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The Impact of Artificial Intelligence on the B2B Sales Funnel

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Abstract

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The fourth industrial revolution, fueled by the emergence of technologies such as virtual reality, the Internet of Things, blockchain, and artificial intelligence, is profoundly impacting the way we live and work. Catalyzed by an increase in computing power and the proliferation of available data, artificial intelligence, one of the most disruptive forces of the twenty-first century, has experienced dramatic progress in recent years and promises far-reaching implications in the global economy and society at large. The implications of artificial intelligence will not only be evident across industries but also across most business functions, with the greatest potential value impact being on sales and marketing. Artificial intelligence is certainly changing the way people interact with businesses, buy products and services, and also how organizations promote and generate demand for their offerings.

The main objective of this thesis is to examine existing artificial intelligence technologies and techniques and analyze their current implementations in B2B sales operations. This study is based on existing research and literature and aims to contribute to the body of knowledge by connecting artificial intelligence solutions to the challenges sales professionals experience at each step of the sales funnel. The sales model proposed by Dubinsky is used to represent the sales funnel.

The study reveals that machine learning and natural language processing are currently playing crucial roles in the sales process, helping sales professionals with data-driven decision making and allowing them to provide a better customer experience. The sales activities that are being enhanced by the use of artificial intelligence include lead generation, sales forecasting, lead qualification, and customer communication. The lack of large historical datasets to train machine learning models and concerns around privacy and security are some of the challenges faced by AI-powered sales organizations.

Keywords:	artificial intelligence, B2B, sales funnel, deep learning, natural language processing, machine learning

Contents

List of Abbreviations

AI:	Artificial Intelligence
ANN:	Artificial Neural Network
B2B:	Business to Business
CI:	Conversation Intelligence
CNN:	Convolutional Neural Network
CRM:	Customer Relationship Management
GPT-3:	Generative Pre-trained Transformer 3
IoT:	Internet of Things
IR:	Information Retrieval
ML:	Machine Learning
MLaaS:	Machine Learning as a Service
NLP:	Natural Language Processing
RNN:	Recurrent Neural Network
STaaS:	Storage as a Service
SVM:	Support Vector Machines

1 Introduction

The world is undergoing a period of unprecedented change, driven by the emergence of new technologies with far-reaching implications in the global economy and society at large.

Klaus Schwab, founder and executive chairman of the World Economic Forum (WEF) has labeled these advances as the fourth industrial revolution. Building on the foundations of the third industrial revolution, also known as the digital revolution, the ongoing transformational changes “will be unlike anything humankind has experienced before” (Schwab, 2016).

The technological innovations driving the fourth industrial revolution, namely blockchain, virtual reality, augmented reality, robotics, IoT (Internet of Things), nanotechnology, biotechnology, and artificial intelligence (Gupta et al., 2017) among others, are profoundly transforming the way we work and live (Daugherty and Wilson, 2018). Unlike previous industrial revolutions, today’s transformations and breakthrough innovations are happening at an unprecedented, exponential pace, and disrupting almost every industry.

Artificial intelligence (AI), for instance, has experienced dramatic progress in recent years, catalyzed primarily by an increase in computing power, amount of available data, and heavy corporate investment. It is one of the most disruptive forces of the twenty-first century and it has become an integral part of modern life: video games, online shopping, music streaming, taxi booking or cryptocurrency trading (Sabry et al., 2020) are all areas that have been enhanced by artificial intelligence.

Artificial intelligence is having a major impact on businesses across all industries and promises to change the foundations of economic growth for countries across the world (Purdy and Daugherty, 2016). McKinsey Global

Institute (MGI) estimates that artificial intelligence can potentially generate between $3.5 and $5.8 trillion in additional annual value (Chui et al., 2018).

The implications of artificial intelligence will not only be evident across industries, but also across most business functions (product development, human resources, service operations, finance), with the greatest potential value impact being on sales and marketing, and in supply-chain management and manufacturing (Chui et al., 2018). MGI predicts that AI will generate up to $2.6T additional annual value in marketing and sales alone (Chui et al., 2018).

Technologies such as artificial intelligence, machine learning (ML), and natural language processing (NLP) have certainly reshaped the way people interact with businesses, buy products and services, and also how organizations promote and generate demand for their offerings. The sales profession is rapidly adapting to these emerging advances, the same way it did with past disruptive technologies such as the telephone, the computer, and the internet (Syam and Sharma, 2018).

The main objective of this thesis is to examine existing artificial intelligence technologies and techniques and analyze their current implementations in B2B (Business to Business) sales operations. This research aims to contribute to the body of knowledge by connecting artificial intelligence solutions to the challenges sales professionals experience at each step of the sales funnel. The model used to represent the sales funnel is the proposed by (Dubinsky, 1981): Prospection, Pre-Approach, Approach, Presentation, Answer to objections, Conclusion, and Follow-up.

The next section provides an overview of artificial intelligence, including classification, evolution, and most important subfields. The section after that introduces the seven steps of the B2B sales funnel, and examines key sales tasks and applications of AI for each step of the funnel.

2 Artificial Intelligence

2.1 Introduction

There is no common or standard definition of Artificial intelligence (Wang, 2019). It can mean different things to different people in different periods or contexts (Eitel-Porter, 2018). AI has been defined in several ways according to the different stages of its development, and the varying research goals established over the years (Wang, 2019).

According to McCarthy (1998), who coined the term, AI is “the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.” In other words, the field of AI attempts to understand intelligent entities and strives to build them (Russell and Norvig, 1995).

AI is not a technology per se, but rather a term that covers various technologies, such as speech recognition, computer vision, machine learning, natural language processing, and expert systems among others. Wang (2019) argues that “to the larger community of computer science and information technology, AI is usually identified by the techniques grown from it, which at different periods may include theorem proving, heuristic search, game playing, expert systems, neural networks, Bayesian networks, data mining, agents, and recently, deep learning. Since these techniques are based on very different theoretical foundations and are applicable to different problems, various subdomains have been formed within AI, such as knowledge representation, reasoning, planning, machine learning, vision, natural language processing, robotics, etc”.

