transactions at banks (Adijat Bello et al., 2023), predictive maintenance for machinery at manufacturing plants (Czarnitzki et al., 2023) and assisted computer programming at software companies (Kanbach et al., 2024).

Despite the interest, it is argued that the potential of AI is far from realized yet. This holds on a macro-economic level (Brynjolfsson et al., 2019) and according to 99% of the interviewed organisations in the recent survey by McKinsey also on their firm-level (Mayer et al., 2025). This unrealized potential makes research on AI and its complements, such as applications for business, relevant (Brynjolfsson et al., 2019). In literature on the intersection of AI and business, it is highlighted that organisations lack understanding on how AI technologies can create business value, making it difficult for them to make decisions on where to implement it (Enholm et al., 2022). Thus far, it has become clear that AI offers a lot of potential, organisations are eager to adopt, but there is a lack of understanding on where in the organisation the technology can be applied successfully. Scholars have identified the capabilities the technology offers (Borges et al., 2021) and antecedents of adoption (Mikalef & Gupta, 2021), but empirical research on opportunity recognition remains scarce. While previous studies addressing this gap aimed for a more holistic understanding by involving factors such as organisational readiness (Aldoseri et al., 2024) or technological infrastructure (Enholm et al., 2022), this paper primarily addresses the opportunity identification process itself. In doing so, this paper aims to make three academic contributions. It, first of all, researches the design of a systematic methodology that addresses this gap. Second, it adopts a transparent methodology that enables evaluation and validation by academics. Third, by applying this framework in practice and evaluating it, it aims to enrich the understanding on how organisations can identify opportunities to apply AI.

For practice, research on this topic is also relevant. It has been mentioned that, currently, organisations are interested in AI adoption, but indicate to struggle to realize its potential. Organisations lack understanding on where to apply the technology. Therefore, for organisations willing to adopt AI, this paper aims to develop a systematic approach guiding the identification of AI opportunities. The aim is to develop this framework from a managerial and business perspective, therefore increasing its relevance for practice.

The identified gap provides potential to contribute to both academia and practice. Therefore, this paper addresses the following research question:

How can organisations systematically identify opportunities to apply Artificial Intelligence to increase efficiency of business processes?

In order to answer this research question, a Design Science Research (DSR) approach is adopted. This means that this paper aims to create an artifact, in this case a framework, that helps organisations identify opportunities to apply AI in a systematic way, thereby addressing the problem (vom Brocke et al., 2020). Because a DSR approach is adopted, this paper has two objectives: 1) develop an artifact (in the form of a conceptual framework) 2) apply it in practice in a case study and evaluate it. For the first aim, by conducting a semi-systematic literature review, a framework is constructed. Then, building on these insights, this paper includes a case study at a data consultancy start-up to apply the framework in practice. By following the found methodology, opportunities to apply AI are aimed to be identified in the BPs of the organisation. The framework is evaluated and areas for future research are addressed.

2. LITERATURE REVIEW

This section, first of all, considers how AI can increase efficiency of BPs. Then it discusses methodology of previous literature addressing the identification of opportunities to apply AI. This leads to the development of the theoretical basis of this paper.

2.1 Increased Efficiency of Business Processes with AI

As mentioned in the introduction, AI offers potential to increase the efficiency of BPs. A BP consists of a set of related tasks or activities that are performed in coordination in an organisational and technical environment. The activities or tasks together realize a business goal, and each BP is enacted by a single organisation, but it may interact with BPs performed by other organisations (Weske, 2019). A task can be defined as an action carried out by an individual in turning inputs into outputs (Goodhue & Thompson, 1995). Because AI can automate or augment tasks, it can lead to less resources such as time or money needed to execute the BP, thereby increasing its efficiency (Enholm et al., 2022; Coombs et al., 2020). Automation refers to AI applications that replace human work, making human input redundant. Augmentation refers to combining AI with human capabilities in order to enhance decisions and optimize actions. Instead of fully replacing human work, which is the goal of automation, augmentation aims to assist humans by leveraging AI for tasks or areas where it outperforms humans or helps overcome human cognitive limitations (Enholm et al., 2022).

2.2 Business Process Management

Identifying opportunities to improve a BP is part of the field Business Process Management (BPM) and this field, therefore, also considers finding opportunities to apply AI. BPM is based on the observation that each product a company provides to the market is the outcome of various performed activities (Weske, 2019, p.4). These activities can be organized in BPs and to gain a competitive advantage or business success it is seen as critical to align BPs with an organisation's perspective. As a means to achieve this, BPM is the field of study that focuses on managing and improving an organisation's BPs. It uses knowledge from management science and information technology (IT) and applies this to BPs with the goal of finding improvements (Gomes et al., 2022). The BPM domain is highly affected by emerging technologies as they often offer new opportunities to support in the execution of tasks (Ahmad & Van Looy, 2025). This applies to the emerging technology AI as well, which is highlighted to have the potential to be of transformative impact in BPM (Abbasi et al., 2024).

Aldoseri et al. (2024) explain a methodology that follows the BPM lifecycle, which is shown in figure 1, and helps organisations to evaluate existing BPs for AI integration. This approach starts, first of all, with identifying processes in an organisation, and, secondly, by mapping these processes. Based on these mappings, in the third step, opportunities for automation or augmentation can be identified along with the right tools. After which, organisations design the automated process and train all involved parties for the fourth and fifth steps respectively. The last step consists of implementation and continuous improvement.

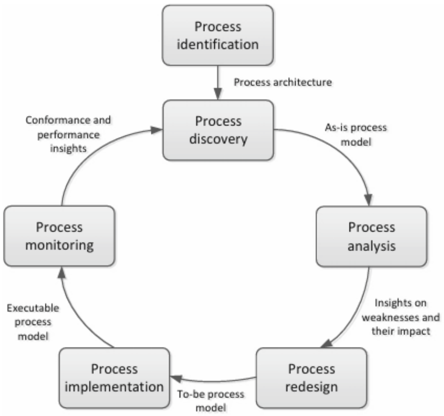

Figure 1: BPM lifecycle from (Dumas et al., 2018, p.23)

In the third and fourth step, which are the *process analysis* and *process redesign* phase of the BPM lifecycle respectively, a gap is identified. As mentioned in the introduction, organisations lack understanding of AI technologies, making it difficult for them to decide where to implement it (Enholm et al., 2022). This means that, after having identified key BPs and modelling them, organisations may get stuck in the *process analysis* and *redesign* phase, because they do not know where and how in the BP AI technologies can support improvements. This indicates a gap in current knowledge: while there is established understanding and theory for identifying BP improvements, the methods for identifying specific opportunities to apply AI remain unclear.

2.3 Task-Technology Fit theory

Literature that discusses BPM in light of technology highlight a more common shortcoming: despite BPM views technology as enabler and relies on it for improving BPs, it lacks methodology to evaluate technology for implementation (Ahmad & Van Looy, 2022; Trkman, 2010). Therefore, according to Trkman (2010), the role of technology in BPM can best be described with the use of Task-Technology Fit (TTF) theory. TTF theory holds that a technology is more likely to have a positive impact on individual performance if the capabilities of the technology match the tasks the user has to perform (Goodhue & Thompson, 1995). In other words, the closer the match between the technology and the task, the higher the benefits it is going to yield. Applied to AI, the TTF model is also used to analyse how well an AI technology aligns with a specific task. This helps to determine whether it can help increase performance (Przegalinska et al., 2025). Certain tasks can, for example, demand high accuracy and speed with which AI automation technologies may help, while other tasks can require more creativity and therefore require a different AI technology (Przegalinska et al., 2025).

This paper finds it theoretical basis in the combination of BPM and TTF. The first helps to identify and map BPs of an organisation and focuses on finding improvements. The second considers technology with its characteristics and supports to assess whether a technology matches with a task. This paper identifies a gap in the *process analysis* and *redesign phase* and aims to develop a framework grounded in TTF to address the gap.

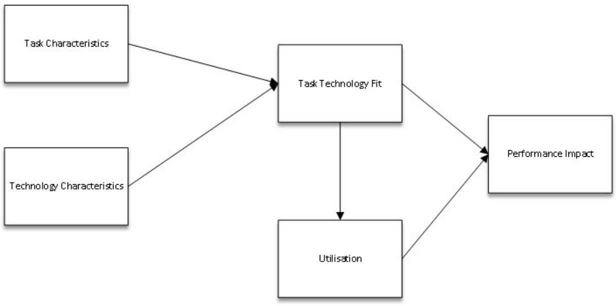

Figure 2: TTF model from (Marikyan & Papagiannidis, 2023)

3. METHODOLOGY

3.1 Research Design

The previous section established the core concepts, the theoretical background and the gap addressed in this study. This section presents the methodological approach developed to address this gap. This paper follows the DSR process as outlined in vom Brocke et al. (2020) and shown in figure 3.

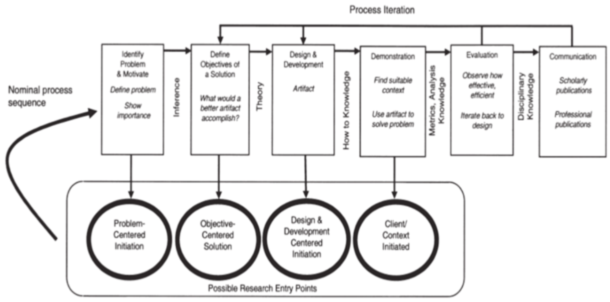

Figure 3: DSR Methodology Process Model from (Peffers et al. 2008)

The first step, problem identification, has been established in the introduction and literature review. In short, AI offers a lot of potential, organisations are eager to implement it, but lack understanding of where to apply it. There is theory to find improvements for BPs, but there lacks methodology to identify opportunities to apply AI. This paper aims to design an artifact, in the form of a framework, providing a methodological approach to address this problem.

