

# The Artificial Intelligence (AI) Model Canvas Framework and Use Cases

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## ABSTRACT

Artificial Intelligence (AI) has grown increasingly in the past decade. The growth and development bring up several issues for a successful AI project. The AI project requires communication across different domains, like specialists, engineers, data scientists, stakeholders, and ecosystem partners (analytic, storage, labeling, and open-source platforms). It offers numerous vital qualities to give deeper insights into user behavior and give recommendations based on the data. The AI project is hard to define, it requires more than mastery of data, and every enterprise needs guidance and a simple plan on how to use AI. This research creates a wide-view approach of different types of AI Model Canvas for companies that do projects, produce, promote and provide AI technology to organizations. We selected three canvases that represented AI, Machine Learning (ML), and Deep Learning (DL) method. We illustrate and interpret those canvas along with some case studies. We conclude our research by writing the final case report for each use case from the AI model canvas. By filling the one-page Canvas, it will help us explain what AI will provide, how it will interact with humans judgment, and how it will be used to influence decisions, how you will measure success & outcome, and the type of data needed to train, operate, and improve AI. The AI Model Canvas purposed a clear description and differentiation of the roles of stakeholders, customers, and AI strategy. This canvas also can be used in analytical and assembly projects in making new product lines.

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## 1. INTRODUCTION

Technology is all around us, with self-driving cars, drones, virtual assistants, scheduled meetings, chatbots working alongside humans as teaching assistants. The future is about a holistic business model, and opportunities become liquid to learn just in time, not just in case. It takes not only a single improvement but complete transformations, not just an individual system but a new ecosystem. Today, we have seen business and technology leaders increasingly interested in AI. Many businesses integrate artificial intelligence into their workflows and businesses. Expectations to use AI are very high in the industry, company size, and geography. Disruption from AI is here, but many corporate leaders are not sure what to expect from AI or how it fits into their business model. For businesses, it is profitable to look at AI from the lens of business proficiencies rather than expertise with technology. Misra and Tripathi [1] propose an AI business model with an integrative business approach for enterprise digital platform business model innovation and business dynamics. Therefore, the opportunity for growth of AI-enabled business models innovation and transformation has become more and more important over the years [2][3][4].

But with the changes that come with a very high speed, it is time for companies to identify AI strategies right now. AI requires more than mastery of data, and companies also face many managerial challenges in introducing AI into their organizations. Adopting AI widely throughout the enterprise requires soft skills and organizational flexibility that allows new forms of collaboration, including project teams composed of people and machines. The survey [5] found companies explored many approaches to developing AI capabilities. Businesses are currently overwhelmed with an AI sales pitch that promotes the potential of technology to automate tasks, cut costs, and improve performance. Every business, customer, and data are unique, and AI is still very new, and we only have a limited product pattern. In addition, every company has existing systems, business processes, and policies which is difficult to change. According to [6], only a small proportion of ML projects succeed in production. Every decision-maker needs to fully understand how deployment works and how to reduce the risk of failure when reaching this important step. Most AI projects are a problem because of the elements of lack of technical know-how, noisy datasets, expensive human resource, and weak computation speed.

Develop an AI strategy for a startup company to become a promoter of digital business model innovation that will need tremendous data so it can build a more accurate search engine as a product that can acquire more users, which will create more data [7]. This study [8][9][10] identifies emerging business models for AI startups in healthcare, pharma, and biotech companies. On the Startup tech squad, programmers usually write software to make decisions about data. In ML projects, programmers use training data to teach algorithms how to make decisions. Our biggest AI challenge is to produce quality training data. AI is a fundamental ability such as electricity, computers, or the Internet. We need a dedicated AI team because work tools, skills, and routines are very different from those used by the current product and engineering team.

Businesses require simple planning to get started. They need a one-page plan, and every company needs a simple tool to start making decisions with the help of AI. Considering the need of the industry for successful AI projects and development, and there is no simple plan and guidance, it becomes clear that developing AI Canvas for deploying ML and DL projects is very important so business and domain experts, as well as data scientists, can work together on a common framework. However, the academic study that proposed the use of AI Model Canvas for deploying ML and DL projects is rare. Most articles on AI research present ways of comparing algorithms applied. Canvas is very popular in the startup community, starting with the very popular Lean Canvas made by Ash Maurya, which comes from the Business Model Canvas made by Alexander Osterwalder [11]. It provides an overview of this complex object which is a Business Model and facilitates collaboration. In the context of data and Artificial Intelligence, the canvas can be useful for describing actual learning that occurs in intelligent systems. Modern organizations generally use organizational learning strategies and therefore operate with not only material resources but also information resources. In the previous article [12], Enterprise AI Canvas is designed for business and domain experts as well as data scientists can work together on a common framework. This consists of two parts, and the first part is mainly aimed at the business perspective of integrating an AI system. The second part focuses more on the underlying machine learning and data model. This Canvas model only focuses on the ML model and does not give a comprehensive interpretation of AI Canvas use cases.

This study will provide a solution on how companies can display AI vision initiatives by using AI Model Canvas. The AI Model Canvas method in our research addresses the key decisions within the organization about lowering the cost of predictions and making predictions better, faster, and cheaper. By filling the one-page AI Canvas, it will help us explain what AI will provide, how it will interact with human judgment, how it will be used to influence decisions, how you will measure success & outcome, and the type of data needed to train, operate, and improve AI. Our research makes the following contributions:

- Create a wide view of Canvas for the AI initiative and project.
- Conduct selected case study for each AI model canvas
- Writing interpretation and final report for each use case from selected AI model canvas

## 2. LITERATURE REVIEW

Data is the new oil, is a phrase often quoted today. Although this sentence still describes the current development well, it does not reach the heart of the real problem. The more suitable is "artificial intelligence empowers the new economy" [13]. The business leader should embrace AI Technology to achieve maximum profit by having a sustainable business model. Therefore, a successful business needs to have "AI-first" in its strategy. The prosperity of a business that aims to increase revenues and profits is highly dependent on brand loyalty. To stay current and competitive, businesses must be involved in various transformation processes.