These subdomains are combined to provide machines with human-level intelligence and capabilities in four main areas: sense, comprehend, act and learn (Purdy and Daugherty, 2016; Eitel-Porter, 2018; Kolbjørnsrud, Amico, and Thomas, 2016).

- Sense: AI enables a machine to perceive the surroundings and the world around it. This includes the acquisition and processing of sounds, images, speech, and other types of data. Examples are facial recognition and audio processing.
- Comprehend: AI enables a machine to evaluate and interpret the data collected. For example natural language processing or KRR (Knowledge Representation and Reasoning).
- Act: AI enables a machine to make data-based decisions, recommend or take action. For example expert systems or auto-pilot features in self-driving cars.
- Learn: AI enables a machine to improve its performance by learning from the results of its actions (i.e. machine learning).

AI is an interdisciplinary field of study, including disciplines such as computer science and electrical engineering, robotics, algebra, philosophy, logic, linguistics, psychology, and neuroscience.

Based on capabilities, AI can be broadly classified into three types: narrow, general, and super AI.

- Narrow AI, also known as weak AI, is a type of AI that is limited to specific domains or areas. Language translators, virtual assistants such as Siri, Cortana, or Google Assistant, recommendation engines, and self-driving cars are examples of this type of AI. They can perform specific tasks but not learn new ones. The idea behind Weak AI is to simulate human intelligence rather than replicate it.

- General or strong AI on the other hand refers to AI that can perform a wide range of independent and unrelated tasks and has the ability to learn new strategies to solve new problems. Strong AI aims to create intelligent machines that can replicate or mimic the human mind. Strong AI only exists as a theoretical concept, there are no tangible implementations (IBM, 2020).
- Super AI or Conscious AI is AI that has human-level consciousness and exceeds human intelligence. Since we are not yet able to clearly define what consciousness and awareness are, having super AI around us is very unlikely in the near future.

2.2 Evolution

Philosophers, scientists, and mathematicians have mused about the idea of intelligent machines and humanoid robots for centuries. The notion of machines that can think and imitate human behavior has been a common theme in science fiction since at least Samuel Butler's 1872 novel “Erewhon”. But it was not until the 1950s that the advances in Artificial Intelligence became more substantial.

The following are some of the most important events that catapulted AI from science fiction to a global industry:

In 1950, Claude Shannon, an American engineer, and mathematician, often referred to as “the father of Information Theory”, published a paper with the title “Programming a Computer for Playing Chess”. This paper was “concerned with the problem of constructing a computing routine or program for a modern general-purpose computer which will enable it to play chess” (Claude E. Shannon, 1950).

That same year, Alan Turing, a British polymath, also known as “the father of modern computer science” (Bowen, 2016), published a paper titled "Computer

Machinery and Intelligence". The paper opens with the question “Can machines think?” (Turing, 2009), and introduces a method to test the ability of a machine to replicate human behavior to the point where it would be impossible for a judge to tell if it is a machine or a human. This method, referred to as the Turing Test, is considered the threshold for AI.

Six years later, in the summer of 1956, the AI research field was formally established. The Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI), organized by Marvin Minsky and John McCarthy, is the first academic seminar on the subject of Artificial Intelligence (Moor, 2006).

In 1957, Frank Rosenblatt, an American psychologist, invented the perceptron algorithm, which is the precursor to the modern artificial neural networks (Marvin and Seymour, 1969).

In 1958, McCarthy developed Lisp, the most popular and widely-used programming language for artificial intelligence research (McCarthy, 1978).

Arthur Samuel, a computer scientist, is credited for coining the term "machine learning" with his research published in 1959 “Some studies in machine learning using the game of checkers” (Ergen, 2019).

Driven primarily by political and military motives, the US government had a particular interest in machine understanding and machine translation capabilities, especially between Russian and English. During the 1960s, considerable progress was made in NLP and formal linguistics, and many accomplishments were achieved. In 1964, for instance, Daniel Bobrow created STUDENT, an algorithm able to solve algebra word problems. It is considered an important milestone in natural language processing (Bobrow, 1964).

A year later, Joseph Weizenbaum developed ELIZA, an interactive program able to carry out conversations in English on any topic (Shah et al., 2016).

The early implementations of NLP were promising and the optimism was high. However, in 1966, a negative report published by the Automatic Language Processing Advisory Committee (ALPAC) brought an end to ML and NLP research for over a decade (Hutchins, 2001). Then in 1973, James Lighthill (1973) published a report about the state of AI to the British Science Council (BSC), concluding that "in no part of the field have discoveries made so far produced the major impact that was then promised" leading the British government to drastically reduce funding and support for Artificial Intelligence.

These events led to what is known as the first AI winter, a period of reduced research and public investment, and lasted from the mid-1970s to early 1980. Then, after a period of growing corporate interest in “expert systems”, a second winter followed, lasting from 1988 to 1994 (Schuchmann, 2019).

Starting from the mid-1990s, and driven by the increase in computational processing power and storage, AI experienced a resurgence and significant milestones were achieved. Deep Blue, developed by IBM, became the first computer to defeat Garry Kasparov, the reigning world chess champion, in 1997. In 2011, IBM' Watson, combining information retrieval (IR) and NLP techniques, defeated the former champions Brad Rutter and Ken Jennings at Jeopardy!. And that same year, Siri, the first modern virtual assistant, was introduced on the iPhone 4S.

Unlimited access to computing power (i.e. cloud computing), the proliferation of big data, and the breakthroughs in machine learning techniques of the last decade, fueled by a dramatic increase in funding and investment, have enabled AI to make the leap from the lab to the real world.

2.3 Technologies

Since the inception of AI as a field of study, various methods and subfields have been developed. In this section, they are briefly outlined and discussed.

2.3.1 Machine Learning

Machine learning is one of the most researched areas of AI. The aim with this technology is to build machines that can improve their performance by learning from experience (Alzubi, Nayyar, and Kumar, 2018).

Unlike traditional programming, where the input data and the rules are provided in order to develop an algorithm to produce output data, machine learning systems take data, both input, and output, and create the rules and the algorithm. Given a training dataset, a machine learning system is able to learn and create a model that predicts outputs based on certain inputs (Mahesh, 2020).