The second step of the DSR process consists of defining the objectives of the solution. The designed artifact has three objectives, which are summarized in table 1. The first is to provide a structured methodology that enables organisations to systematically identify opportunities to apply to increase efficiency of BPs. Specifically, it provides a step-by-step approach that can be followed and lead to an evaluation of the opportunities to apply AI to increase efficiency of the BPs of the organisation. In case there are, it should bring forth the specific AI technology that can be applied in the BP. The second objective is that the framework facilitates the assessment of the fit between the possible AI technology and task or tasks. It guides in determining whether the AI technology can be applied in practice. The third objective is that the artifact can support managers in making decisions on AI implementation. The objective is that the framework is sufficiently clear and straightforward that it can be utilised by managers in organisations. This implies that not much knowledge about AI or BP improvements is needed to utilise the framework to identify opportunities.

Table 1: Objectives of Solution (2nd step DSR methodology)

Objective 1	Provides step-by-step approach that can be followed and lead to an evaluation of opportunities to apply AI to increase efficiency of the BPs of the organisations
Objective 2	Provides and assesses specific AI technologies for the BP
Objective 3	Supports managers in decision-making on AI implementation

The third step, design and development of the artifact, is conducted with a semi-systematic literature review. By developing answers to sub-questions through reviewing relevant literature, a framework is constructed. This process is discussed in more detail in the following section.

For the fourth step, demonstration, a case study is conducted at an actual organisation. There, opportunities to apply AI are aimed to be identified by utilising the artifact. In the section after the literature review, the case study is discussed in more detail.

The fifth step, evaluation, consists of measuring whether the objectives of the solution were realized with the designed artifact. The last sub-question considers finding criteria to evaluate the usefulness. At the end of the case study, the artifact is evaluated.

The sixth step is communication. This implies that all aspects of the designed artifact are communicated to relevant stakeholders. For this paper, this comes in the form of publishing this paper on the website where theses of students of the University of Twente are published and presenting it during the bachelor thesis conference.

The next section discusses the semi-systematic literature review, including its data collection and analysis process. Then, the section after does the same for the case study.

3.2 Semi-Systematic Literature Review

The first part of the research methodology is a semi-systematic literature review, which is a more or less systematic way of collecting and synthesizing previous research (Snyder, 2019). The aim is to find papers that help develop answers to the sub-questions, thereby laying the foundation to result in a framework that helps systematically identify opportunities to apply AI to increase efficiency of BPs in organisations.

A semi-systematic literature review differs from a systematic literature review by not reviewing every article about a topic, but rather focusing on relevant literature while maintaining a more or less systematic approach (Snyder, 2019). Sub-questions have been used to guide the literature review. These are presented after explaining the data collection and data analysis methodology.

3.2.1 Data Collection

In order to have a transparent search process, a protocol for searching and reviewing literature has to be designed for the literature review (Kraus et al., 2020; Snyder, 2019). As indicated, the literature review is semi-systematic. This means that not every article about the topic is reviewed, but the focus rather lies on finding articles relevant to answering the sub-questions.

This has been operationalized by searching and reviewing literature with a mixed methodology. On the one hand, for each sub-question, specific search strings have been developed as well as eligibility criteria. These have been used to search for literature on Scopus and Web of Science in a systematic way. The results were first screened and then the retrieved literature was assessed on inclusion and exclusion criteria, leading to a final selection for the review for each sub-question. The process can be found in Appendix A. On the other hand, articles have also been searched and reviewed with a non-systematic or integrative approach (Snyder, 2019). This allowed to explore for additional literature that supported answering the sub-questions. An example is that a few articles from the Computer Science domain have been included to support gaining a more complete understanding of AI. The systematic part has mainly been used to gain an overview of different categories or concepts, while the integrative approached helped to further delve into the specifics of the technologies.

For document type, which applies to both the systematic and non-systematic part, peer-reviewed journal articles are preferred as they have been checked through the academic process (Kraus et al., 2020). However, since the initial scoping of literature for the literature review showed that books and conference papers can help explain concepts or yield interesting application of AI, these two document types have also been included in the data collection.

3.2.2 Data Analysis

The aim of the data analysis is to analyse the literature in order to facilitate the development of answers to the sub-questions. For the systematic part, the literature for each sub-question is kept and analysed separately. This means that not all results of the literature search are put together and synthesized, but rather considered for each sub-question individually. To avoid summarizing or describing literature, the focus of the data analysis lies on concepts rather than on authors or studies (Kraus et al., 2020). This approach is operationalized through the analysis of literature to categorize concepts and characteristics in a pre-determined article matrix developed for the first three sub-questions. This approach is inspired on the example of the article matrix of Popenoe et al. (2021). The article matrices can be found in Appendix A. The additional literature, found outside the systematic approach, is not included in the article matrices. This literature has not been analysed in a systematic way, but relevant findings have been incorporated in answering the sub-questions.

3.2.3 Sub-Questions

The sub-questions are based on the theoretical basis of this paper: BPM and TTF. BPM provides the foundation to identify and model BPs in an organisation, while TTF helps to find and assess how well technologies fit with the tasks of those BPs. The first three sub-questions consider the elements of the TTF theory. The fourth sub-question considers how the framework can be evaluated.

Sub-question 1: ***What are categories of AI technologies and what are their characteristics?***

The first sub-question considers the Technology and Technology Characteristics part of TTF theory. It aims to define categories of different AI technologies as well as their characteristics.

Sub-question 2: ***What are categories of tasks and what are their characteristics?***

The second sub-question considers the Task and Task Characteristics part of TTF theory. It aims to define categories of tasks as well as their characteristics.

Sub-question 3: ***What criteria determine the fit between AI technology and task category and therefore to what extent the AI technology can be applied?***

The third sub-question considers the Task-Technology Fit part of TTF theory. It aims to develop criteria to determine to what degree an AI technology can be used for a specific task.

Sub-question 4: ***What evaluation criteria are relevant to determine the effectiveness of the framework to identify opportunities to apply AI to increase the efficiency of BPs?***

The fourth and last sub-question considers the evaluation part of DSR. It aims to find in literature criteria that can be used to evaluate the effectiveness of the artifact in the case study.

3.3 Case Study

For the second part of the research methodology, a case study is conducted. A case study is an empirical inquiry that investigates a contemporary phenomenon within its real-life context; therefore it should have a 'case', which is the object of study. The case should be a complex functioning unit that is investigated in its natural context. The case study is considered as a powerful method to realize both theoretical and practical aims and the method is particularly relevant for research in technology and innovation management. It allows to answer 'what'-, 'how'- or 'why'- questions with a relatively full understanding of the nature and context of the phenomenon (Ebneyamini & Sadeghi Moghadam, 2018). For this paper, the case study is used to explore at an organisation in practice how opportunities to apply AI can be identified in a systematic way. Therefore, it aims to use the framework resulting from the semi-systematic literature review to come up with recommendations for possible AI applications and solutions in the organisation.

This case study is conducted at TS, which is the pseudonym for a data consultancy start-up located in Enschede. The firm's primary service is to advise and assist other organisations, which are their clients, in becoming more data-driven. This is done by helping with data management, retrieving insights from data in the form of dashboards, making BPs of their clients more efficient and giving strategic advice on how to deal with data. A key selling point of TS is that they work software independent, meaning that they strive to offer solutions that are not bound to any specific software platform, allowing clients to work with tools or software they already use. Since the beginning of TS, in 2020, they have gathered parts of previous work in their own database, among which is written code for data engineering, created dashboards and mappings of analysed BPs of clients. As of now, despite opportunities AI could bring, the majority of tasks are still performed manually by the employees. The founder has identified the domains that involve writing code and mapping BPs of clients as interesting to be researched for possible AI applications. Therefore, the aim of the case study is to research what opportunities to apply AI that could help increase the efficiency of the BPs in these domains can be identified.

3.3.1 Data Collection

For the case study, data is collected through the method of interviews. The interview is a common methodology to collect data for a case study (Ebneyamini & Sadeghi Moghadam, 2018). An interview is a data collection encounter in which one person, an interviewer, asks questions of another person, a respondent (Babbie, 2020). The chosen methodology is a semi-structured interview. This is an interview with a set of pre-determined questions but allows the interviewer to explore pertinent ideas that may come up during the interview (Adeoye-Olatunde & Olenik, 2021). The latter is preferred as it allows to better understand the participant's unique perspective (Adeoye-Olatunde & Olenik, 2021). At TS, four different employees are interviewed. Three hold the title data trainee and one is a junior data consultant. Two of the interviewees are predominantly occupied with data engineering processes, while the two others consider more the consultancy areas. The aim of the interview is to get a better understanding of the job of the employees, and specifically about how the BPs are conducted. The aim is to gather information necessary to map the BPs. For the TTF theory part, questions are also asked about characteristics of the tasks. The interviews were conducted in Dutch. The exact interview questions can be found in Appendix B.

3.3.2 Data Analysis

The aim of the interviews for the case study is to gather information about the job, the BPs, the tasks and the AI use of the interviewed employees. The data is gathered through transcribing the interviews and organizing the responses from the different respondents by interview question. Consequently, the answers for each question are compared. The focus lies on finding similarities and differences between the responses. These responses are used to make an analysis of the organisation and, specifically, its BPs.

This analysis forms the foundation on which the framework is applied. Therefore, based on the interview data, the BPs of the organisation are identified and mapped. Within these BPs, the tasks are evaluated. This analysis helps to apply the framework and try to identify in a systematic way opportunities to apply AI at the organisation. After application of the framework, it is evaluated using the criteria developed with the fourth sub-question. This evaluation aims to reflect on how well the designed framework performed in the case study.

4. THEORETICAL RESULTS

This section presents the theoretical results of the semi-systematic literature review. It discusses the findings for each sub-question.