## 2.1. History of AI and Opportunities Across Technology

The roots of AI can be traced to 1942 when Isaac Asimov, the American Science Fiction writer, published a short story *Runaround* explicitly listing The Three Laws of Robotics [14]. The English mathematician Alan Turing worked developed a code-breaking machine called “The Bombe” for the British government to decipher the Enigma code used by the German army in the Second World War [15]. He continued publishing his article in 1950, “Computing Machines and Intelligence,” which explained how to build and test intelligent machines. The word artificial intelligence was first invented by John McCarthy (a computer scientist at Stanford) in 1956 when he held the first academic conference on the issue. Five years later wrote a paper on the idea of machines that can simulate humans and the ability to do intelligent things, such as playing Chess [15]. Arthur Samuel was a pioneer and coined the phrase “Machine Learning” in 1959. He used the game checkers in ML and became the world’s first successful self-learning program [16]. The beginning of the first decade of the XXI century turned out to be a turning point in the history of ML and became three synchronous trends, which together gave a noticeable synergistic effect [17]. The first trend is Big Data. The second trend is to reduce the cost of parallel computing and memory (when Google unveiled its MapReduce technology, followed by Hadoop in 2006). Nvidia made a breakthrough in the GPU market, and in 2014, the Apache Spark framework for distributed processing of unstructured and weakly structured data appeared, which is convenient for the implementation of machine learning algorithms. The third trend is the development of new deep machine learning algorithms, inheriting and developing the perceptron idea in combination with successful scientific PR campaigns. Deep learning could be called the sub-discipline of machine learning that is inspired by the structure and function of the human brain, which has the interconnection of many neurons, whereas Neural Networks are algorithms that mimic the biological structure of the brain. After many years of study of multilayer neural networks, a concept technology of deep neural networks (DNN) was born, and the term deep learning was proposed in 1986 by Rina Dechter Dechter [17]. The different points of history and evolution of deep learning can be found in [18][19][20]. Fig. 1 summarizes and describes the history of AI, ML, and DL.

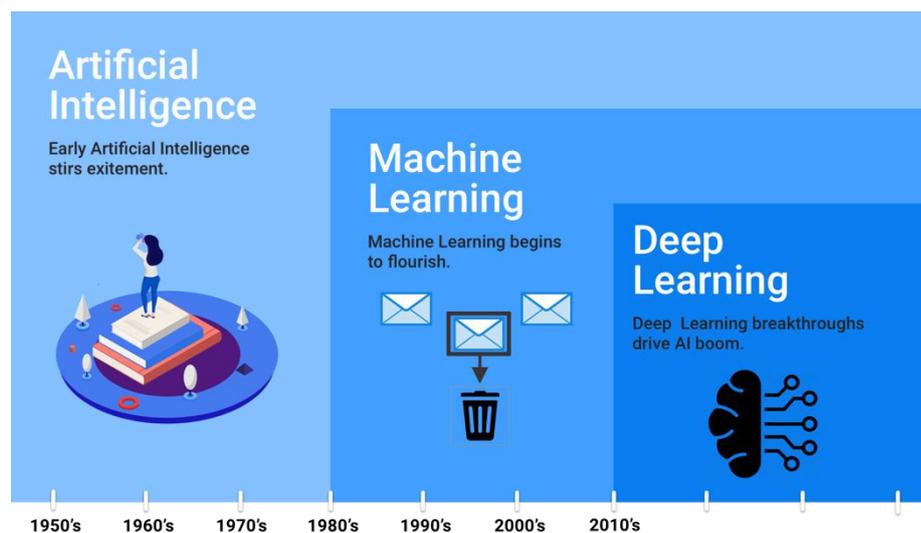


Fig. 1. History of AI, ML, and DL

## 2.2. Opportunities of AI Across Industries

Herewith is some research that applied AI, ML, and DL, in the retail and e-commerce industries. The application of AI is the most observable to the majority of end-users. AI facilitates new ways of winning customers and markets. Software like Chatbot, which can respond to requests in a natural way, is a strategically important opportunity to handle cost increases and customer expectations [21]. This study [22] proposed a slope one algorithm based on the fusion of trusted data and user similarity to automate the recommendation process using the Amazon dataset. This study [23] proposed model-based approaches for advanced matching and dynamic pricing (DP) algorithms for Ride-hailing platforms such as Uber, Lyft, and DiDi. Artificial Intelligence of Things (AIoT)-based automated picking system was proposed for the development of online stores and services for automated delivery systems [24]. The picking algorithm is based on You Only Look Once (YOLO) and correctly takes the purchased products with a success rate of 0.835 in a convenience shop.

The healthcare industry is conducting groundbreaking research and development in digital health due to the following reasons. To assist medical professionals in better treatment of illnesses, improve patient outcomes, early disease detection, patient care, and community services need an accurate analysis of medical

data. The accuracy of the algorithm reaches 94.8% convergence speed, which is faster than that of the CNN-based unimodal disease risk prediction algorithm. Cognitive computing systems in health services collect individual, clinical, and social data from various health service sources to increase patient involvement and multidisciplinary combinations of technologies such as the Internet of Things (IoT), big data analysis, and cloud computing [25]. Furthermore, machine learning methods are now routinely used in various fields of research, including biomarker development and drug discovery [26][27][28][29], and machine learning techniques utilizing Deep Neural Networks (DNNs) can capture high-level dependencies in health data [30]. Convolutional neural networks (CNNs) are trained to classify cancer patients using tumor tissue immunohistochemistry [31].

Banking and financial service are undergoing a major transformation due to the start of AI applications. This study [32] tests various models of machine learning algorithms using various classifiers for banking service making better customer segmentation and enhancing the performance of the sales agents for better recommending the ideal product to the customer and enhancing the overall customer experience. This study [33] proposed a survey and implementation of accurate financial fraud detection under an IoT environment, and the result was that the machine learning method has a higher fraud detection rate than the artificial neural network. In the financial advisor sector, Robo-advisors forecast the trading market using DL techniques (Markowitz, Black Litterman models, and ANN framework) that will bring more intelligent services to the financial industries [34][35].