Machine learning systems are able to create models by analyzing and examining large datasets to find common patterns. For instance, a machine learning program could be given a large dataset of pictures of cars and train the model to return the label “Car” whenever we provide it with a picture of a car. The same program can be trained to detect boat pictures and return the label “Boat”.

Arthur Lee Samuel, who coined the term in 1959, defines machine learning as a field of study that gives machines the ability to learn without being explicitly programmed (Samuel, 1959).

Mitchell (1997) offers a more technical definition:

“A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E.”

Depending on the way the algorithms are being trained (learning approach) and the availability of the results during the training, ML algorithms are grouped into multiple learning types. The most important are: supervised, unsupervised, reinforcement, and semi-supervised.

Supervised learning methods require the input data to be labeled in order to create a classification model. Both the inputs and the outputs are provided, and the algorithm has to build a model that is able to predict the outputs based on the inputs.

Supervised learning algorithms are applied to two types of problems: regression and classification.

Regression algorithms are ideal for numeric predictions, and they are widely used in statistical applications. Regression algorithms are commonly applied to problems that involve questions starting with ‘how much’ or ‘how many’ (Alzubi, Nayyar, and Kumar, 2018). Applications of regression algorithms include predicting real estate prices or sales revenues. Linear, logistic and polynomial regression are common regression algorithms.

Classification algorithms are used to group test data into different categories based on a set of training data. Based on the number of categories, the classification problem can be binary or multi-class (Alzubi, Nayyar, and Kumar, 2018). Real-world applications of classification algorithms include spam email detection, image classification, and medical diagnosis (Joshi, 2020). Multiple classification algorithms have been developed over the years; the most common are decision trees, linear classifiers, support vector machines (SVM), k-nearest neighbors, and random forest.

Unsupervised learning algorithms identify hidden patterns in unlabelled input data. This technique is appropriate for clustering and outlier detection purposes, where the goal is to identify clusters of items that are similar to each other but different from items in other clusters. Unsupervised learning is regarded as a statistical-based learning approach.

Unsupervised learning is used for three main tasks: association, clustering, and dimensionality reduction.

Association is used to uncover patterns and find hidden relationships between items in a dataset. Clustering is a method used for grouping non-labeled data based on their commonalities. When the number of attributes (also known as dimensions) in a given dataset is excessively high, dimensionality reduction is used to decrease the quantity of data inputs to a tolerable level, without affecting the integrity of the dataset.

Common unsupervised learning applications include anomaly detection (security breaches, fraud, faulty equipment), computer vision for object detection and recommendation engines by discovering data trends that can be used for up-selling or cross-selling strategies (IBM, 2020).

Reinforcement learning algorithms learn by interacting with the environment. Algorithms are provided with unlabeled inputs and a reward function that penalizes bad actions and rewards good ones. The goal of this algorithm is to decide which actions maximize the value of the reward function (Sutton and Barto, 2018). In some cases, “actions may affect not only the immediate reward but also the next situation and, through that, all subsequent rewards” (Sutton, 1992).

Although it shares some similarities with supervised learning, reinforcement learning algorithms are provided with only partial feedback about the predictions. The roots of this learning approach lie in behavioral psychology: learning by trial and error (Jones, 2017). Learning by trial and error and learning from delayed reward are the most defining characteristics of reinforcement learning. Common reinforcement learning algorithms include temporal difference learning, state-action-reward-state-action, and Q-Learning.

Semi-supervised learning is a technique that combines supervised and unsupervised learning. In supervised learning, labels are provided for all the inputs, while in unsupervised learning, no labels are provided at all. In many real-world scenarios, labeled data is limited or expensive, while unlabeled data is readily available.

Semi-supervised learning combines labeled and non-labeled data during training to increase the performance of the algorithm. It is appropriate in situations when the majority of input data is unlabeled; as data labeling can be a time-consuming and costly task.

Common semi-supervised learning models include mixture models, self-training, multiview learning and co-training, semi-supervised support vector machines, and graph-based methods (Zhu and Goldberg, 2009).

2.3.2 Deep learning

Deep learning is a subfield of ML that uses layered artificial neural networks (ANNs) to simulate the structure and functionality of the brain by combining inputs, outputs, weights, and thresholds.

An artificial neural network is organized into layers (input, hidden, and output), and each layer contains multiple processing units called nodes. Each layer ingests data for processing and passes its outputs to the next layer, which processes it and passes to the next layer. When the output of a node is above a specific threshold value, that node gets activated and allows data to pass to the next layer of the network. Most deep neural networks flow in one direction, from input to output.

An artificial neural network consisting of more than three layers is considered a deep learning neural network. The difference between deep learning and other ML algorithms is that deep learning algorithms become more efficient as the dataset increases in volume, due to the deep layered architecture, while other algorithms plateau.

Deep learning algorithms are used in problems that involve unstructured data, like text and images, where patterns and trends are hard to detect.

Deep learning has been used in fields such as speech recognition, computer vision, medical imaging, driverless cars, and natural language processing.

Various types of ANN are used to address different challenges and data types. For instance, recurrent neural networks (RNNs) are commonly used for speech recognition and natural language processing, whereas convolutional neural networks (CNNs) are more often used for computer vision and classification applications.

2.3.3 Natural Language Processing

Natural language processing, currently one of the most important subfields of machine learning (Jones, 2019), enables machines to communicate with and comprehend human natural language. The focus of this field of research is the creation of algorithms that are able to take natural language, written or spoken, and extract meaning from it. NLP involves multiple areas of study: speech recognition, speech generation, natural language generation (NLG), natural language understanding (NLU), ontology (i.e. knowledge representation).

NLU is the process of converting natural language to artificial language, and understanding the language in its context. NLU carries multiple challenges: word-sense disambiguation (words that can be used in multiple senses), domain-specific understanding (e.g. legal, medical), or the use of proxy words (for example “google it” meaning “search for it”).

NLG is the process of generating text from a semantic representation of artificial language and can be considered as the inverse of NLU (Tur et al., 2018). The generated text must be readable, coherent, and grammatically correct. NLG systems play a crucial role in dialog systems, machine translation, and text summarization.