4.1 AI Technologies

The first sub-question considers finding different categories of AI technologies with their respective characteristics. This section first defines Artificial Intelligence, then it provides a description of each category and its respective characteristics.

4.1.1 Definition Artificial Intelligence

The term 'Artificial Intelligence' has been around since the 1950s, when it was coined by John McCarthy, who defined it as "the science and engineering of making intelligent machines". Since then, scholars from different fields have come up with new and different definitions for the term (Borges et al., 2021). Enholm et al. (2022) noted that within these definitions, two groups can be distinguished. The first group defines AI as a tool that solves a specific task that could be impossible or time-consuming for humans by correctly applying learnings from external data. The second group regards AI as a system mimicking human intelligence and cognitive processes.

For management and organisational science, Mikalef & Gupta (2021) have brought up the point that in an organisational setting, many AI applications exhibit complementary characteristics to those of humans. Therefore, they have chosen to avoid inference of AI to human-like behaviour in their definition. Because this paper researches AI in management and organisational science, this stance is adopted. The definition should help to distinguish what AI does and does not constitute in an organisational setting. Therefore, the definition of AI for this paper is: "AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals" (Mikalef & Gupta, 2021).

4.1.2 Robotic Process Automation (RPA)

With the term Artificial Intelligence defined, four different categories of AI technologies have been distinguished in the literature results. Table 2 shows a summary of the four categories.

The first AI technology category found is technologies falling under the term Robotic Process Automation (RPA). RPA enables to automate administrative processes by imitating the work steps of employees in human software. Although traditional RPA technologies often require to be explicitly programmed to perform tasks and are therefore not universally considered as AI technology, more recent developments have enabled for RPA to work better with different types of data, making it broader applicable (Gotzen et al., 2021). For this paper, therefore, RPA is considered under the set definition of AI and is a distinct category. Two identified characteristics of the technology are the ability to automate pre-defined or rule-based tasks or processes in multiple software systems and its requirement for structured data and processes (Kokina & Blanchette, 2019).

4.1.3 Machine Learning (ML)

The second category of AI technologies is Machine Learning (ML). ML consists of learning algorithms that possess the ability to learn from training data in order to make inferences, thereby reducing the need for humans to explicitly program instructions. For example, in spam email detection, a model is trained on a dataset of emails, some labelled as spam and others as not. By analysing this data, the learning algorithm identifies patterns and features, which result in an AI application able to classify new emails as either spam or not (Sarker, 2021). The review shows that ML can be used in a wide variety of situations across sectors such as healthcare (Ali et al., 2023) and supply chain management (Riahi et al., 2023). The first identified characteristic of ML is its dependence on data required for successful implementation (Ali et al., 2023; Javaid et al., 2022; Riahi et al., 2023). Sarker (2021) explains that for the tree training types supervised, unsupervised and semi-supervised learning, a dataset of sufficient volume and quality is required. For the training type reinforcement learning, an environment to interact with is needed for the algorithm to gather sufficient data for learning. The second characteristic is the functionalities of ML. The most occurring functionalities of ML are classification, regression, clustering and association (Sarker, 2021).

4.1.4 Deep Learning (DL)

The third identified AI technology category is Deep Learning (DL). DL is formally a subset of ML; therefore it also uses the same four training types. It, however, distinguishes by using a different architecture, namely artificial neural networks (Ali et al., 2023). This allows for better performance in situations with larger or more complex datasets (Sarker, 2021). As a result, the emergence of DL has driven rapid advancements in the field of AI (LeCun et al., 2015). One of the key advancements DL methods offer over traditional ML methods is the ability to better work with raw unstructured data, such as text, images or even video (Dwivedi et al., 2023; LeCun et al., 2015). This allows among for better performance in Natural Language Processing (NLP) and Computer Vision (CV), which are subsets of AI (Enholm et al., 2022; Dwivedi et al., 2023). The first, NLP, is the ability to understand and work with natural language as used by humans, such as letters, words and sentences (Enholm et al., 2022). This allowed for the development of AI applications on and with textual data as documents or articles. The second subset, CV, deals with images or videos. AI applications in this domain are able to analyse and understand images or videos. The first and second characteristics of DL are its need for large volumes of high quality data and the functionalities of classification, regression, clustering and association. The third characteristic, distinguishes it from ML and is the ability of working with complex or unstructured data.

4.1.5 Generative AI (GenAI)

The DL algorithms powering the subsets NLP and CV predominantly require two things: 1) abundant data 2) sufficient computational power (Dwivedi et al., 2023). As a result of large volumes of data becoming available, and graphic cards for running learning algorithms becoming a lot more efficient, in the last decade, rapid advancements in AI were made, and a new subset generative AI (GenAI) was able to emerge (Dwivedi et al., 2023; Kanbach et al., 2024). GenAI is considered as the fourth and last distinct AI technology category. It distinguishes from other AI technologies by its capability to create new content, such as text, images, code or videos (Kanbach et al., 2024). It uses DL methods to find patterns in data. However, instead of, for example, performing a regression or classifying data, GenAI models learn patterns in the data in order to for example predict the next word in a sentence based on detected patterns in training data (Dwivedi et al., 2023).

GenAI has different applications, but the most known example are Large Language Models (LLMs), such as ChatGPT (Kanbach et al., 2024). LLMs are versatile language models capable of assisting with a wide variety of tasks, such as text generation, translation, coding and text summarization (Ray, 2023). During initial training, LLMs are first pre-trained on a large amount of textual data, such as web pages and books. This pre-training uses unsupervised learning: the algorithm learns patterns and relationships that exist within language. This knowledge is used to generate coherent texts. After the pre-training stage, LLMs can be fine-tuned using supervised learning: by providing clear examples of how LLMs should respond to certain questions, it learns these patterns and can be trained to respond in a specific way. The result is a NLP chatbot able to generate coherent text capable of assisting humans in a wide variety of tasks. (Ray, 2023)

An additional key feature of LLMs, which makes it different from the other AI techniques, is zero- or few-shot learning. This means that, because the LLM is already trained, in many scenarios LLMs can understand new tasks with no or very limited additional training, which often reduces the need for additional training on labelled datasets, saving time and resources in the development process (Ray, 2023). A risk of this feature, however, is hallucination, which refers to instances where the LLM generates factually incorrect or nonsensical output although it may sound plausible. The latter problem can be mitigated by applying a technique called Retrieval-Augment Generation (RAG). This entails the user providing the LLM with sufficient context in the prompt and can result in more accurate responses. (Tao et al., 2024). The two identified characteristics are generation of content and zero- or few-shot learning.

Table 2: Categories of AI technologies

AI Technology	Characteristics
Robotic Process Automation (RPA)	Automate pre-defined tasks or processes Requires structured data
Machine Learning (ML)	Requires large volumes of high quality data Functionalities: classification, regression, clustering and association
Deep Learning (DL)	Requires large volumes of high quality data Similar functionalities as ML High performance with complex or unstructured data (text, image, audio)
Generative AI (GenAI)	Generation of content Zero- or few-shot learning

4.2 Categories of Tasks

The second sub-question considers finding different categories of tasks with their respective characteristics. The identified categories are routine, analytical, creative and interpersonal tasks. The results are summarized in table 3.

4.2.1 Routine

The first category, routine tasks, can be defined as tasks that follow a specific set of rules or procedures (Przegalinska et al., 2025). This category is characterised by tasks having predictable responses to inputs (Peng et al., 2018). Examples are simple calculations, bookkeeping or correcting text or data (Spitz-Oener, 2006).

4.2.2 Analytical

The second category, analytical tasks, can be defined as tasks that refer to the ability of workers to logically think, reason and solve problems (Spitz-Oener, 2006). These tasks have as characteristic to be non-routine, meaning they exhibit a high number of exceptions (Peng et al., 2018). It involves breaking down complex problems, interpreting data and assessing alternatives. Examples are researching, planning and evaluating (Spitz-Oener, 2006).

4.2.3 Creative

The third category, creative tasks, can be defined as tasks that involve the generation of new and innovative ideas, concepts or solutions (Przegalinska et al., 2025). This category is non-routine as well. The difference is that where analytical tasks focus on thinking and reasoning to analyse data or a situation to come up with a solution for a specific problem, creative tasks focus on finding new ideas and solutions. This can come from combining existing things in a novel way or by coming up with new ideas. Examples are developing a marketing concept or a unique software interface.

4.2.4 Interpersonal

The fourth and last identified category are interpersonal tasks. These tasks refer to communication, establishing and maintaining relationships with other people (Dicarlo et al., 2016). Examples are supervising others and giving presentations (Spitz-Oener, 2006).

4.3 Fit Criteria

The third sub-question considers the fit criteria. These criteria aim to help evaluate to what extent an AI technology can be applied to a task.

4.3.1 Data Characteristics

The first criterion found is the characteristics of the data available in the task. These namely need to match with the technology. For RPA, it was found that structured data is required for a good fit (Aydıner et al., 2023), whereas GenAI, because of zero-shot learning, can make inferences on new tasks (Przegalinska et al., 2025). Previously it was already mentioned that ML and DL require sufficient volumes of high quality data to train a model (Enholm et al., 2022; Sarker, 2021). DL's main point of distinction from ML is the type of data it is able to work with. The data available in the task needs to facilitate the characteristic of its AI technology and therefore plays a role in determining the fit.

4.3.2 Output Characteristics

The second criterion is the output characteristics of the task. It was found that while GenAI can help to automate tasks (Zhang et al., 2025) and augment individuals in their tasks (Przegalinska et al., 2025), RPA is merely used for automation (Kokina & Blanchette, 2019). Certain tasks may require or desire human-AI collaboration (Rastogi & Pandita, 2025), while others are desired to be automated. Organisations need to distinguish whether they want to automate or augment the task and is a criterion to determine whether an AI technology can be applied to a task.