The hotel and travel sector is derived significant benefits from the widespread use of AI. This study [36] proposed three types of forecasting hotel occupancy methods with the concepts of neural networks and proposed two long short-term memory (LSTM) models based on recurrent neural networks. To measure the relative performance, six ML models of the decision tree, multilayer perceptron, lasso, linear regression, random forest, and ridge are also estimated and tested against the same datasets. Meanwhile, this study [37] constructs a DL forecasting framework using long short-term memory (LSTM) network to make forecasting and handle the prediction problem in the hotel accommodation demands. Chatbot, combined with natural language processing (NLP), can analyze the request and extract some keywords in ticketing services for booking conversation terms is as departure and destination city and also the date of flight [38].

In the entertainment and gaming industries, this study [39] proposed an accurate music recommendation system with the Tunes Recommendation System (T-RECSYS) that uses content-based and collaborative filtering as input into a deep learning classification model with real-time prediction. This recommendation system could be applied to many different platforms and domains, including Youtube, Netflix, and Amazon. This study [40] surveyed, analyzed, and evaluated the video description research and reviewed popular benchmark datasets that are commonly used for training and testing. The survey from several methods and algorithms shows that built metrics that are learned from the data itself are the key to advancing video description research. This study [41] implemented non-player characters (NPC) in video games by comparing popular methods in intelligent behavior, and the best results can be achieved using a hybrid method consisting of multilayer perceptron NN with a Q-learning rule and genetic algorithm.

There is no doubt that the manufacturing industry is leading the way in the adoption of AI technologies. Artificial neural networks and machine learning combined with IoT are employed to support predictive maintenance of the health status of industrial equipment, which can accurately predict asset malfunction [42][43][44]. It helps the management take timely measures to restore the equipment and increase the utilization rate of the components and increase their remaining useful lives. AI technologies have promoted the development of smart manufacturing, especially in production monitoring: fault diagnosis, remaining useful life prediction, and quality inspection that apply common AI-based methods (e.g., CNN, Generative Adversarial Networks (GAN), attention mechanism, Graph Neural Networks (GNN)) to accomplish different tasks while these methods are customized concerning specific applications [45]. The use of AI in robotics as an integral part of the production process can ensure productivity, flexibility, sustainability, and reduced cost [46][47]. The concept of Human-Robot Collaboration (HRC) or collaborative robots (cobots) that can take instructions from humans and work productively alongside them has been touted in the past decade. Cobots have become the main technology of Industry 4.0. Cobot is an innovative industrial technology introduced to help operators carry out manual activities called cyber-physical production systems and combines the unrivaled capabilities of humans with the power of smart machines [48][49][50].

### 2.3. Existing AI, ML, DL Canvas

We are familiar with the business model canvas, pioneered by Alexander Osterwalder [51], a high-level strategy document designed to replace the business plan. This is a tool that you can use to interrogate business strategies while also truly defining a value proposition, understanding customer segments, and calculating the costs we might incur while building our business. It is a perfect template for testing all parts of our business

ideas or models. This is a visual graph that businesses can use to remove the complexity of any kind of challenge by looking at all the elements that can affect the route to completing this challenge. As the popularity of this tool increased, various other types of canvas and AI solutions for businesses began to emerge. It becomes increasingly necessary to develop canvases that will help map out AI strategies and ML and DL projects.

The AI Canvas was proposed by A. Agrawal et al. in their book "*Prediction Machines. The Simple Economics of Artificial Intelligence*" [52] is an aid for contemplating, building, and assessing AI tools. This requires you to define the three types of data required: training, input, and feedback. It also requires you to articulate what you need to predict, the judgment needed to assess the relative value of different actions and outcomes, possible actions, and possible outcomes. Another AI Canvas was proposed by Kevin Dewalt [53], who has researched by talking to hundreds of companies about AI. This canvas will help you take an in-depth look at your AI strategy to identify which processes, products, or departments would benefit from automation. The AI & U Canvas proposed by Christian Ehl [54] as an AI strategy blueprint that consists of 8 fields that define the components of the AI solution

While the AI canvas above represents a high-level structured approach to AI implementation, then at some point, we want to define a vision for an ML or DL system and a system specification. The ML canvas is proposed by Louis Dorard [55]. Simple visual charts are used to describe complex, intelligent systems simply. The DL Canvas was proposed by Carlos E. Perez in the book "*The Deep Learning AI Playbook: Strategy for Disruptive Artificial Intelligence*" [56], which was created to determine the scope and resources needed to achieve successful DL deployment.

### 3. METHOD AND FRAMEWORK

#### 3.1. Research Method

The case study methodology [57] was adopted to create, review and interpret an AI-based model canvas framework and make a comparison to a similar AI Canvas method from previous works along with some use-cases. Our research phase is divided into three phases, shown in Fig. 2. The first phase is the preparation phase, and this will explain how we develop theory and do a literature review. After that, we collected the AI canvas design and framework along with the preferred case study. Each of Canvas has a unique purpose, depending on the AI initiatives, AI product, and an AI project. The case studies spanned the AI, ML, and DL methods in real-world business problems. Three further case study was useful for small to large organizations. We developed "how" and "why" questions to be explored in depth during the interviews with AI researchers, data scientists, engineers, and stakeholders. The second phase is the collection phase, and this will explain how we conduct three case studies for AI, ML, and DL problems, along with writing review and interpretation for each case study. In the final or Analyzing phase, we write the final case report.