Common NLP approaches are one-hot encoding and word vectors.

3 Sales funnel

A sales funnel is a visual representation of the B2B sales process. It shows the different stages a prospect goes through to become a customer. This section examines the B2B sales funnel using the seven steps of selling as proposed by Dubinsky: Prospecting, Pre-Approach, Approach, Presentation, Answer to objections, Conclusion, and Follow-up (Dubinsky, 1981). This section also includes an overview of the different AI applications and techniques used to solve the challenges faced at each step of the sales funnel.

Dubinsky's model is one of the most popular in the sales field, and it has served as a conceptual framework in sales research and training since its publication (Moncrief and Marshall, 2005). Over the decades, there have been numerous attempts to update and enhance Dublinsky's sales model (Liu, Leach, and Chugh, 2015).

Moncrief and Marshall (2005) for instance, suggest an updated model of selling, where the process is more customer-oriented and the focus is on relationship-based selling. The seven steps proposed by Moncrief and Marshall consist of "customer retention, knowledge management, relationship selling, product marketing, problem-solving, value-adding and satisfaction, and customer relationship maintenance" (Moncrief and Marshall, 2005).

Plouffe, Nelson, and Beuk (2013) provide a different perspective and argue that given the challenges of modern sales, such as higher customer demand, longer sales cycles, and a shift from a product-centric to a services-centric economy, conventional selling frameworks may be incomplete, and more steps need to be considered in the modern sales process, such as negotiation.

Sales management has certainly evolved since the publication of the seven steps of selling. Moncrief and Marshal (2005) state that "technology, a changing customer base, new selling tools, and globalization all have had a major influence on the salesperson of today.” Nonetheless, after Marshall, Moncrief, and Lassk (1999) collected and analyzed the activities performed by salespeople on a daily basis and contrasted them with the activities collected by Moncrief (1986) in 1981, their results showed that, although new activities have emerged as a result of the development of new selling approaches (value-added selling, relationship selling, consultative selling) and technological progress (communication tools, databases, web), most of the activities remained the same (Moncrief and Marshall, 2005).

Given its widespread adoption, both in research and industry, and because it can be applied to most B2B sales scenarios (Sheth and Sharma, 2008; Syam and Sharma, 2018), the selling method proposed by Dubinsky (1981) is the appropriate selling framework for this study.

The next sections provide an overview of the B2B sales process, examining key sales tasks and applications of AI for each step of the funnel.

3.1 Prospecting

Prospecting is the first step of the sales process and includes methods for searching and qualifying potential customers, and expanding the customer base. In this step, “the salesperson searches for and identifies potential buyers who have the need, willingness, ability, and authority to buy the salesperson’s offering” (Dubinsky and Rudelius, 1980).

The challenges involved in this step are highly dependent on the industry and market (Long, Tellefsen, and Lichtenthal, 2007). While for some organizations the market size is small and the prospects are clearly identified, for others, the number of potential customers is very large and the data available is inadequate.

Research conducted by Trailer and Dickie (2006), indicates that about 20% of salespeople's time is spent prospecting.

The main activities associated with this step are lead generation, lead qualification, and sales forecasting (Syam and Sharma, 2018).

Lead generation is the process of identifying potential customers. Common techniques and strategies used for lead generation include referrals, networking, newsletters, webinars, Ads, search engine optimization (SEO), and social media activities. AI is also becoming increasingly used in this stage of the sales process. Natural language processing algorithms, for instance, are used to build prospects lists by analyzing massive amounts of publicly available data (e.g. news, social media and blog posts, corporate websites) and internal data (e.g. emails, website traffic, analytics) in search of intent and interest (Paschen, Wilson, and Ferreira, 2020). Another way AI contributes to lead generation is by building "lookalike" audiences, potential customers that share similar characteristics to current customers. Typically used machine learning algorithms for building lookalike audiences involve Semi-supervised classification models, Rule-based models, Recommendation based models, Hybrid models, and Transfer learning models (Popov and Iakovleva, 2018).

In lead qualification (also known as lead scoring), the goal is to filter the list of prospects and identify those that are more likely to become customers (Long, Tellefsen, and Lichtenthal, 2007). This is key to increasing sales efficiency and reducing customer acquisition costs that may result from engaging with unfit prospects later in the sales process (Söhnchen and Albers, 2010).

ML algorithms that perform predictive analytics can be used for lead scoring. Some of the common tools are ANNs, SVMs, K-nearest neighbor, Naïve Bayes, and Discriminant Analysis (Syam and Sharma, 2018).

A sales forecast is an estimate of future revenue. Accurate sales forecasting is crucial for informed business decisions and provides insights for financial planning, inventory management, and resource allocation. Many machine learning algorithms are used to help generate accurate sales forecasts (Lee, Shih, and Chen, 2012; Yu, Choi, and Hui, 2011; Martínez et al., 2020). Machine learning algorithms analyze structured and unstructured data from a myriad of sources (both internal and external), including historical sales data, marketing spend, economic, political, and environmental conditions, customer satisfaction, consumer trends, and competitors strategies to build models that can estimate future sales. Depending on the type, quality, and quantity of the data available and the specific business goals, some algorithms are more suitable than others. The most common algorithms used for sales forecasting include ARIMA/SARIMA, ExponenTial Smoothing (ETS), Autoregressive Distributed Lag (ADL), Support Vector Regression (SVR), Random Forest, Gradient Boosting Regression Trees (GBRT) (Pavlyshenko, 2019; Ma and Fildes, 2021).

3.2 Pre-approach

The pre-approach step includes all the activities that are performed after a potential customer has been identified and qualified, and prior to the actual interaction with a prospect (Moncrief and Marshall, 2005).

This step involves acquiring detailed information about the prospect (personal and company level), learning about their needs and challenges, reviewing any previous interactions, and deciding on the best method of approach.

NLP algorithms can be used to analyze internal and publicly available data about a prospect to get relevant data points such as industry, number of employees, location, revenue, social media activity, etc. The collected data can also reveal buying signals, like expansion news, key decision-maker hiring, new job openings, or fundraising news.