4.4 Framework

Based on the theoretical results, the framework can be constructed. This section describes the whole framework including the BPM components. The five steps the framework encompasses are discussed.

<u>Step 1: Identify Key BPs</u>

The first step consists of identifying the key BPs in the organisation. Organisations need to establish which BPs are present in the organisation and which are relevant for possible improvements.

<u>Step 2: Model BPs</u>

The second step consists of modelling the BPs. For this step, notations, such as BPMN can be used.

<u>Step 3: Categorize each Task</u>

For the third step, each task in the modelled BP is categorized in one of the four identified task categories.

Table 3: Categories of Type of Tasks

Task Category	Characteristics
Routine	• Specific set of rules or procedures • Predictable responses to inputs
Analytical	• Requires reasoning • Problem-solving with predefined output • High number of exceptions
Creative	• Novel ideas and solutions: problem-solving without predefined output
Interpersonal	• Collaboration with other individuals

<u>Step 4: Identify the theoretically possible AI technologies</u>

For the fourth step, based on the matrix, which is shown in figure 4, the AI technology or technologies that have the potential to be applied to the task can be identified. This results in an overview that links, for each task, the theoretical possible technology. The next step considers the criteria to evaluate whether this technology is suitable for application in practice. Before addressing the criteria, the matrix is discussed in more detail.

The fit between the technology and task categories in the matrix is based on the characteristics of each. Green means that a fit is likely, and yellow means it is unlikely but possible. Red means that a fit is not possible.

RPA is suitable for Routine tasks because it can help automate structured rule-based tasks (Kokina & Blanchette, 2019). This technology is, however, not suitable for the other task categories as these have a high number of exceptions and RPA does not offer functionality to deal with that.

ML and DL have the potential to support parts of Routine tasks. A pretrained ML or DL model can, for example, classify new instances in groups and that can speed up administrative tasks. Both technologies do not excel at them as well as RPA does, because they cannot automate tasks in software. They can, however, be used as support. ML and DL are both suitable for Analytical tasks. Both can analyse large amounts of data. ML can, for example, forecast product demand, which is useful for analytical tasks in inventory management (Javaid et al., 2022). DL, which distinguishes from ML by being able to work with unstructured data as text or images, can support analytical tasks that deal with complex or unstructured data. An example is detection fractures in images of human bones (Kale et al., 2024). For creative tasks not suitable as they rely on identified patterns in past data. Creative tasks require the creation of novel ideas and this is therefore not possible with ML or DL. For interpersonal tasks, ML are DL are not suitable as they do not provide options to support communication between humans.

GenAI can support routine tasks by having specific instructions to generate something in a structured way (Przegalinska et al., 2025). Compared to RPA, it misses functionality to automate something in a software system and therefore does not excel at them. For analytical tasks, GenAI is suitable. The technology can handle a high number of exceptions and with clear instructions can result in a pre-defined output (Tao et al., 2024). For creative tasks, GenAI is also suitable. It can create novel ideas and there is even possibility to change settings of a GenAI model to increase randomness of the model, resulting in possible more novel outputs (Zhang et al., 2025). For interpersonal tasks, GenAI has some possibilities to assist. It could help write or give communication strategy.

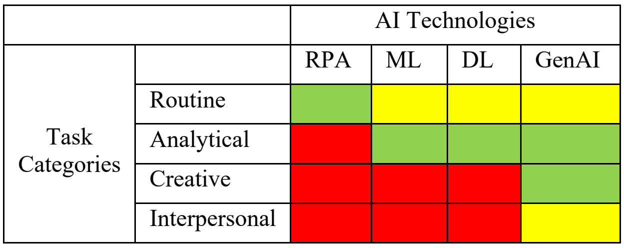

Figure 4: Matrix linking AI Technologies to Task Categories

<u>Step 5: Evaluate to what extent the AI technology can be applied</u>

For the fifth step, by using the two fit criteria data and output characteristics, it can be evaluated to what extent the AI technology can be applied in the instance.

4.5 Evaluation Criteria

The previous section presented the framework that results from the theoretical findings. In the next section the application of the framework in a case study is discussed. Because this paper adopts the DSR methodology, it aims to evaluate the designed artifact. This section discusses the found evaluation criteria in the literature. Peffers et al. (2007) explain that in DSR methodology, the evaluation part observes and measures how well the artifact supports the solution to the problem. This involves comparing the objectives of the solution to the observed results from use of the artifact in the demonstration. Therefore, the evaluation criteria should be linked to and derived from the objectives established for the artifact. In literature, several evaluation criteria for DSR, are found. Two of these relate to the objectives and, therefore, are relevant to support evaluation of the artifact of this paper. The first evaluation criterion is utility. Gill & Hevner (2013) define that in DSR utility refers to the efficacy in performing the task and cost-benefit. This criterion relates to the first and second objective; the artifact is evaluated on its efficacy to identify opportunities to apply AI and the cost-benefit of using the framework. The second criterion is usability. Usability is a criterion that can be used to evaluate and artifact (Venable et al., 2016). It relates to the third objective; it aims to evaluate to what extent the artifact can be used by managers. It does so by evaluating how practical and easy-to-use the framework is.

5. CASE STUDY

5.1 Introduction

The first part of the methodology, the semi-systematic literature review, has resulted in a framework that provides a systematic approach for identifying opportunities to apply AI. The second part of this paper's methodology aims to apply and evaluate the framework in a case study. This case study has taken place at data consultancy start-up TS in May and June 2025. Data has been gathered by conducting interviews with four employees. The results are discussed in this section; first the framework is applied, then it is evaluated.

5.2 Application of the Framework

TS is a data consultancy firm that supports other organisations in becoming more data driven. This involves helping with and giving advice on data management, extracting insights from data and optimising BPs of clients by smart utilisation of available data. For all these activities, TS never stores client data. This means that client data stays within the client's environment. Instead, TS develops custom scripts and interactive dashboards that operate on this data within the client's environment. This enables clients to be assisted in the handling of their data while maintaining control and ownership of it. For this case study, the manager has indicated to be interested in finding out what the opportunities are to apply AI for the own internal operations at TS. These operations among concern writing code in different programming languages, developing dashboards and analysing and modelling BPs of clients. An interest was indicated to explore how and which AI solutions can support these activities. Two domains were highlighted by the manager to be particular interesting to be researched for AI applications. These are programming and BP analysis. The case study, therefore, focused on applying the framework in order to identify opportunities to apply AI for the BPs of these domains.

The first step of the framework consists of identifying the key BPs in the organisation. In both domains, two key BPs have been identified, which is shown in figure 5. For the first category, programming, the identified BPs are Extraction Transform Load (ETL) of data and the development of dashboards. For the second category, which is BP analysis, modelling clients' BPs and mapping data sources were identified.

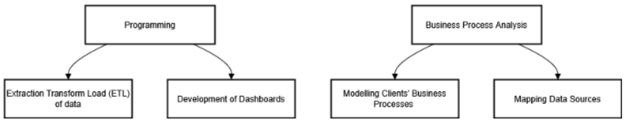

Figure 5: Four key Business Process in categories Programming and Business Process Analysis

Following the framework, the next step is to model the four BPs. The interviews provided information on the tasks and sequences for the four BPs. By structuring the answers of the four interviewees and using these findings, the BPs were modelled. In Appendix C, the modelled BPs can be found.

For the third step, each task was put in one of the four task categories. This was done by assessing the description of the task with the task characteristics of table 3. The results of the modelled BPs with categorised tasks are also shown in Appendix C. In this case study, the category most occurring was analytical tasks; a lot of tasks in the BPs involved problem-solving with a high number of exceptions. Examples are testing an API connection or cleaning data. These tasks were also assessed to have pre-defined output, such as having data extracted from software of a client or having cleaned data that can be used for a dashboard, and therefore were categorised as analytical. It was found that each BP contains a few interpersonal tasks; most of the time consisting of communication with the client and taking place both at the beginning and at the end of the BP. An example of such an interpersonal task is to request access to software or validate a design idea for a dashboard. In one BP, a few tasks were categorized to be creative. This was in the development of dashboards BP and concerned the tasks about design and layout. The category routine occurred two times for a task; both consisted of extracting and loading of data in other software and therefore follow a specific set of rules in that software.

Based on the categorisation of the tasks, for the fourth step, AI technologies that theoretically are possible to be applied to a task could be identified. This results in a table with every task in the BP, its task category and the theoretically possible AI technologies. The table is shown in Appendix C. Theoretically means that for every task in the BP an AI technology has the potential to automate or augment it in any way. For some tasks, such as for routine tasks, only one AI technology needs to be assessed, namely whether RPA can be applied. For analytical tasks, ML, DL and GenAI are theoretically possible and therefore the fit criteria of the fifth step are needed to evaluate this choice.

The fifth and last step of the framework uses the fit criteria to evaluate to what extent the technology matches with the specific task in the BP. The two criteria are Data Characteristics and Output Characteristics. These two have to match between the technology and designated task in practice.

For the category programming, the available data at TS are scripts with written code for current or previous projects. These scrips are stored in the company's private GitHub. For the category BP analysis, the available data are modelled BPs with mapped data sources of current or previous projects. As mentioned in the beginning of this section TS works with client data, but they do not store or own it. This all stays in the client's environment. Therefore, this data is excluded from training purposes at all. For this case study, the available data consists of scripts and modelled BPs with mapped sources. This data is, first of all, unstructured. It is mostly text and therefore ML can be excluded. Furthermore, it is identified that there is insufficient data available to train an own DL model. Therefore, for this case study, both ML and DL cannot be applied to the tasks because it does not match with the required data characteristics. Based on the data characteristics, for the analytical tasks, the remaining AI technology is GenAI. The second criterion considers the output characteristics of the tasks. The two options are automation and augmentation. The manager has indicated to view AI technology as supportive and aims to prioritize human input and oversight at every step of the process. Consequently, automation is not one of the preferred output characteristics. For this reason, this case study further focuses on identifying augmentation opportunities. As a result, for all four BPs, the remaining technology is GenAI. The next section discusses the specific AI solutions identified to apply GenAI at TS's BPs.