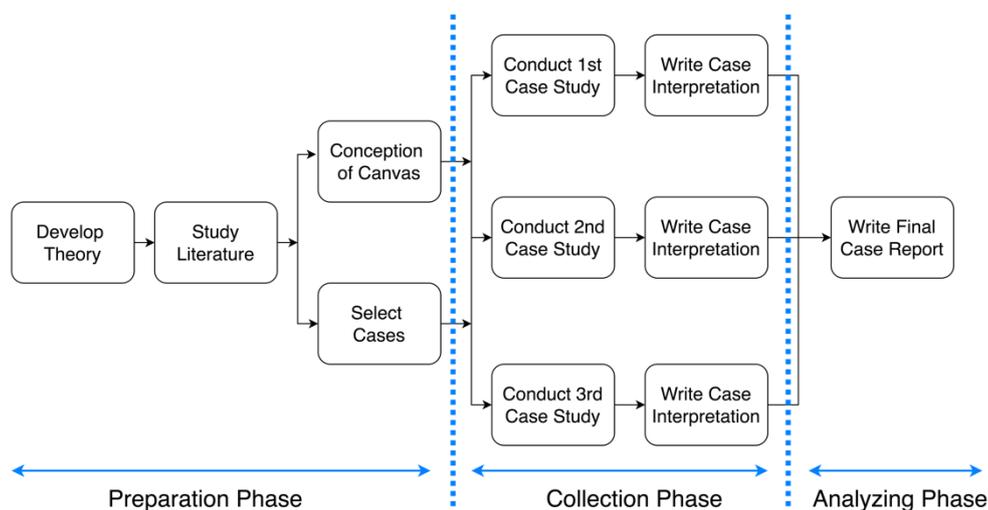


Fig. 2. Case Study Metodology

#### 3.2. Conception of Canvas

AI projects are difficult to determine where business, customers, and data are truly unique. AI is a relatively new technology, and there are currently limited product patterns. Every company has business processes, systems, and policies that are difficult to change. Understanding all of these key elements will almost certainly help you make decisions about how to pursue AI in your organization, and the AI canvas will act as

a road map for everyone involved in the project. This is not only useful for our development team but will also help us when we need to explain the AI project to business and domain experts who don't know much about technology. We have presented several canvases for implementing AI projects in the literature review. At first glance, we might be tempted to leave the Business Model Canvas [51], AI Canvas [52][53][54] to the business expert or project manager, and then the ML Canvas [55] and DL Canvas [58] to the Data Scientist in the next step. This does happen quite often in industry and applications, though, where various canvases are rarely used in practice, and instead, potential projects are discussed and revealed in presentations or flip charts.

Developing data-driven applications using machine learning or deep learning requires a detailed understanding of the data sources, methods, and metrics for a particular use case, as well as ongoing maintenance costs and reasonable time for the feasibility of developing model architecture. While these aspects can be well understood by data scientists, business experts or project managers are often less savvy about these details. On the other hand, Data Scientists typically have only limited insight into how to create business value, optimize operational decisions in enterprise settings, and which organizational change or change management is required to integrate AI projects across enterprises. Project ideas and details, technical aspects, and organizational implications are closely intertwined. Discussing business aspects first and getting them approved by senior management before engaging deeply with data scientists can lead to unnecessary repetition. In addition, business experts and data scientists have very different backgrounds and use different languages or jargon.

We selected three canvases that represented AI, ML, and DL methods and tested them along with a case study. The three canvases are AI Canvas from Kevin Dewalt [53] and then, ML Canvas from Louis Dorard [55], and DL Canvas from Carlos E. Perez [58]. The three canvases specifically designed for relevant communities in the AI project, such as business and domain experts and data scientists, can work together within the same framework. This will allow to capture the expertise of diverse project planning teams and ensure that all relevant aspects of the entire project are considered. Below is parameter and guidance on how we use the canvases that we have already chosen.

### 3.2.1. AI Canvas

Each block on the canvas answers an important question that needs to be answered as we develop strategies for AI solutions. The business blocks in the left half address the business issues. The technical blocks in the right half address the technical issues and proper technical feasibility. This canvas also considers the types of skills needed to carry out the project and the possibility of integration that will be needed. And also, look at the cost of the solution is and whether it will help the business generate revenue, even if it's not from direct sales. Understanding all of these key elements will almost certainly help you make decisions about how to pursue AI in your organization, and your AI canvas will act as a road map for everyone involved in the project. This is not only useful for your development team but will also help you when you need to explain this project to people in businesses who don't know much about technology.

- The business blocks (left):
  - Opportunity: A high-level description of the business benefit of the AI models. Revenue growth, cost reduction, speed, etc.
  - Consumers: AI models produce results from input data sources. Consumers are the products, systems, and people who use the model results to deliver business value.
  - Strategy: Unique data assets provide the only ongoing sustainable advantage in AI products. Data differentiation is required in order to maintain a competitive trench.
  - Policy & process: AI can present unique legal and policy questions. For instance, you may have to address model interpretability challenges or data rights issues.
- The technical blocks (right) :
  - Solution: is a high-level description of the models, workflow, and system architecture.
  - Data: is primarily internal and external sources of data for model inputs. Consider accessibility, cleansing challenges, and costs—the important block on the canvas.
  - Model development: The most technically challenging block of the canvas. It is how we identify existing models, and datasets, for research papers that the development team can use to accelerate deployment.
  - Success criteria: is model benchmarks (e.g., existing baseline performance) or necessary business metrics which need to be measured to compare with the industry.

### 3.2.2. ML Canvas

ML canvas is useful for describing actual learning in intelligent systems, explaining what data we need to learn from, how we use predictions supported by that learning, and how we ensure that everything will work

through time. It begins with a central block dedicated to the Value Proposition of the system in which ML will be used. Then the left-hand side is dedicated to how predictions are used based on the various model elements of the ML system and data. The right-hand side is dedicated to the information we will learn from the data. Finally, the lowest block is used for Live Evaluation and Monitoring. This is where you will specify methods and metrics to evaluate the system after deployment and quantify value creation.

- The predictions block (left) it's made of the following blocks:
  - ML task: Which type (e.g., classification, regression), input, and what is the output to predict along with possible values?
  - Decisions: How are predictions used to make decisions that provide the proposed value to the end user?
  - Making predictions: When are new inputs predicted, and how much time do we have for that?
  - Offline evaluation: Which methods and metrics can we use to evaluate the way predictions are going to be made and used before deployment?
- The learning block (right) it's made of the following blocks:
  - Data sources: Which raw data sources can we use?
  - Collecting data: How do we get new data to learn from inputs and outputs?
  - Features: An input representation to extract from the raw data sources.
  - Building models: When do we create/update models with new training data, and how long do we have for that?

The upper canvas provides more of the background, and the lower part describes the system specifications. The upper left and right blocks deal with domain integration, how predictions are used and how data is collected in the application domain. The lower left and right blocks relate to the predictive engine and its constraints in terms of latency and throughput for making predictions and updating models. Finally, the last part of the canvas is dedicated to measuring how well the system works in the domain of Live Evaluation and Monitoring. This is where you'll specify methods and metrics to evaluate the system after deployment and to quantify value creation.