The pre-approach could also involve identifying the role of the prospect in the buying process (e.g. influencer or decision-maker), and the best time to make contact (Meghişan, 2008).

3.3 Approach

This step involves the initial interaction with the potential customer and the end goal is to capture and maintain the prospect's interest and attention, establish rapport and build trust.

At this stage the first impression is critical (Meghişan, 2008), and to succeed, several ways are suggested by Dubinsky (1981): (1) product-based approaches (service or product demonstration), (2) non-product-based approaches (introductory, reference, or mutual acquaintance), (3) consumer-based approaches (questions or surveys) and (4) interest-based approaches (curiosity, consumer benefit). The most suitable tactic will depend on the information gathered in the previous stages (i.e. prospecting and pre-approach) about the prospect's interests and preferences (Meghişan, 2008).

A common tactic used in this step is known in the marketing literature as "lead nurturing". Lead nurturing involves providing customized and personalized content (newsletters, surveys, white papers, birthday cards) related to the prospect's interest, and intended to build trust and awareness (Paschen, Wilson, and Ferreira, 2020). The aim is to keep high levels of engagement and the relationship active until the prospect is ready to become a customer (Stevens, 2011).

The following are some of the technologies and applications of AI at this stage of the sales funnel.

Generative Pre-trained Transformer 3 (GPT-3) is an autoregressive language model that generates text in natural language using deep learning neural networks (Floridi and Chiriatti, 2020). The technology, released by OpenAI (2020), an artificial intelligence research institute, can be applied in a variety of ways. It can be used for instance to generate introductory emails for potential customers, or schedule meetings with minimal intervention from the sales professional.

Additionally, a firm can automate customer interactions through chatbots, computer programs that can engage in conversations with a person, via voice or text-based methods. Modern chatbots perform complex natural language processing and are able to grasp the intentions and complex demands of users (Molnár and Szüts, 2018). Another way AI can create value at this stage is by automating lead nurturing. Based on real-time data about the prospect’s interest and behavior, AI can generate (using GPT-3 for example) and deliver highly tailored and relevant content to keep the prospect engaged.

3.4 Presentation

The presentation step involves providing the prospect with tailored information about the product or service, its price, competitors' comparisons, and overall benefits. This stage should occur after the prospect's needs have been well defined (Moncrief and Marshall, 2005). While a presentation can be a mere standardized, scripted message conveyed to every prospective customer (canned sales presentation), modern approaches support adaptability and personalization (adaptive sales). Research shows that more adaptive sellers are more likely to be successful at closing sales (Giacobbe, Jackson, Crosby, and Bridges, 2006). However, since the number of decision-makers involved in the B2B buying process has dramatically increased in recent years (Toman, Adamson, and Gomez, 2017), understanding the needs and providing a customized solution to every one of them has become considerably challenging.

There are multiple tools and applications designed to assist sales professionals during this step of the funnel. Conversation intelligence (CI) software is among the tools with the biggest impact on how sales presentations are created and delivered. Powered by machine learning and NLP, conversation intelligence software provides the ability to analyze conversations and extract insights in real-time. Common features in CI tools include call or video recording, transcription (generation of a written version of the conversation), sentiment analysis, scoring (based on levels of interest), and keyword and topic detection (Jaso, 2019). Advanced conversation intelligence systems are able to trigger actions based on what is being discussed; for example, they could send information to other tools, schedule meetings, create call tags or send emails. Trained with data from historical conversations, a CI system would be able to provide suggestions or recommend useful actions to the sales professional in real-time (Rathore, 2021). Sales managers can also benefit from CI tools, helping them monitor calls, uncover trends, and identify strategies that result in successful sales. The recordings can be used to create guidelines and best practices, coach underperforming sales professionals and train new team members (G2, 2020). CI can track key metrics from a sales presentation, such as prospect sentiment, length of the conversation, time to conversion (prospect to customer), cadence, silence ratio, or script compliance. In addition, CI can be a valuable tool for sales forecasting. Combining data from customer relationship management (CRM) systems (e.g. number of interactions with a prospect) and conversation intelligence recordings (customer sentiment analysis), sales managers are better equipped to assess the outcome of certain opportunities.

3.5 Overcoming objections

Objections are verbal (questions, comments, or disagreements) and non-verbal expressions (body language or face expressions) that might indicate reluctance and hesitation about the product, service, or the selling organization. They might come at any stage of the sales process, and not necessarily after the presentation step.

Objections can be justified and based on evidence: quality of the product, delivery method, price or competition, or merely caused by the prospect’s skepticism, indifference, or lack of knowledge (Meghişan, 2008). Either way, sales professionals are tasked with dealing with and managing objections. There are numerous techniques and procedures on how to overcome objections and are extensively discussed in most sales textbooks (Moncrief and Marshall, 2005).

One way sales professionals prepare for this stage of the sales funnel is by using sales battle cards. Sales battle cards are short documents, usually a one-pager, that include information about the firm’s product or service, as well as differences with major competitors. The purpose of the sales battle cards is to equip sales professionals with insights and guidelines to handle objections and win deals against competitors. Comprehensive battle cards require considerable efforts to create, and even more to maintain. AI-enabled systems, such as Competitive Intelligence tools, use NLP technologies to analyze massive amounts of data from publicly available sources such as websites, reviews sites, and online forums, to generate ready to use battle cards, saving the sales team copious amounts of time, and making sure the information is always up to date.

In addition to Competitive Intelligence software, Conversation Intelligence tools, mentioned in the previous step, can also be very valuable during this step. By analyzing behavior patterns displayed by the most successful sales professionals, Conversation Intelligence tools are able to extract insights that can be used to elaborate guidelines and best practices for effective objection handling (Orlob, 2018).

Price optimization algorithms can also have a major impact during this step for handling objections related to pricing and maximizing profits. Based on historical data about the prospect, market conditions, competitors, and other variables, AI can suggest the right price or discount for different potential customers (Paschen, Wilson, and Ferreira, 2020).