5.3 AI Solutions

The framework has been applied and has shown for several tasks the opportunity to be augmented by GenAI. This has resulted in several identified opportunities to apply AI at TS. These are discussed in this section.

First, it is mentioned that all BPs contain interpersonal tasks. These tasks have the potential to be augmented by GenAI. LLMs could be used to, for example, help write e-mails, gather a better understanding of clients' needs from interviews or e-mails or give a strategy on how to present a final deliverable. In these cases, the use of GenAI can save time on tasks as writing, but can also function as a sparring partner to provide a different perspective on an evaluation or a presentation. Second, for the analytical and creative tasks of each BP, GenAI solutions have been identified. The remainder of this section discusses these solutions for each BP individually.

For the first BP, ETL of data, for the analytical tasks, two opportunities for GenAI are identified. The first is assisting in reading API or system documentation. The use of a LLM can speed this task up because it can help to retrieve relevant information of documentation. There is no need to read everything, but a chatbot can be used to answer questions about relevant parts. The second opportunity is to assist with writing or debugging code. LLMs are able to understand and generate code and therefore can support these tasks. As a result, employees can spend less time on typical coding tasks, such as dealing with syntax or finding the right function, and can focus more on the strategic and problem-solving side. Instead of being taken away by technical issues, it becomes possible to concentrate more on developing the solutions. This can result in higher efficiency as it allows employees to spend less time on redundant aspects around writing code, but rather on strategic aspects of the outcome of code. When the available data of the case study is considered, an additional opportunity is identified. TS has code of previous and existing projects stored. Since GenAI can assist in reading documentation or writing code, it could leverage these old projects to more accurately help TS in their specific use cases. This could come in the form of providing a LLM with context data to have more accurate responses.

For the second BP, development of dashboards, for the analytical tasks, two opportunities have been identified. The first is the suggestion of ideas for a dashboard based on available data in the project. A LLM could be used to analyse the available data and come up with suggestions for a dashboard. This solution can speed up the task of coming up with ideas for dashboards. The second GenAI solution is to assist with coding and complex logic. For dashboards, some code has to be written, GenAI can augment this in similar ways explained for the previous BP. For the creative tasks, GenAI can support with design of the wireframe by utilising image generation. Currently, this task is executed in design software, but using image generation based on prompts has the potential to save time.

For the third BP, which is modelling clients' BPs, two opportunities for GenAI to augment have been identified. The first is that based on the description of the BP, a LLM can create the BPMN model of the BP. The LLM can distinguish the distinct tasks in the description given by the client and therefore can create the notation. Employees can later verify this BPMN and it can be used as a starting point to save time. The second opportunity is, for a LLM, to have a look at or analyse a BP of a client. This could come in the form of a LLM having access to an image of the BPMN or the code of notation. Consequently, the LLM can generate suggestions to improve the BP. This solution has the potential to save time or provide a different perspective on ways a BP can be optimized.

For the fourth and last BP, Data Sources Mapping, the identified opportunity is to assist with reading software documentation. An application would be to provide a LLM with the documentation and employees can ask questions about where specific data can be found in the software.

In particular, the solutions of GenAI supporting with reading documentation, writing code and creating the notation of a BP could be promising for TS. The manager also indicated to see serious potential in these applications powered by GenAI.

5.4 Evaluation

The evaluation considers measuring how well the framework has performed in practice. The two evaluation criteria are considered separately in this section.

5.4.1 Utility

The first criterion is utility and encompasses two pillars: efficacy and cost-benefit of the framework.

5.4.1.1 Efficacy

The first pillar, efficacy, aims to measure to what extent the framework was able to produce the desired or intended result. The desired outcome was a step-by-step approach that guides the identification of opportunities to apply AI in a systematic way.

On first sight, the framework has provided this systematic approach in the case study. By following the methodology, several tasks that can benefit from AI were identified. An example is using GenAI to create the notation of a client's BP. Because the framework highlighted that this step is analytical, and there was a lack of available data, GenAI was brought forth as suitable. For the other BPs, several tasks that benefit from AI were also identified by following the steps. This implies that the framework has provided a system to identify opportunities. In addition, the fit criteria were shown to be relevant in the case study, because they resulted to distinguish between the different AI technologies.

There are, however, also considerations about the efficacy of the framework. The first being that the aspects of data characteristics is considered inadequately. In the case study, after identifying several tasks that potentially could benefit from ML or DL, it turned out it was not possible to utilise these technologies because of the lack of data. Despite this can be considered a common issue around AI and especially for ML or DL, the framework highlighted it in the final step. This could have been indicated sooner or clearer and would make the framework more effective. In addition, possible ways to mitigate such an issue by using, for example, fake or synthetic data could have been considered in hindsight. There was, however, no indication of this possibility in the framework. Data plays a prominent role in AI, and despite the framework considers it, it is addressed relatively late. Furthermore, it also relies on subjective judgement of the quantity and quality of the data and does not provide guidelines for this. The same applies to the criterion of output characteristics. It was considered late in the framework and in a rather subjective way. The last consideration about the framework is its ability to actually identify opportunities. The framework supported by providing an overview of all tasks in the BP and the suitable AI technology. This was, consequently, used to come up with more specific solutions. In other words, the framework highlighted the suitable AI technology for a specific task, but the way the actual task could benefit from this technology relied on human ideation. Despite, the framework was found to be useful. It should, however, be considered the framework functions more as a basis or overview of the tasks and suitable technologies in an organisation. This is helpful to come up with ideas for AI applications, but the framework does not result in the concrete solutions.

5.4.1.2 Cost-Benefit

The second pillar of utility, cost-benefit, considers the outcomes of the framework in relation to the efforts. In the case study, it was found that the framework takes relatively low effort to apply. Especially when the BPs are relatively clear, it is straightforward to categorize the tasks, link the technologies and assess the fit. The costs of the framework are, therefore, relatively low. The benefits, as discussed in the efficacy pillar, are evaluated to be fine, but less concrete. The framework supports the identification of opportunities by providing an overview and this is considered to be helpful. It is also found that the framework, however, does not result in concrete solutions. As a result, its value or benefits are not considered to be high. Overall, the cost-benefit of the framework is evaluated to be reasonable as the costs to apply are low, while the practical value is helpful but less tangible.

5.4.2 Usability

The second criterion is usability and relates to the third objective: the framework should be usable for managers. The framework was in practice straightforward to apply. Managers with a general understanding of BPM should be able to apply it. However, an identified downside of the framework is its reliant on human judgement in several steps. This the case for the categorisation of tasks. There, it can be sometimes unclear to distinguish between tasks, especially, for example, between an analytical or creative task. Furthermore, for assessing the fit criteria, the framework can be difficult to apply for managers with less understanding of IT or data. The output characteristics criterion is straightforward, but the data characteristics can cause issues. In the case study, it was judged that the written code in the database was insufficient for ML or DL purposes, but someone with expertise on AI could better make such a decision. Therefore, it can be concluded that despite the first four steps of the framework are straightforward, the last step of assessing the fit relies too much on human judgement and expertise to accomplish the third objective.

6. DISCUSSION

6.1 Conclusion

This paper's objectives were to design a framework, apply it in a case study and evaluate it, in order to develop an answer to the following research question:

How can organisations systematically identify opportunities to apply Artificial Intelligence to increase efficiency of business processes?

The answer to this question consists of a five-step framework that guides organisations to evaluate BPs for opportunities to apply AI. It uses, for the first and second step, components of BPM to identify and model BPs in an organisation, after which, for the third step, this paper designed a method to put each task in a specific task category. Then, for the fourth step, based on these categories, using a matrix designed in this paper, for each task, possible AI technologies can be found. This results in an overview of for every task of the process the potential AI technology or technologies. The fifth step considers fit criteria to evaluate to what extent the technology can be applied in practice.

A case study, in which the framework was applied, showed it can lead to the identification of opportunities to apply AI. In each analysed BP, at least one opportunity to apply AI to a task has been identified. Evaluation of the framework highlighted its ease of use and reasonable cost-benefit for organisations to apply. However, it was also found to rely in some aspects on subjective judgement and expertise and it considers data and output aspect at a late stage. Furthermore, the framework does not result in concrete solutions directly; it produces rather an overview of tasks in a BP with the most suitable AI technology. This overview forms a basis for coming up with concrete solutions in an organisation. While application of the framework does not result in concrete solutions, it enables organisations to systematically map AI opportunities across their BPs, thereby providing a useful basis that supports the identification of opportunities to apply AI.

6.2 Practical Implications

In the introduction, it was stated that organisation have become eager to apply AI, but lack understanding of where to apply it. The approach developed in this paper aimed to provide a systematic method guiding managers to identify opportunities to apply AI in BPs. The framework's primary value for practice lies in the systematic approach. It provides organisations a step-by-step approach, which is evaluated to be straightforward and inexpensive to use, that results in an overview supportive to evaluate BPs for AI applications. Organisations can, therefore, in a relatively accessible way identify the opportunities to apply AI in BPs. The value arising from this is that it lowers the bar to apply the technology. AI holds potential to drastically increase efficiency of BPs by automating or augmenting tasks. Because before it was unclear how organisations can identify these opportunities, it was difficult recognize where the technology can be implemented. The framework supports this identification process by providing a structured approach that supports finding these opportunities, making it easier for organisations to realise more of AI's potential.