### 3.2.3. DL Canvas

DL Canvas is not meant to replace another business-grade canvas. Rather it is introduced to complement these canvases so that it has a framework on how to build and deploy DL solutions. Begins with a central block Value Proposition, describe the specific final solution and what, when, and how cognitive capability will be delivered. Then the right-hand side is aimed at the business perspective of integrating an AI system. The left-hand side is more focused on the underlying deep learning and data model. The lowest block is used for technical debt to document what these are and their dependencies. The key elements are:

- Customer: determine the role that the customer is performing and identify the specific role that is being addressed in this canvas. Include here any pain points the customer is experiencing in their performance of the job. We should also include information on the current automation that the customer uses.
- Context: this is where we evaluate the context in which the tasks of the job are being performed. List down the tasks that are being performed and details of the context that enable the customer to perform the task. Include details of customer interactions with other parties or systems. If possible, document in detail the flow of interactions.
- Cognitive Limits: determine the specific cognitive limitation that needs to be addressed. This will be found by examining the context furthermore because of the client's pain points. The limits are a combination of needing to act fast, information overload, lack of meaning, and memory limits.
- Key Metrics: here, we tend to list down the metrics that we can measure. That is, understand first which cognitive limitation we wish to handle, measure a baseline and then monitor and compare against the baseline. Develop automation to ensure that metrics are continually evaluated.
- Value Proposition: This is where we describe the output and the final solution. Here we pinpoint the job to be done and what, when, and how cognitive capability will be delivered.
- Features: here, we want to spot the kind of DL network that is going to be developed. Specifically, this is one of the following: classification, translation, generation, planning, or optimization. Each kind might need different software system parts to be used in concert with the DL network.
- Model Development: here, we identify the model architecture and address any curriculum training that may be required.
- Technical Debt: there are many moving parts in the final solution. Here we tend to document what these are and their dependencies. We identify processes that may be required in the event of changes in the environment.

- Decision Support: we want to identify here how the features of the developed system enhance the customer's decision-making process. The expectation here is that a solution will have a human-in-the-loop, and we wish to characterize how the human will interact with the systems. Understand the consequences of errors made by automation.
- Data Logistics: we want to document all the processes required to gather data as well as the tasks required to prepare data for the curriculum.

### 3.3. Select Cases

Three further case studies that are using AI Canvas, ML Canvas, and DL Canvas

1. AI Canvas: Image super-resolution for e-commerce  
XYZ is a start-up food and restaurant marketplace that works with amateur chefs who cooks dinner for several guests straight from their kitchen. The problem is that the chefs have low-resolution photos of the food. The photos they take have poor quality, which can limit sales. The chefs are good at cooking traditional Indonesian cuisine but not so good at marketing. Most of them use low-resolution camera phones to take pictures of dishes. After they tried to cut the image, the low-resolution image version did not meet consumer expectations as higher resolution images will increase sales. This XYZ company explores the possibility of using professional photographers to capture images of dishes, but they are very expensive. The XYZ company now wants to explore the possibility of using AI technology to improve image quality automatically. The company spent several months exploring options and finally decided to explore a super special resolution algorithm to automatically improve the quality of dishes. We will use AI Canvas to answer the challenge of how this company makes a plan with its AI project.
2. ML Canvas: Fake Reviews Detection  
We often encounter cases of detection of fake reviews in e-commerce, especially on hotel booking platforms, and it must be generalized to websites where reviews are posted. This use case is about reducing customer disappointment by rejecting fake product reviews and approving others automatically, and thus the company can have a product rating that is closer to the truth. The end-user is from a hotel booking platform, and the goal is to improve hotel satisfaction and user experience of the platform with more accurate ratings.  
We will use ML Canvas to answer the challenge.
3. DL Canvas: Automated Reply for Google Email  
Email is one of the most popular modes of communication on the web. With the rapid increase and overload of email, it is increasingly challenging for users to process and respond to incoming messages. It is very time-consuming to type an email reply on a mobile device. The question is, how can we help users compose short messages and suggest short responses or automated replies with just one tap. Automated responses to messages are now a common feature in email as well as in other messaging systems. This uses case is about creating an automated response for google email, and details of two different systems are provided in the following article [59][60]. We will focus on the second article since it appears to have superseded the first paper. Exploring both papers gives us insight into the thinking behind the development of a state-of-the-art smart reply system. We will use DL Canvas to answer the challenge.

## 4. RESULTS AND DISCUSSION

The AI solution has interactions with customers internally or externally, which can deliver business value. Satisfied and happy customers are characterized as people who benefit from solutions if the value provided meets or exceeds their needs. Ultimately, the total solution should provide overall business benefits to your business, as well as we can win new customers, generate higher revenue, lower costs, or allow expansion into other geographies. In this section, we conduct and test three case studies to highlight the use of the AI, ML, and DL canvas, along with interpretation and writing a final report for each case study. This canvas can be used at the team, departmental, and business levels, and it is also necessary to collaborate with every department that might touch or be affected by the proposed AI strategy. This means taking a few hours and getting the core people around the table to talk about it.

### 4.1. AI Canvas - Image super-resolution for e-commerce

Every company today has a highly crucial need for digital photographs for the creation of an effective marketing design for their products. Properly edited and manipulated photos make a visual impact on customers and make them become very interested in buying our products. So this makes photo editing an important component of any online seller to increase its scope in winning potential customers. Photos not only showcase your products but also effectively and indirectly represent your company's products and can increase demand. Due to the primary need for branding and communication with customers, Image Enhancement is one of the

most performed processes in the industry. The first case study will be illustrated how XYZ is a start-up food and restaurant using AI technology to improve image quality automatically because hiring professional photographers to capture images of dishes is very expensive. They realized that higher resolution pictures would boost sales. Fig. 3 explores how AI Canvas is filled up for the above project, along with how we illustrated the use case.