3.6 Close

After handling and overcoming all the objections raised during any of the previous stages, the sales professional must guide the prospect towards acceptance of the offer in the most efficient and appropriate way (Dwyer, Hill, and Martin, 2000). The close involves obtaining a purchase commitment from the prospect. Closing deals that involve multiple decision-makers require that all must come to an agreement, which makes it more challenging.

Although many deals can be closed remotely, physical meetings are still necessary for complex sales processes (Rodríguez, Svensson, and Mehl, 2020). Given that interpersonal relationship skills are still required to win deals, AI applications are not as substantial in this stage as in other stages of the funnel.

3.7 Follow-up

This step includes two main activities: order filling and following up once the order is completed. Order filling refers to the process of recording and processing the order, inventory management, and order fulfillment. After the initial order has been completed, following up requires making sure the service or product has been successfully fulfilled, providing training or maintenance, handling complaints and answering questions, measuring customer satisfaction, and uncovering new needs.

This stage of the sales funnel has two main objectives: retaining customers and uncovering opportunities for additional sales.

Studies show that, depending on the industry, getting a new customer costs anywhere between five and twenty-five times more than maintaining an existing one (Gallo, 2014). In addition, there may be opportunities to increase revenue from existing customers (up-selling or cross-selling). Up-selling is a sales strategy where the customer is offered a premium (more expensive) product, an upgrade, or an add-on, while cross-selling encourages the purchase of additional products or services (Kubiak and Weichbroth, 2010).

Multiple ML algorithms have been successfully applied to predict churn rates and uncover up-sell and cross-sell opportunities. Churn rate, also known as attrition rate, is the rate at which a company loses customers over a certain period of time. There could be several reasons for a customer to stop doing business with a company: dissatisfaction with the product or service, unsatisfactory customer service, or a better offer from a competitor. Accurate churn prediction models provide the ability to identify the customers with the highest probability to churn and their motivations to do so. The sales organization can then take appropriate steps to reduce or even prevent churn before it happens. Modeling techniques that are being used to predict churn rates include logistic regressions, random forest, support vector machines, neural networks, decision trees, discriminant analysis, Bayesian networks, regression forests, and more (Verbeke et al, 2011).

Similarly, specific patterns and characteristics (business expansion, funding, trends, buyer behavior, etc.) present in a particular group of customers, can be used to determine potential candidates for up-sales and cross-sales initiatives (Syam and Sharma, 2018). Uplift modeling, also known as incremental modeling, is a technique commonly used for this purpose (Christoffersen, 2017).

Finally, AI-powered chatbots use existing content and resources generated by the organization, like Frequently Asked Questions (FAQs) and knowledge base articles, to answer and resolve customers' questions. Chatbots provide real-time, ongoing customer support through a variety of channels: website, email, SMS, or social media (e.g. Facebook Messenger or WhatsApp).

By delegating certain aspects of the follow-up step to AI, sales professionals can spend more time and energy on value-adding activities.

4 Conclusion

The technological innovations driving the fourth industrial revolution are profoundly transforming the way we work and live. Fueled primarily by an increase in computing power, amount of available data, and heavy corporate investment, AI is disrupting businesses across all industries.

The impact of AI on the B2B sales funnel is evident. ML and NLP algorithms are able to automate and scale a broad range of repetitive and non-productive activities. Among other applications, artificial intelligence is used to generate lookalike audiences, qualify leads, forecast sales revenues, schedule meetings, predict churn rates and detect up-sell opportunities. Consequently, sales professionals can devote more time to value-adding tasks.

Artificial intelligence is able to process massive amounts of data in search of patterns, deliver next best actions, and provide relevant insights for data-driven decision making. However, it is only playing a supporting, rather than a leading role in the sales process. Human judgment is still a critical component and is required at every step of the sales process. In addition to engaging and building rapport with potential customers, sales professionals are also required to monitor and analyze machine learning results.

The rise of new cloud computing solutions such as Storage as a Service (STaaS) and Machine Learning as a Service (MLaaS), makes it possible for any business to harness the benefits of artificial intelligence. Organizations of all sizes and industries can resort to MLaaS service providers to access machine learning capabilities, without the cost, time, and risk required to deploy in-house solutions.

Although access to the technology is not a limiting factor, there are certain practical challenges organizations must overcome to unlock the full potential of artificial intelligence. Most machine learning applications require vast amounts of training data to produce valuable results. Despite the fact that businesses are collecting more data than ever, the scarcity of comprehensive, labeled historical datasets, prevents organizations from applying predictive models to critical sales activities such as lead scoring or sales forecasting.

Data privacy and the use of sensitive personal data are also critical issues that organizations need to address. For certain applications, deep knowledge of prospects and customers' interests and behaviors is required to provide accurate machine learning predictions; nonetheless, organizations must find the right balance between need and demand to remain in compliance with regulatory rules.

This study has provided an overview of various artificial intelligence technologies, and explored their impact and current implementation on the B2B sales funnel, hopefully serving as the basis for further research and development of new innovative applications.

5 References

Alzubi, J., Nayyar, A. and Kumar, A. (2018). Machine learning from theory to algorithms: an overview. In Journal of physics: conference series (Vol. 1142, No. 1, p. 012012). IOP Publishing. [Online]. Available at: https://iopscience.iop.org/article/10.1088/1742-6596/1142/1/012012/pdf (Accessed: 15 October 2021)

Bobrow, D.G. (1964). Natural language input for a computer problem solving system. [Online]. Available at: https://dspace.mit.edu/bitstream/handle/1721.1/6903/AITR-219.pdf?sequence=2 (Accessed: 11 October 2021)

Bowen, J.P. (2016). Alan Turing: founder of computer science. In School on Engineering Trustworthy Software Systems. Springer, Cham.

Christoffersen, S. (2017). 6 ways to use Data Science to drive your cross-sell and upsell activity. [Online]. Available at: https://www.ibm.com/blogs/nordic-msp/six-ways-use-data-science-drive-cross-sell-upsell-activity (Accessed: 07 September 2021)

Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P. and Malhotra, S. (2018). Notes from the AI frontier: Insights from hundreds of use cases. McKinsey Global Institute.