6.3 Theoretical Implications

The theoretical basis of this paper consists of BPM and TTF. These were complemented to form the basis for the design of the framework. Previous papers combining the methodology of BPM with theory of TTF, explored how BPM could be extended (Trkman, 2010) and aimed to define criteria for a Process-Technology Fit (Ahmad & Van Looy, 2022). To the author's knowledge, both were not complemented before for the construction of a framework to identify suitability of a technology in BPs. The first academic contribution of this paper, therefore, is the design of a framework with the theoretical basis of BPM with TTF. The practical application of the framework is evaluated and it is found that the task perspective results in a narrow view on the process; it provides a task-specific analysis of the suitability of technology. An advantage is that, for each task, the potential for a specific technology is evaluated. A disadvantage of this narrow perspective is that bigger improvements to a BP or possible process-redesigns may get neglected. The capabilities of AI hold the potential to lead to complete re-design of BPs (Wamba-Taguimdje et al., 2020). This more transformative impact risks being neglected with the granular perspective of looking at tasks. In the case study, it was found that potential opportunities to, for example, combine elements of two BPs were overlooked by the framework, whereas it theoretically could be possible. A theoretical implication of using TTF, therefore, is that while it provides to assess every task for its technological opportunities, it may miss larger process re-design opportunities. The second academic contribution comes from designing a solution to address the gap in the *process analysis* and *redesign* phase of the BPM lifecycle when it comes to AI. Previous methodology to identify opportunities to apply rely on BPM methodology (Aldoseri et al., 2024). It was, however, found that organisations lack understanding of AI to identify where to apply it (Enholm et al., 2022). This paper aimed to develop a solution which has come in the form of a five-step approach guiding organisation through the opportunity identification process. Furthermore, because DSR methodology has been followed, it is possible for other scholars to evaluate and validate the choices made in the design (Peffers et al., 2007). This can be used among to further enrich literature on AI and organisations, but also for example for research on how DSR is applied in practice. The last academic contribution comes from the case study. It provides insights into how in practice in an organisation in a systematic way opportunities are identified. It revealed some practical problems like data accessibility because of privacy issues or a managerial preference towards augmentation. These were not considered in the theoretical framework and limits its applicability, thereby enriching literature on application of AI in practice.

6.4 Limitations

This paper was subject to several limitations, both in terms of the framework and in terms of the case study. Related to the framework, there are four identified limitations. The first is that the framework is oversimplistic in categorisation of technologies and tasks. Because it was aimed to have the framework easy and straightforward in use, the categories have been categorised in the most relevant, still distinguishable, ones. As a result, the matrix of the fourth step is also simplistic and does not consider the relation between each technology and task category in detail. This forms a limitation because in practice there are more nuances to applying a technology to a task. The second limitation is that GenAI is considered to potentially fit with every type of task. This comes from the technology being versatile and it not requiring training data. Therefore, in the framework it seems to have the potential to be applied in every instance. This is a limitation. GenAI is versatile and can make inferences without training data, but there are instances where other technologies should be applied. The framework does not explain this sufficiently. The third limitation is that it is found that application of the framework does not result in concrete solutions, but rather in an overview of for each task the most suitable AI technology. The reason this does not lead to concrete solutions immediately is that applying a technology is not solution on itself. Technology is a tool that can assist individuals in performing tasks (Goodhue & Thompson, 1995). This tool still has to be operationalised to function as a solution or tool to increase efficiency of BPs. This last step is something the framework did not capitalise on and still requires ideation on how a specific AI technology can be leveraged for a task. Future research into this aspect is needed. It could come in the form of conducting multiple case studies and analysing how a found AI technology leads to a concrete solution. Another option would be to review literature about developing solutions for organisation and exploring whether findings could further extend the framework to result to in more concrete solutions. A fourth limitation of the framework is that AI develops at a rapid pace. This framework encompasses the current AI technologies. It does, however, not account for future developments of the technology.

In regards to the case study, the first limitation is the fact there was only one case in which the framework was applied. This made the insights of the evaluation limited. Another limitation of this particular case study was the limited availability of data. This resulted in not considering ML or DL technologies. In hindsight, the problem could have been tried to be mitigated by using synthetic or fake data, but this was not considered during the case study.

6.5 Future Research

Based on the limitations of this paper, several directions can be pursued for future research aiming to address the process of identification of opportunities to apply AI in organisations. The first directions are related to the framework. Future research could address current issues of the framework. First of all, the issue of the framework being t oversimplistic could be aimed to be addressed. It could capture the distinct categories of AI in more detail, while still aiming to keep its use straightforward. An example could be to distinguish more between different functionalities of ML or DL, such a classification or regression. Secondly, it could develop methods to assess the fit criteria of data and output characteristics. Right now, these rely on subjective judgement and a matrix to, for example, to evaluate data availability could be developed. This could make it more objective and increase its consistency in practice. Thirdly, future research could aim to address GenAI more adequately. GenAI can in the current framework be applied in almost every instance because of its versatility and lack of required training data. The exact or most relevant use cases for GenAI could, therefore, be theorised in future research. The second future research direction is that the framework can be applied and evaluated in multiple case studies. This has the potential to yield interesting results about its effectiveness. It would be interesting to do this in organisations of different sizes in different industries. The third and last direction for future research is to design a framework that addresses the same gap, but then in a different way with a different theoretical basis. BPM and TTF were chosen, but for example, using the resource-based view to look from a more strategic perspective (Przegalinska et al., 2025) or Technology Organisatiation Environment to look at adoption (Enholm et al., 2022) could lead to different perspectives.

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APPENDIX A

Search Results: Semi-Systematic Literature review

Sub-question 1: ***What are categories of AI technologies and what are their characteristics?***

Search Query:	("Artificial Intelligence" OR "AI") AND ("categor*" OR "types" OR "taxonomy" OR "classif*") AND ("characteristics" OR "attributes" OR "features" OR "capabilities") AND ("framework" OR "review" OR "typology")

Eligibility criteria:

Category	Filter
Years	2020-2025
Field/category	Scopus: Business, Management, Accounting WoS: Business, Management
Language	English
Document type	Article, Conference Paper, Review, Book Chapter
Keyword	Artificial Intelligence

Results:

Scopus	WoS
152	143

Unique results: 245

After screening: 27

Retrieved: 22

Included in review: 11

<u>Inclusion criteria:</u>

Papers need to explicitly discuss categories or types of AI technologies.

Papers need to explicitly discuss characteristics, capabilities, or functionalities of specific AI categories/technologies.

<u>Exclusion criteria</u>

Papers that discuss AI algorithms and not focus on broader technology categories

Sub-question 2: ***What are categories of tasks and what are their characteristics?***

Search Query	("task categor*" OR "task classification" OR "task typology" OR "task framework")

Eligibility criteria:

Category	Filter
Years	1995-2025
Field/category	Scopus: Business, Management, Accounting WoS: Business, Management
Language	English
Document type	Article, Conference Paper, Review, Book Chapter

Results:

Scopus	WoS
58	11

Total: 69

Duplicates: 5

Unique results: 64

After screening: 10

Retrieved: 9

Included in review: 11

<u>Inclusion criteria:</u>

Papers need to explicitly discuss categories or types of tasks.

Papers need to explicitly discuss characteristics, capabilities, or functionalities of specific tasks types or categories.

<u>Exclusion criteria</u>

Sub-question 3: ***What criteria determine fit between AI technology and task category?***

Search Query	Scopus	WoS	Unique results
("task-technology fit" OR "TTF") AND ("AI" OR "Artificial Intelligence")	2020-2025 Business, Management, Accounting Article, conference, book 31	2020-2025 Business, Management Article 25	44
(“Robotic Process Automation” OR RPA) AND ("task-technology fit" OR "TTF")	2 (2019 included)	2	2
("Machine Learning" OR "ML") AND ("task-technology fit" OR "TTF")	4 (2021-2025)	5 (2019-2025	7
("Deep Learning" OR dl) AND ("task-technology fit" OR "TTF")	0	0	
("Generative AI" OR genai OR llm) AND ("task-technology fit" OR "TTF")	8	5	10

Eligibility criteria:

Category	Filter
Years	2015-2025
Field/category	Scopus: Business, Management, Accounting WoS: Business, Management
Language	English
Document type	Article, Conference Paper, Review, Book Chapter

Total: 56

Duplicates: 8

Unique results: 48

After screening: 14

Retrieved: 14

Relevant : 6

<u>Inclusion criteria:</u>

Papers need to explicitly discuss criteria related to a fit between AI technology and task.