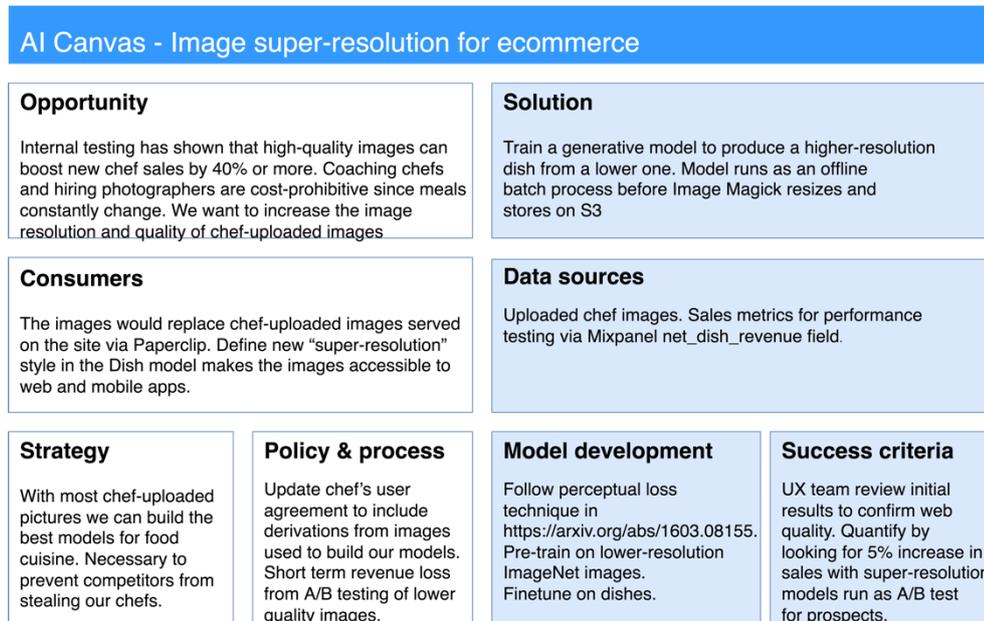


Fig. 3. AI Canvas for image super-resolution

The business block on the left starts with an opportunity that needs to increase the image resolution and quality of chef-uploaded images since internal testing has shown that high-quality images can boost new chef sales by 40% or more. We decide to upload multiple images that replace chef-uploaded images on the site via Paperclip. How to upload multiple images using a paperclip is shown on this code hosting platform [61]. Define a new super-resolution style in the Dish model that makes the images accessible for customers on the web and mobile. With most chef-uploaded pictures, we can build the best models for food cuisine. These become our strategy elements in creating unique data assets as well as necessary to prevent competitors from stealing our chefs. The policy and process elements are updated chef's user agreement to include derivations from images used to build our models. Also, prevent short-term revenue loss from A/B testing of lower quality images.

The technical blocks (on the right) start with how we create a solution. Train a generative model to produce a higher-resolution dish from a lower one. Model runs as an offline batch process before using the ImageMagick website to resize images and stores on S3, which is capable of storing diverse and generally unstructured data. The sources of data come from uploaded chef images. Sales metrics for performance testing using product analytic Mixpanel and include an event property called revenue for the dish. The model development is based on an article proposed by Justin Johnson et al. [62], which combined the benefits of feed-forward image transformation tasks and optimization-based methods for image generation by training feed-forward transformation networks with perceptual loss functions. The high-quality images can be generated by defining and optimizing perceptual loss functions based on high-level features extracted from pre-trained networks—the success criteria achieved by UX team review initial results to confirm web quality. Quantify by looking for a 5% increase in sales with super-resolution models run as an A/B test for prospects.

The AI Canvas brings together business and data science experts and systematically evaluates potential new business opportunities. The AI Canvas consists of two parts, the left part focuses on the business perspective for integrating AI systems, and the right part focuses more on the technical feasibility of that underlying AI model. Both parts are interlinked and related to each other to enable optimal evaluation of the business and data science aspects of new AI projects. Just like the Business Model Canvas, the AI Canvas is a useful tool for quickly explaining the value-added of our AI projects, structured AI startups, and AI products. It helps us think with customers in mind and design AI projects that truly impact. The AI Canvas can educate Data Scientists in the areas of customer-centric thinking and business acumen.

**4.2. Machine Learning Canvas – Fake Reviews Detection**

Online reviews are an important source of information for making decisions about available products and services, for example, before booking a hotel room. However, not all information provided through online platforms can be trusted and reliable. Online reviews on sites like Amazon, Google, Facebook, Tripadvisor, Expedia, Yelp, booking.com, or Airbnb aren't always written by real customers with real hotel experiences. In fact, some of the reviews are fictitious and fake. Fake reviews with false information can lead to wrong decisions for travelers, as they lack the ability to detect. We need trustworthy information that gives the right decisions for travelers, as well as hoteliers who can keep their hotel reputation. Therefore, identifying fake online reviews becomes very important. We illustrated how a fake detection system could reduce customer disappointment by rejecting fake product reviews and automatically approving others, thus having a product rating that is closer to the true customer rating. Fig. 4 explores how ML Canvas is filled up for the above project, along with how we illustrated the use case.