Daugherty, P. R., and Wilson, H. J. (2018). Human + Machine: Reimagining Work in the Age of AI: Harvard Business Press.

Dubinsky, A.J. (1981). A factor analytic study of the personal selling process. Journal of personal selling & sales management, 1(1), pp.26-33.

Dubinsky, A.J. and Rudelius, W. (1981). Selling techniques for industrial products and services: are they different?. Journal of Personal Selling & Sales Management, 1(1), pp.65-75.

Dwyer, S., Hill, J. and Martin, W. (2000). An empirical investigation of critical success factors in the personal selling process for homogenous goods. Journal of Personal Selling & Sales Management, 20(3), pp.151-159.

Eitel-Porter, R. (2018). What is AI exactly?. [Online]. Available at: https://www.accenture.com/fi-en/insights/artificial-intelligence/what-ai-exactly (Accessed: 27 September 2021)

Ergen, M., (2019). What is artificial intelligence? Technical considerations and future perception. Anatolian J. Cardiol, 22(2). [Online]. Available at: https://jag.journalagent.com/anatoljcardiol/pdfs/AJC-79091-REVIEW-ERGEN.pdf (Accessed: 10 November 2021)

Floridi, L. and Chiriatti, M. (2020). GPT-3: Its nature, scope, limits, and consequences. Minds and Machines, 30(4), pp.681-694.

G2. (2020). Best Conversation Intelligence Software. [Online]. Available at: https://www.g2.com/categories/conversation-intelligence (Accessed: 07 October 2021)

Gallo, A. (2014). The Value of Keeping the Right Customers. [Online]. Available at: https://hbr.org/2014/10/the-value-of-keeping-the-right-customers (Accessed: 25 October 2021)

Giacobbe, R.W., Jackson Jr, D.W., Crosby, L.A. and Bridges, C.M. (2006). A contingency approach to adaptive selling behavior and sales performance: Selling situations and salesperson characteristics. Journal of personal selling & sales management, 26(2), pp.115-142.

Gupta, M.S., Keen, M.M., Shah, M.A. and Verdier, M.G. (2017). Digital revolutions in public finance. International Monetary Fund.

Hutchins, W.J. (2001). Machine translation over fifty years. Histoire épistémologie langage, 23(1). [Online]. Available at: https://www.persee.fr/doc/hel_0750-8069_2001_num_23_1_2815 (Accessed: 02 November 2021)

IBM (2020). Strong AI. [Online]. Available at: https://www.ibm.com/cloud/learn/strong-ai (Accessed: 09 November 2021)

IBM (2020). Unsupervised Learning. [Online]. Available at: https://www.ibm.com/cloud/learn/unsupervised-learning (Accessed: 01 November 2021)

Jaso, K. (2019). What Is Conversation Intelligence? (+How It Impacts Sales). [Online]. Available at: https://learn.g2.com/conversation-intelligence (Accessed: 10 September 2021)

Jones, T. (2017). Train a software agent to behave rationally with reinforcement learning. [Online]. Available at: https://developer.ibm.com/articles/cc-reinforcement-learning-train-software-agent/ (Accessed: 04 November 2021)

Jones, T. (2019). A beginner’s guide to natural language processing. [Online]. Available at: https://developer.ibm.com/articles/a-beginners-guide-to-natural-language-processing/ (Accessed: 01 October 2021)

Joshi, A.V. (2020). Machine learning and artificial intelligence. Springer.

Kolbjørnsrud, V., Thomas, R.J. and Amico, R. (2016). The Promise of Artificial İntelligence: Redefining Management in the Workforce of the Future (Accenture Institute for High Performance and Accenture Strategy Research Report May, 19). Accenture.

Kubiak, B.F. (1970). Cross and up-selling techniques in e-commerce activities. The Journal of Internet Banking and Commerce, 15(3), pp.1-7.

Lee, W.I., Shih, B.Y. and Chen, C.Y. (2012). Retracted: A hybrid artificial intelligence sales-forecasting system in the convenience store industry. Human Factors and Ergonomics in Manufacturing & Service Industries, 22(3), pp.188-196.

Lighthill, J. (1973). Artificial intelligence: a paper symposium. Science Research Council, London.

Liu, A., Leach, M. and Chugh, R. (2015). A sales process framework to regain B2B customers. Journal of Business & Industrial Marketing. [Online]. Available at: http://mural.maynoothuniversity.ie/11323/1/RC_Sales_2015.pdf (Accessed: 20 September 2021)

Long, M.M., Tellefsen, T. and Lichtenthal, J.D. (2007). Internet integration into the industrial selling process: A step-by-step approach. Industrial Marketing Management, 36(5), pp.676-689.

Ma, S. and Fildes, R. (2021). Retail sales forecasting with meta-learning. European Journal of Operational Research, 288(1), pp.111-128.

Mahesh, B. (2020). Machine Learning Algorithms - A Review. International Journal of Science and Research (IJSR). [Online]. Available at: https://www.researchgate.net/profile/Batta-Mahesh/publication/344717762_Machine_Learning_Algorithms_-A_Review/links/5f8b2365299bf1b53e2d243a/Machine-Learning-Algorithms-A-Review.pdf (Accessed: 14 October 2021)

Marshall, G.W., Moncrief, W.C. and Lassk, F.G. (1999). The current state of sales force activities. Industrial Marketing Management, 28(1), pp.87-98.

Martínez, A., Schmuck, C., Pereverzyev Jr, S., Pirker, C. and Haltmeier, M. (2020). A machine learning framework for customer purchase prediction in the non-contractual setting. European Journal of Operational Research, 281(3), pp.588-596.

Marvin, M. and Seymour, A.P. (1969). Perceptrons.

McCarthy, J. (1978). History of LISP. In History of programming languages.

McCarthy, J. (2007). What is artificial intelligence? Basic questions. [online]. Available at: http://www-formal.stanford.edu/jmc/whatisai/node1.html (Accessed: 16 September 2021)

Meghişan, G. (2008). Personal selling process. Annals of the University of Craiova, Economic Sciences Series, 7(36).

Mitchell, T. (1997). Machine learning. McGraw Hill.