Article matrices:

Sub-question 1: ***What are categories of AI technologies and what are their characteristics?***

Nr.	Author(s)	Title	Year	Type of document	Source	Type of study	AI categories
1	Iqbal H. Sarker	Machine Learning: Algorithms, Real-World Applications and Research Directions	2021	Journal Article	SN Computer Science	Review	Machine Learning: Supervised, Unsupervised, Semi-Supervised, Reinforcement Learning Deep Learning
2	R. Chopra and G. D. Sharma	Application of Artificial Intelligence in Stock Market Forecasting: A Critique, Review, and Research Agenda	2021	Journal Article	Journal of Risk and Financial Management	Systematic Literature Review	Artificial Neural Networks
3	R. Gotzen, G. Schuh, V. Stich and R. Conrad	Classification of software-based automation technologies: Derivation of characteristics through an empirical investigation	2021	Conference paper	IEEE International Conference on Engineering, Technology and Innovation	Systematic Literature Review	RPA, Cognitive Process Automation
4	M. Javaid, A. Haleem, R. P. Singh and R. Suman	Artificial Intelligence Applications for Industry 4.0: A Literature-Based Study	2022	Journal Article	Journal of Industrial Integration and Management	Review based reporting	Machine Learning Big Data Robotics Factory Automation Internet of Things Cognitive Computing

5	O. Ali, W. Abdelbaki, A. Shrestha, E. Elbasi, M. A. A. Alryalat and Y. K. Dwivedi	A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities	2023	Journal Article	Journal of Innovation and Knowledge	Systematic Literature Review	Multimedia processing Textual data processing
6	M. Del Gallo, G. Mazzuto, F. E. Ciarapica and M. Bevilacqua	Systematic Literature Review of Artificial Intelligence in production scheduling problems in real cases	2023	Conference paper	Proceedings of the Summer School Francesco Turco	Systematic Literature Review	Particle Swarm Optimization, Neural Network
7	P. K. Nag, A. Bhagat, R. Vishnu Priya and D. K. Khare	Emotional Intelligence Through Artificial Intelligence: NLP and Deep Learning in the Analysis of Healthcare Texts	2023	Conference paper	International Conference on Artificial Intelligence for Innovations in Healthcare Industries	Systematic Literature Review	Machine Learning, Natural Language Processing, Deep Learning
8	L. Sundberg and J. Holmström	Innovating by prompting: How to facilitate innovation in the age of generative AI	2024	Journal Article	BUSINESS HORIZONS	Integrative Literature review of Academic and Grey Literature	Deep Learning: neural networks Natural Language Processing: AI understanding language Generative AI: neural networks to generate new content Large Language Models: chatbots that can be used for a wide

							range of use cases
9	J. Tao, L. N. Zhou and X. Fang	Generative AI for Intelligence Augmentation: Categorization and Evaluation Frameworks for Large Language Model Adaptation	2024	Conference paper	AIS TRANSACTIONS ON HUMAN-COMPUTER INTERACTION	Literature review & empirical investigation by testing use cases	Generative AI Large Language Model
10	P. P. Kale, U. B. Shinde, D. L. Bhuyar, K. T. V. Reddy and H. B. Mahajan	Human Body Bone Fracture Identification using Improved Deep Learning Model	2024	Conference paper	International Conference on Artificial Intelligence in Healthcare, Education and Industry	Case test	Deep Learning, Computer Vision, Convolutional Neural Network
11	Y. Riahi, T. Saikouk, I. Badraoui and S. Fosso Wamba	Researched topics, patterns, barriers and enablers of artificial intelligence implementation in supply chain: a Latent-Dirichlet-allocation-based topic-modelling and expert validation	2023	Journal Article	Production Planning and Control	Systematic topic modelling & semi-structured interviews with experts	Machine Learning Computer Vision Natural Language Processing Speech Recognition Knowledge representation
12	M. Reddy and R. Pallerla	Using AI to Detect and Classify Suspicious Mobile Messages in Real Time	2025	Conference paper	International Conference on Intelligent Data Communication Technologies and Internet of Things	Case test	Machine Learning, Natural Language Processing, Deep Learning

Sub-question 2: ***What are categories of tasks and what are their characteristics?***

Nr.	Year	Author(s)	Title	Publication	Document Type	Methodology	Task Categories

1	2013	S. Mohammed and D. A. Harrison	The clocks that time us are not the same: A theory of temporal diversity, task characteristics, and performance in teams	Organizational Behavior and Human Decision Processes	Journal Article	Literature review	1.Decision-Making tasks 2.Action-Oriented Tasks 3.Component complexity 4.Coordinative complexity 5.Dynamic complexity
2.	2018	G. Peng, Y. Wang and G. Han	Information technology and employment: The impact of job tasks and worker skills	Journal of Industrial Relations	Journal Article	Surveys	1. Routine 2. Non-Routine 3. Cognitive 4. Manual
3.	2023	S. Nzobonimpa	Artificial intelligence, task complexity and uncertainty: analyzing the advantages and disadvantages of using algorithms in public service delivery under public administration theories	Digital Transformation and Society	Journal Article	Literature review	1. Low complex 2. High complex 3. Low uncertainty 4. High uncertainty
4.	2024	N. Salimgereyev, B. Mukhamediyev and A. A. Shaikh	Measuring the routine and non-routine task contents: a comparative study between state and industrial sector employees	International Journal of Productivity and Performance Management	Journal Article	Surveys	Nonroutine interactive Nonroutine analytic Routine cognitive
5.	2006	Alexandra Spitz-Oener	Technical Change, Job Tasks, and Rising Educational Demands: Looking	Journal of Labor Economics	Journal Article	Surveys	Nonroutine analytical Nonroutine interactive Routine Cognitive Routine Manual

			outside the Wage Structure				Nonroutine manual
6.	2025	A. Przegalinska, T. Triantoro, A. Kovbasiuk, L. Ciechanowski, R.B. Freeman, K. Sowa	Collaborative AI in the workplace: Enhancing organizational performance through resource-based and task-technology fit perspectives	International Journal of Information Management	Journal Article	Experiment	Automation Decision-support Creation Innovation

Sub-question 3: ***What criteria determine fit between AI technology and task category?***

Nr.	Year	Author(s)	Title	Publication	Document type	Methodology	Discussed technologies	Criterion categories
1.	2019	J. Kokina and S. Blanchette	Early evidence of digital labor in accounting: Innovation with Robotic Process Automation	International Journal of Accounting Information Systems	Journal Article	Interviews	Robotic Process Automation (RPA)	task that are labor intensive, repetitive, high volume, rule based, digital -> suitable RPA structured data -> suitable RPA external applications -> less suitable
2.	2023	A. S. Aydıner, S. Ortaköy and Z. Özsürünç	Employees' perception of value-added activity increase of Robotic Process Automation with time and cost efficiency: a case study	International Journal of Information Systems and Project Management	Journal Article	Survey	Robotic Process Automation (RPA)	Routineness task knowledge intesive

3.	2025	D. Chakraborty, C. Troise and S. Bresciani	Exploring consumer intentions to continue: Integrating task technology fit and social technology fit in generative AI based shopping platforms	Technovation	Journal Article	Survey	Generative AI	Task: complexity, intedependence, variability Technology: scale, adaptability, intelligence
4.	2025	A. Przegalinska, T. Triantoro, A. Kovbasiuk, L. Ciechanowski, R. B. Freeman and K. Sowa	Collaborative AI in the workplace: Enhancing organizational performance through resource-based and task-technology fit perspectives	International Journal of Information Management	Journal Article	Experiment, Survey	Generative AI	Task type (routine/creative and easy/complex)
5.	2025	S. Rastogi and D. Pandita	From code to collaboration: influence of artificial intelligence on workforce dynamics	International Journal of Organization Theory and Behavior	Journal Article	Interviews	AI (: ML, data analysis, robotics)	Task complexity Employee Skill Level

6.	2025	H. Zhang, Z. Xiang and F. J. Zach	Generative AI vs. humans in online hotel review management: A Task-Technology Fit perspective	Tourism Management	Journal Article	Empirical analysis of experiment	Generative AI, specifically LLM	Task: different tasks have different demands Technology: different temperature offer different outputs

APPENDIX B

<u>Interview vragen</u>

3 categorieën:

- Algemeen/Functie
- Programmeren/ Git
- ProcessView software/ Bedrijfsprocessen analyseren

<u>Functie:</u>

Wat is jouw functie bij TS?

Bij welke bedrijfsprocessen van TS ben jij betrokken?

<u>Programmeren/ Git:</u>

Technisch

Welke programmeertalen gebruik je en waarvoor? Welke Code Editors / IDEs gebruik je?

Algemeen

Kun jij iets vertellen over projecten waarvoor je programmeert of code schrijft?

Wat zijn de verschillende doeleindes van het programmeren voor een project? (Bijv. maken van dashboards, prijsmodel, data migratie)

Proces

Kun je beschrijven hoe het proces eruitziet van de eerste vraag of behoefte van de klant tot aan het opleveren van de werkende code?

(Bij deze vraag: achterhalen en samen doornemen uit welke stappen het proces bestaat, hierbij zijn de volgende zaken relevant:

- Wie zijn er bij betrokken (<u>actoren</u>)
- Welke <u>actie</u> wordt er genomen
- Waar wordt <u>informatie</u> vandaan gehaald om de taak/stap uit te kunnen voeren
- Mogelijk nog interessant: op basis waarvan beslissingen in het proces worden genomen)

In hoeverre komen programmeerprojecten overeen tussen klanten?

(eventueel voorbeelden vragen)

GIT

Kun jij uitleggen hoe jij gebruik maakt van GIT binnen het dagelijkse ontwikkelproces?

Wordt code van oude projecten hergebruikt?

Zo ja, hoe vind je oude code en hoe pas jij het aan?

AI

Maak jij gebruik van AI tijdens het programmeren?

Zo ja, welke tools gebruik jij en waarvoor?

Zo ja, wat vind jij van deze tools: wat zijn de voor- en nadelen?

Heb jij zelf ideeën over hoe AI ingezet kan worden tijdens het programmeren in jouw werk?

ProcessView software:

Deze vragen behoren tot het onderdeel van de bedrijfsproces analyse software.

Algemeen

Voor welke verschillende doeleindes gebruik je de software (ProcessView)?

Proces

Hoe ziet het proces eruit wanneer jij een bedrijfsproces van een klant gaat noteren in de software?

(Achterhalen en samen doornemen uit welke stappen het proces bestaat, hierbij zijn de volgende zaken relevant:

- Wie zijn er bij betrokken
- Welke actie wordt er genomen
- Waar wordt informatie vandaan gehaald om de taak/stap uit te kunnen voeren
- Mogelijk nog interessant: op basis waarvan beslissingen in het proces worden genomen)

Welke elementen komen overeen tussen verschillende projecten? Een voorbeeld is wanneer klanten dezelfde software gebruiken en jij de databron op dezelfde manier kan verzamelen, zijn er meer van zulke gevallen dat er zaken overeenkomen?

In hoeverre maak jij gebruik van eerder werk voor andere klanten of projecten?