ML Canvas - Fake Reviews Detection				
<p><b>Decision</b></p> <p>If probability of Positive &gt; M: approve &lt; m: reject Otherwise request human decision</p> <p>Thresholds m and M are chosen to maximize offline evaluation (performed right after model update)</p>	<p><b>ML Task</b></p> <p>"Is this review legit or fake?"</p> <ul style="list-style-type: none"> <li>Input: review</li> <li>Output: "legit" or "fake" (Positive class)</li> </ul> <p>-&gt; Binary classification</p> <p>Note: the distribution of outputs is typically 70-30 (legit vs fake)</p>	<p><b>Value Propositions</b></p> <p>Reduce customer disappointment by rejecting fake product reviews and automatically approving others.</p> <p>Have ratings which are closer to the truth will improve customer experience and satisfaction (less surprises).</p>	<p><b>Data Source</b></p> <ul style="list-style-type: none"> <li>User database</li> <li>Reviews database</li> <li>Social networks</li> <li>Crowdsourcing platform (e.g. Mechanical Turk)</li> </ul>	<p><b>Collecting Data</b></p> <ul style="list-style-type: none"> <li>Initially: active learning using crowdsourcing platform</li> <li>Internal, manual labelling</li> <li>When explicitly requested (complaint, or model's probability in between thresholds)</li> <li>Randomly selected reviews every day (as many as allowed for a budget of \$X /day)</li> </ul>
<p><b>Making Predictions</b></p> <p>We receive X reviews / minute on average. We can allow a delay of 1 day /review, but including 1/2 day for manual review if we're in between thresholds.</p>	<p><b>Offline Evaluation</b></p> <p>Train model with data up until 1 week ago. Compute total cost on last week's data, for different values of m and M (starting at m=0 and M=1), taking into account :</p> <ul style="list-style-type: none"> <li>Gain of correct, automated decision =</li> <li>- Cost of manual decision</li> <li>• Cost of FN (when review sentiment positive / negative)</li> <li>• Cost of FP (smaller)</li> </ul>		<p><b>Features</b></p> <ul style="list-style-type: none"> <li>Content of review: rating, text, length, # capitals...</li> <li>Other predictions: sentiment, emotion, etc.</li> <li>User: basic info, # previous bookings, # approved reviews, # rejected reviews</li> <li>Metadata (e.g. IP)</li> <li>Product being reviewed (e.g. hotel chain)</li> <li>Similarity with prev. reviews (total score)</li> </ul>	<p><b>Building Models</b></p> <p>One model per language/country</p> <p>Somewhat adversarial setting =&gt; Keep on learning =&gt; Every week we update our models by adding all the data from last week. We allow a day for this.</p>
	<p><b>Live Evaluation &amp; Monitoring</b></p> <p>Every week:</p> <ul style="list-style-type: none"> <li>Average customer satisfaction</li> <li># customer complaints</li> <li># hotel complaints</li> <li># manual reviews</li> </ul>			

**Fig. 4.** Machine Learning Canvas Fake Reviews Detection

- Value propositions: is to reduce customer disappointment by rejecting fake incoming reviews and approving legit reviews automatically. Flag fake reviews in the database can stop displaying or using them to compute average ratings; having ratings that are closer to the truth will improve customer experience and satisfaction.
- Data source: this step is preliminary to thinking about the actual data to be fed to ML algorithms, which will be extracted from other sources. We can use internal or external databases, APIs, static files, web, etc. We used a user database, reviews database, social networks, and a Crowdsourcing platform (e.g., Mechanical Turk). We need to be able to get data from all this by connecting to their API and then combining that data.
- Collecting data: the question is how do we get new data to learn from inputs and outputs. There can be a cost associated with getting output data, and we need humans to manually look at example reviews and assign them a *fake* or *real* label. Initially, we did active learning using a crowdsourcing platform. We find that deceptive reviews collected through crowdsourcing are very different from fake reviews published online. So, it is important to collect data in the long term. We get data internally with manual labeling by collecting explicitly requested such as complaints or model's probability in between thresholds and got randomly selected reviews every day (as many as allowed for a budget of \$X /day).

- Features: the input to prediction problems must have a computer representation with numerical, categorical, or textual values. Feature values should be selected in a way that allows good enough characterization of the input so that the output for fake reviews can be determined from the features. Below are the features:
  - Content of review: rating, text, length, capitals.
  - Other predictions: sentiment, emotion, etc.
  - User: basic info, previous bookings, approved reviews, rejected reviews
  - Metadata (e.g., IP)
  - The product being reviewed (e.g., hotel chain)
  - Similarity with prev. reviews (total score)
- Building models: before we can train the model, we need to create a set of training inputs and outputs, and we need to recalculate the feature values for the inputs. To implement a fake review detection system, we need one model per language. A different model for different countries that speak the same language is because the dynamics might be different in those countries. Keep on learning; every week, we update our models by adding all the data from last week, which allows a day for this.
- ML Task: uses a question in a certain format for which the system we are building finds answers. The question must refer to certain objects of the real world that we call inputs. Questions to answer need to be specific: "Is this review valid or fake?" The input in these questions is a review, and the result is: "legit" or "fake," and the distribution of outputs is typically 70-30 (legit vs. fake).
- Decisions: predictions must be turned into decisions that give the proposed value as a starting point for the creation of the ML system. Decisions are often based on the model's confidence in its predictions. If the model strongly believes that the review is real or fake, we can let the system automatically decide to accept or reject the review. Otherwise, we can leave the decision to the humans.
- Making predictions: is a technical constraint on predictions made to support decisions (volume, frequency, time, etc.). How many of them and at which frequency, or in this case, how often do we get new reviews? We receive X reviews per minute on average. We can allow a delay of 1 day per review but include 1/2 day for manual review if we're in between thresholds.
- Offline Evaluation: these methods and metrics evaluate the system before deployment, and it should be performed every time a new model is created. Train model with data up until one week ago, and compute total cost on last week's data.
- Live evaluation and monitoring: the performance of our system can be measured in several ways, but we need to choose a single-number evaluation metric for our team to optimize. Every week we evaluate average customer satisfaction from customer complaints, hotel complaints, and manual reviews.

Using ML Canvas allows you to define a vision for your ML system and communicate it with your team. We have to collect data in the long term because this is how we can keep our model relevant, and we might think that detecting the falsity of a comment is like detecting sentiment in that the nature of the problem persists. Evaluating the accuracy of the model is not interesting, but what we want to do is first evaluate the impact of future decisions so that we can build confidence that the system is ready to be placed. But fakester will continue to introduce new fake patterns because the goal is to deceive the existing system.

#### 4.3. Deep Learning Canvas –Automated Reply for Google Email

Email is the most common and effective source of communication for most individuals and companies. In companies, the volume of emails received each day is significant and requires timely replies from each email. This results in a significant amount of work for the organization, particularly for staff in help desk roles. Automated responses to messages are now a common feature in email as well as in other messaging systems. The good news is that Google already has such a mechanism called Smart Reply, which can be seen in Gmail. Google launched technology using deep learning to improve the Inbox by Gmail app so it can analyze email content and then suggest a few short responses. So we can quickly respond to someone on the go without having to manually tap a new message onto the smartphone keyboard. Although the projects have been deployed, we will show how to develop the automated reply for Gmail on the DL canvas. Fig. 5 explores how DL Canvas is filled up for the above project, along with how we illustrated the use case.