Molnár, G. and Szüts, Z. (2018), September. The role of chatbots in formal education. In 2018 IEEE 16th International Symposium on Intelligent Systems and Informatics (SISY) (pp. 000197-000202). IEEE.

Moncrief, W.C. (1986). Selling activity and sales position taxonomies for industrial salesforces. Journal of Marketing Research, 23(3), pp.261-270.

Moncrief, W.C. and Marshall, G.W. (2005). The evolution of the seven steps of selling. Industrial Marketing Management, 34(1), pp.13-22.

Moor, J. (2006). The Dartmouth College artificial intelligence conference: The next fifty years. AI Magazine, 27(4). [Online]. Available at: https://ojs.aaai.org/index.php/aimagazine/article/view/1911/1809 (Accessed: 05 October 2021)

OpenAI. (2020). OpenAI API. [Online]. Available at: https://openai.com/blog/openai-api/ (Accessed: 04 October 2021)

Orlob, C. (2018). This Is How Successful Salespeople Handle Objections, According to New Data. [Online]. Available at: https://www.gong.io/blog/handling-sales-objections/ (Accessed: 25 October 2021)

Paschen, J., Wilson, M. and Ferreira, J.J. (2020). Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel. Business Horizons, 63(3), pp.403-414.

Pavlyshenko, B.M. (2019). Machine-learning models for sales time series forecasting. Data, 4(1), p.15.

Plouffe, C.R., Nelson, Y.H. and Beuk, F. (2013). Testing an enhanced, process-based view of the sales process. Journal of Personal Selling & Sales Management, 33(2), pp.141-163.

Popov, A. and Iakovleva, D. (2018). Adaptive look-alike targeting in social networks advertising. Procedia computer science, 136, pp.255-264.

Purdy, M. and Daugherty, P. (2016). Why artificial intelligence is the future of growth. Accenture. [Online]. Available at: https://dl.icdst.org/pdfs/files2/2aea5d87070f0116f8aaa9f545530e47.pdf (Accessed: 04 October 2021)

Rathore, S. (2021). The 5 Dimensions of Conversation Intelligence. [Online]. Available at: https://blog.symbl.ai/blog/the-5-dimensions-of-conversation-intelligence/ (Accessed: 02 November 2021)

Rodríguez, R., Svensson, G. and Mehl, E.J. (2020). Digitalization process of complex B2B sales processes–Enablers and obstacles. Technology in society, 62, p.101324.

Russel, S. J. and Norvig, P. (2003) Artificial intelligence: A modern approach. EUA: Prentice Hall, 178.

Sabry, F., Labda, W., Erbad, A., and Malluhi, Q., (2020). Cryptocurrencies and Artificial Intelligence: Challenges and Opportunities. IEEE Access, 8. [online]. Available at: https://ieeexplore.ieee.org/iel7/6287639/8948470/09200988.pdf (Accessed: 09 November 2021)

Samuel, A.L. (1959). Some studies in machine learning using the game of checkers. IBM Journal of research and development, 3(3). [Online]. Available at: https://hci.iwr.uni-heidelberg.de/system/files/private/downloads/636026949/report_frank_gabel.pdf (Accessed: 27 September 2021)

Schuchmann, S. (2019). Analyzing the Prospect of an Approaching AI Winter. [Online]. Available at: https://www.researchgate.net/publication/333039347_Analyzing_the_Prospect_of_an_Approaching_AI_Winter (Accessed: 06 October 2021)

Schwab, K. (2016). The fourth industrial revolution: what it means, how to respond. [Online]. Available at: https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/ (Accessed: 02 November 2021)

Shah, H., Warwick, K., Vallverdú, J. and Wu, D. (2016). Can machines talk? Comparison of Eliza with modern dialogue systems. Computers in Human Behavior, 58.

Shannon, C.E. (1950). XXII. Programming a computer for playing chess. The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, 41(314).

Sheth, J.N. and Sharma, A. (2008). The impact of the product to service shift in industrial markets and the evolution of the sales organization. Industrial Marketing Management, 37(3), pp.260-269.

Stevens, R.P. (2011). Maximizing lead generation: the complete guide for B2B marketers. Pearson Education.

Sutton, R.S. (1992). Introduction: The challenge of reinforcement learning. In Reinforcement Learning. [Online]. Available at: https://link.springer.com/content/pdf/10.1007/BF00992695.pdf (Accessed: 07 October 2021)

Sutton, R.S. and Barto, A.G. (2018). Reinforcement learning: An introduction. MIT press.

Syam, N. and Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. Industrial marketing management, 69, pp.135-146.

Söhnchen, F. and Albers, S. (2010). Pipeline management for the acquisition of industrial projects. Industrial Marketing Management, 39(8), pp.1356-1364.

Toman, N., Adamson, B. and Gomez, C. (2017). The new sales imperative. Harvard Business Review, 95(2), pp.118-125.

Trailer, B. and Dickie, J. (2006). Understanding what your sales manager is up against. Harvard Business Review, 84(7-8), pp.48-55.

Tur, G., Celikyilmaz, A., He, X., Hakkani-Tür, D. and Deng, L. (2018). Deep learning in conversational language understanding. In Deep learning in natural language processing. Springer, Singapore.

Turing, A. (2006). Computing machinery and intelligence. Theories of Mind: An Introductory Reader.

Verbeke, W., Martens, D., Mues, C. and Baesens, B. (2011). Building comprehensible customer churn prediction models with advanced rule induction techniques. Expert systems with applications, 38(3), pp.2354-2364.

Wang, P. (2019). On defining artificial intelligence. Journal of Artificial General Intelligence, 10(2). [Online]. Available at: http://crowley-coutaz.fr/jlc/Courses/2020/MOSIG.SIRR/Wang-OnDefiningAI.pdf (Accessed: 21 October 2021)

Yu, Y., Choi, T.M. and Hui, C.L. (2011). An intelligent fast sales forecasting model for fashion products. Expert Systems with Applications, 38(6), pp.7373-7379.

Zhu, X. and Goldberg, A.B. (2009). Introduction to semi-supervised learning. Synthesis lectures on artificial intelligence and machine learning.