In hoeverre zou jij hier gebruik van kunnen maken?

AI

Gebruik je wel eens AI wanneer jij bezig bent met ProcessView?

Heb jij zelf ideeën over hoe AI kan helpen tijdens het werk in ProcessView?

Translated to English for purpose of this Appendix (using DeepLtranslate.com)

Interview questions

3 categories:

- General/Function
- Programming/ Git
- ProcessView software/ Analyze business processes

Function:

What is your function at TS?

What business processes at TS are you involved in?

Programming/ Git:

Technical

What programming languages do you use and what for? Which Code Editors / IDEs do you use?

General

Can you tell something about projects for which you program or write code?

What are the different purposes of programming for a project (e.g. creating dashboards, price model, data migration)

Process

Can you describe what the process looks like from the first question or need of the customer until the delivery of the working code?

(For this question: find out and go through the steps of the process together, the following are relevant:

- Who is involved (actors)
- What action is taken
- Where does the information come from to carry out the task/step
- Possibly even more interesting: on the basis of which decisions are made in the process)

To what extent do programming projects correspond between customers?

(ask for examples if necessary)

GIT

Can you explain how you use GIT within the daily development process?

Is code from old projects reused?

If so, how do you find and modify old code?

AI

Do you use AI while programming?

If yes, what tools do you use and what for?

If so, what do you think of these tools: what are their advantages and disadvantages?

Do you have any ideas on how AI can be used during programming in your work?

ProcessView software:

These questions belong to the business process analysis software section.

General

For what different purposes do you use the software (ProcessView)?

Process

What does the process look like when you record a customer's business process in the software?

(Find out and go through the steps of the process together, the following are relevant:

- Who is involved
- What action is taken
- Where is information obtained to be able to execute the task/step?
- Possibly even more interesting: on the basis of which decisions are made in the process)

Which elements correspond between different projects? An example is when clients use the same software and you can collect the data source in the same way, are there more such cases where things match?

To what extent do you use previous work for other clients or projects?

To what extent could you make use of this?

AI

Do you use AI while programming?

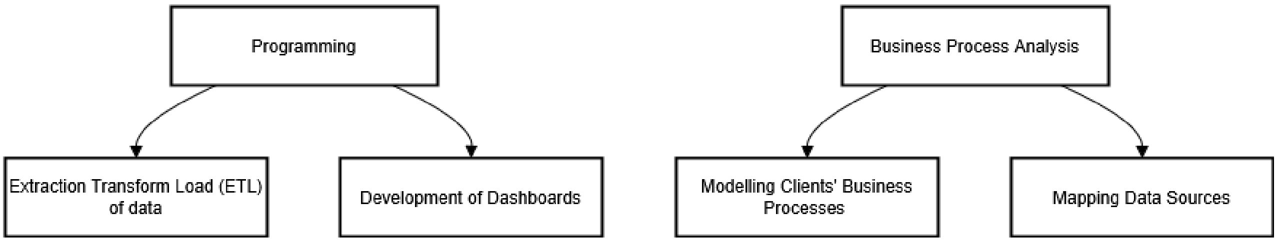
If yes, what tools do you use and what for?

If so, what do you think of these tools: what are their advantages and disadvantages?

Do you have any ideas on how AI can be used during programming in your work?

APPENDIX C

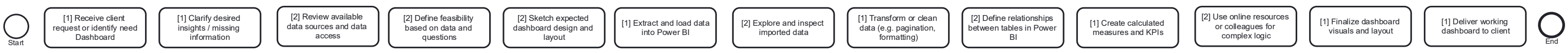
Step 1: Identify Key Business Processes



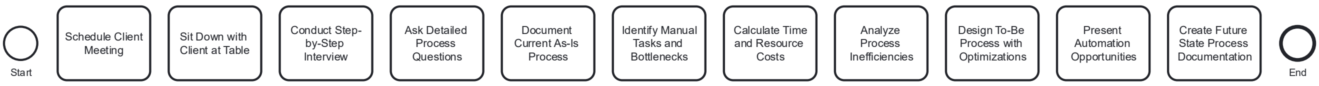
Step 2: Model BPs

BP1: Extraction, Transform, Load (ETL)

BP2: Development of Dashboards



BP3: Modelling Clients' Business Processes



BP4: Mapping Data Sources

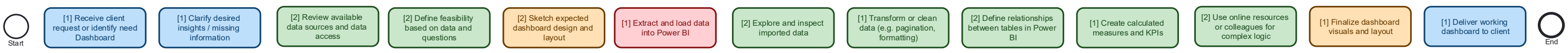
Step 3: Categorize each task

Task category	Characteristics	Colour
Routine	• Specific set of rules or procedures	Red
Analytical	• Requires reasoning • Problem-solving with predefined output • High number of exceptions	Green

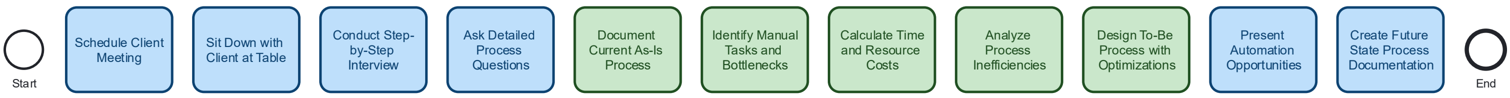
Creative	• Novel ideas and solutions: problem-solving without predefined output • Combining inputs	Yellow
Interpersonal	• Collaboration with other individuals	Blue

BP1: Extraction, Transform, Load (ETL)

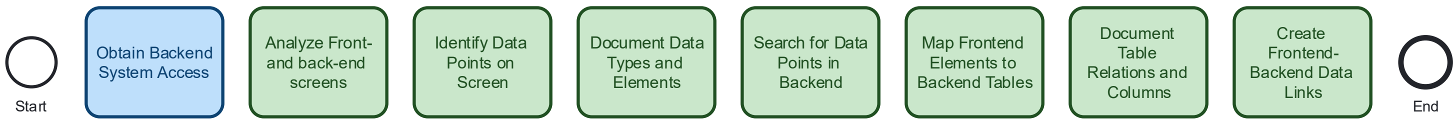
BP2: Development of Dashboards



BP3: Modelling Clients' Business Processes



BP4: Mapping Data Sources



<u>Step 4: Identify theoretically possible AI solutions</u>

BP1: Extraction, Transform, Load (ETL)

Task	Task Category	Possible AI technology
Clarify client need or detect need for data internally	**Interpersonal**	**GenAI**
Read API/system documentation	**Analytical**	**ML, DL or GenAI**
Request API access / authentication	**Interpersonal**	**GenAI**
Develop and test API connection	**Analytical**	**ML, DL or GenAI**
Handle errors or access issues	**Analytical**	**ML, DL or GenAI**
Extract data	**Routine**	**RPA**
Clean and transform data	**Analytical**	**ML, DL or GenAI**
Validate with client or stakeholder	**Analytical**	**ML, DL or GenAI**
Integrate data into target system (e.g., BI tool)	**Analytical**	**ML, DL or GenAI**

Debug or iterate if needed	Analytical	ML, DL or GenAI
Final delivery	Interpersonal	GenAI

BP2: Development of Dashboards

Task	Task Category	Possible AI technology
Receive client request or identify need Dashboard	Interpersonal	GenAI
Clarify desired insights / missing information	Interpersonal	GenAI
Review available data sources and data access	Analytical	ML, DL or GenAI
Define feasibility based on data and questions	Analytical	ML, DL or GenAI
Sketch expected dashboard design and layout	Creative	GenAI
Extract and load data into Power BI	Routine	RPA
Explore and inspect imported data	Analytical	ML, DL or GenAI
Transform or clean data (e.g. pagination, formatting)	Analytical	ML, DL or GenAI
Define relationships between tables in Power BI	Analytical	ML, DL or GenAI
Create calculated measures and KPIs	Analytical	ML, DL or GenAI
Use online resources or colleagues for complex logic	Analytical	ML, DL or GenAI
Finalize dashboard visuals and layout	Creative	GenAI
Deliver working dashboard to client	Interpersonal	GenAI

BP3: Modelling Clients' Business Processes

Task	Task Category	Possible AI Technology
Schedule Client Meeting	Interpersonal	GenAI
Sit Down with Client at Table	Interpersonal	GenAI
Conduct Step-by-Step Interview	Interpersonal	GenAI
Ask Detailed Process Questions	Interpersonal	GenAI
Document Current As-Is Process	Analytical	ML, DL or GenAI
Identify Manual Tasks and Bottlenecks	Analytical	ML, DL or GenAI
Calculate Time and Resource Costs	Analytical	ML, DL or GenAI
Analyse Process Inefficiencies	Analytical	ML, DL or GenAI
Design To-Be Process with Optimizations	Analytical	ML, DL or GenAI
Present Automation Opportunities	Interpersonal	GenAI

Create Future State Process Documentation	**Interpersonal**	**GenAI**

BP4: Mapping Data Sources

Task	Task Category	Possible AI Technology
Obtain Backend System Access	**Interpersonal**	**GenAI**
Analyze Front- and back-end screens	**Analytical**	**ML, DL or GenAI**
Identify Data Points on Screen	**Analytical**	**ML, DL or GenAI**
Document Data Types and Elements	**Analytical**	**ML, DL or GenAI**
Search for Data Points in Backend	**Analytical**	**ML, DL or GenAI**
Map Frontend Elements to Backend Tables	**Analytical**	**ML, DL or GenAI**
Document Table Relations and Columns	**Analytical**	**ML, DL or GenAI**
Create Frontend-Backend Data Links	**Analytical**	**ML, DL or GenAI**

Step 5: Evaluate fit

- Data Characteristics:
    - Code written for previous or in-progress projects
- Output Characteristics
    - Strong preference for augmentation

Remaining technology is Generative AI