- Customer: is a Google email user.
- Cognitive Limits: the information that overloads and needs to act fast.
- Value propositions: Quick responses email can easily give potential customers the information they need for scheduling appointments or services. Many times, a simple response is more than enough. 25% of

responses have 20 words or less. Allowing automation to detect these situations reduces the number of responses a user needs to create manually. Responding even in a simple way is better than not responding at all. The responses that customers choose or not will help the inbox app improve its suggestions in the future.

DL Canvas - Automated Reply For Google Email				
<b>Decision Support</b> User can always ignore the suggested responses. The system design only suggests a variety of responses to a user. User can select an appropriate response or ignore the suggestions entirely	<b>Features</b> System estimates the probability user will reply short message. Threshold will present a selection of 3 short responses that come from a restricted set of common responses. System ensures that the response suggestions are sufficiently diverse	<b>Value Propositions</b> Quick responses email can easily give potential customers the information they need for scheduling appointments or services.  A simple response is more than enough. 25% of responses have 20 words or less.  The responses that customers choose or don't choose will help the Inbox app improve its suggestions in the future.	<b>Cognitive Limits</b> Information overload and need to act fast	<b>Customer</b> An Google email user
<b>Data Logistics</b> Training set: 238 million messages with 153 million messages without response will pre-processed in the pipeline that includes only English text, infrequent terms are replaced by special tokens, quoted messages are removed, salutations are removed, sentence boundaries are identified in the body, and body and subject are tokenized	<b>Model Development</b> LSTM Seq2Seq was originally developed model. More efficient hierarchical feed-forward network using a sum of n-gram embedding as input replaced the original system. Networks built on n-gram embeddings are less expensive than RNNs or CNNs	<b>Key Metrics</b> System latency was given high priority in this re-design. Response quality suggest that a response delivers a positive experience. Response utility means that suggested responses capture different intentions		<b>Context</b> User has too many emails & doesn't have time to respond all of them. A smart-reply system allows users to quickly respond to emails
<b>Technical Debt</b> The set of responses are carefully selected. This may require effort for continuous maintenance				

Fig. 5. Deep Learning Canvas Automated Reply for Google Email

- **Context:** a user has too many emails that he doesn't have the time to respond to all of them. A smart-reply system can make users quickly respond to emails.
- **Key Metrics:** the latency of the system was given high priority in this re-design—the response quality and utility. Response quality suggests that a response delivers a positive experience.
- **Features:** the system estimates the probability that a user will reply with a short message. If it is above a threshold, the user is presented with a selection of 3 short responses. The responses that are presented come from a restricted set of common responses. The system ensures that the 3 response suggestions are sufficiently diverse.
- **Data Logistics:** the first article describes the size of the training set [59]. The size is 238 million messages, with 153 million messages without a response. All messages are preprocessed in a pipeline that includes only English text, infrequent terms are replaced by special tokens, quoted messages are removed, salutations are removed, sentence boundaries are identified in the body, and body and subject are tokenized.
- **Model Development:** an LSTM Seq2Seq model from the article [60] that used sequences of word vectors was originally developed. A more efficient hierarchical feed-forward network using a sum of n-gram embedding as input replaced the original system. Networks built on n-gram embeddings are less expensive than RNNs or CNNs.
- **Technical Debt:** the set of responses is carefully selected. This may require effort for continuous maintenance.
- **Decision Support:** a user can always ignore the suggested responses. The system does not automatically respond to the user, which is designed in such a way that it only suggests various responses to the user. It is up to the user to choose an appropriate response or ignore the suggestion completely.

The Smart Reply system and quick response features reveal the accelerating pace of our lives and what we choose to prioritize with the time we have. Communication becomes more of a chore than social interaction, making our relationships shallower and less honest, but leading us to believe that we are actually more deeply connected to others than before. Google creates products that minimize the outpouring of emotions that may be inappropriate. We can assume that the algorithm that generates this automatic response controls not only

affection but also humor, sadness, anger, and any other feeling. The DL Canvas describes the smart email reply system for automatically generating short, complete email responses. Smart Reply tries to strike a balance between responding appropriately to the office and maintaining a certain level of personality. As we know, the smart reply is an experiment, and now, Google is combining Smart Compose and Smart Reply Gmail. There are still flaws in this automated response system. Such replies can launch Maps and Calendar integrations that can offer appointment suggestions or travel estimates based on the user's current location and traffic conditions. Researchers of smart replies systems in the future can use DL Canvas that can frame the design process by filling out details of the canvas.

## 5. CONCLUSION

Companies have different priorities and therefore need to deploy competitively superior products. Having our strategy in place and our AI project or product defined is just the beginning. Product development is a learning activity and alternatively expressed as a knowledge creation activity. There is a massive knowledge gap on how we can take AI and build valuable products out of it. This study discusses the conceptual design approach how to making a plan for AI projects and ideas by using several AI model canvases. The AI model canvas is a technique, strategy blueprint, and conceptual design for the project, production, promotion, and providing AI technology to organizations. Organizations can apply AI by using simple blocks and elements to enable interdisciplinary communication and collaboration between various stakeholders in the AI project. The variety of AI Model Canvas has already been discussed and tested, along with a case study that provides enough examples for the reader to get a better understanding of the canvas. Regardless of what kind of model development you try to recommend, if your AI solution involves Machine Learning, we really recommend you make use of an ML canvas. If your AI solution involves Deep Learning, we really recommend you make use of a DL canvas. Through the use of the canvas design approach, we explore the customer's space in more detail and more thoroughly. This gives us not only a more concise understanding of a problem but also a language that we can use in our conversations. The AI, ML, and DL canvas can build internal advocates that can be applied to improve business processes that can achieve the greatest return on investment. As a further step towards implementation, the ML canvas and DL canvas can determine more specific steps in building an AI system. Further research requires an overall framework, which defines all activities and conditions within the company in the business context. We do hope that there will be sufficient samples that allow another research to bootstrap the AI canvas model initiative.

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