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Leveraging The Power Of Deep Tech Within The Realm Of Digital Marketing: An Explorative Insight Into The Relationship Between Artificial Intelligence And Sports Fan Engagement

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"A year spent in Artificial Intelligence

is enough to make one believe in God"

- Alan Perlis

To my mum, my dad, my sister.

You are my everything, the one thing I could not live without.

To Zoe and Bocio, you kept a light on when darkness was all-consuming.

To Simona, hoping we will reach out once again.

To all my friends who stood by me when I needed you.

This is for you.

I love you.

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Abstract

The digital revolution has long been between us, and it has firmly established itself as the primary driving force of everything that deals with commerce, including marketing. It is now impossible to find a company, regardless of the sector it operates in, that refrains itself from employing digital marketing to reach its customers; sport is no stranger to this.

The ever-increasing pervasiveness of digitalization has radically transformed fans' experience, allowing them to feel more immersed inside both the game on-pitch and everything in between. Deep Tech is poised to disrupt this even more, deploying tools such as blockchain technology or Artificial Intelligence that carry unprecedented potential. Namely, the potential of AI is so strong that, paired with its estimated market size set to reach jaw-dropping levels, it forebodes a complete and total revolution of the sports marketing world.

Whether they like it or not, sports managers and marketers must consider this and adapt accordingly, thus riding the wave of the digital revolution rather than being submerged by it.

This thesis will delve into the matter, exploring the disruptive channels whereby AI can engage fans and sports together. A survey is conducted among sports consumers to gather data on (the perceived usefulness of) AI-powered technologies and fan engagement. The data are subsequently analyzed with SmartPLS 4. Recommendations for sports headmasters are then derived, together with future research directions to enrich this field of study.

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I. Introduction

1.1 Contextualization

Sports encompass more than mere physical activity or entertainment; they foster a sense of togetherness, create a community, and cultivate passionate and devoted fan bases. The energy of the crowd at live games and the exhilaration of a thrilling comeback are integral to the triumph of any sports organization. Fan engagement plays a pivotal role in driving attendance, merchandise sales, and media coverage, while it also establishes a robust and unwavering support network for the team in the long run.

In our digital era, fan engagement has become more vital than ever, given that fans have unprecedented access to information and content about their beloved teams and players. Social media, online forums, and other digital platforms have facilitated enhanced connections between fans and their favorite athletes and organizations, compelling sports entities to invest in novel technologies and strategies that promote fan engagement. Hence why it is crucial to understand the role of artificial intelligence in this: set to be the next digital revolution, it boasts a mammoth potential to turn the world of sports upside down, especially in terms of fan engagement. Even though it is still in an embryonal state, the rate at which it is being developed is astounding, almost exponential to a certain degree. The world of AI is in constant evolution, with such technologies being continuously refined and made better.

Why all this fuss about AI, though? It has to do with personalization. AI technology is known for its ability to automate tasks and continuously learn from data, making it an essential tool for data-focused analytics and decision-making. Its automation capabilities extend to various activities related to information collection, storage, management, and retrieval, which can help in developing and managing business offerings.

Therefore, AI looks like just what the sports world needs. As a consequence of the massive wave of information and technology that has redefined every industry, and sports was no stranger to this, consumer attention has been severely fragmented, which in turn caused audiences for television to dwindle perilously and also put the monetization of sports' appeal on the line.

Such a revolution has forced teams and managers to stop considering sports fans as just fans, rather as customers with various choices and preferences who can also vote with their attention. Consequently, to interact with them as customers, sports organizations should not treat all fans as a single entity but rather as a collection of diverse consumer segments with similar but distinct needs.

Since one of AI's biggest strengths is its focus on personalization, coupling it with fan engagement seems just like a match made in heaven that could yield numerous benefits.

1.2 Research Objectives

The literature on fan engagement is currently missing an investigation of AI technologies and how they could impact fan engagement. Considering that, albeit being in their early stages as we stated before, AI solutions are being studied and, in some cases, already applied to the sports world, this research wants to gain at least a rural understanding of this relationship. More specifically, this study will investigate if and how AI-powered chatbots, sentiment analysis, and virtual assistants influence fan engagement, considered in this research as transactional behavior. These specific technologies were considered as they are the most developed ones and those that could bear the greatest degree of relevance since they focus mainly on personalization.

To achieve this, quantitative research was the best-fitting model. A survey was used as the research method, with respondents asked to fill in a questionnaire with different questions that dealt with the theme of the study.

1.3 Thesis Structure

The second chapter of the thesis comprises a literature review of both artificial intelligence and fan engagement. The former is discussed in terms of its development, classification, and application to marketing. The latter, on the other hand, is discussed after having presented the broader picture, with a brief discussion on the notion of engagement and customer engagement.

The third chapter deals with hypothesis development. The research gap is identified, and the hypotheses are formulated, all of them justified by the literature. Additionally, the hypothesized research model is presented graphically.

The fourth chapter is the densest one, as it comprises a description of the methodology used to carry out the research and collect data. The structure of the survey is presented, together with a table that includes the constructs of the questionnaire, their respective items, and the source from which the scales were derived.

In the fifth chapter, the empirical findings from the analysis of the questionnaire on the Qualtrics software are presented, with validation of both the measurement model and the structural model.

The sixth chapter presents a discussion of the results obtained, where each hypothesis is analyzed in light of both the literature on the theme and the actual, real-world scenario that pertains to each one. Moreover, managerial implications are provided as a result of the aforementioned analysis.

Lastly, the seventh chapter discusses the various limitations of the study, providing a framework within which to position this study. Lastly, the eighth chapter entails the conclusion of the study.

II. Literature Review

2.1 A New Intelligence

"*I believe that at the end of the century, the use of words and general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted."* (Alan Turing, 1947).

Such were the words uttered by the English mathematician Alan Turing, best known for his work on *The Bombe*, a code breaking machine that he developed for the British government with the aim of deciphering the Enigma code that the German army wielded during the Second World War. It is generally considered as the very first working electro-mechanical computer, and it went down in history as the offspring of what we now call "Artificial Intelligence." Indeed, how *The Bombe* managed to decipher the Enigma code, something that was deemed impossible even to the best mathematicians, planted the seed of doubt in Turing's mind: is it feasible to talk about machine intelligence?

Fast forward to 1950, his seminal article "Computing Machinery and Intelligence" illustrated how to build intelligent machines and particularly how to assess their intelligence. The Turing test is still to this day widely accepted as the touchpoint to pinpoint the intelligence of an artificial system: posing the condition that a human is interacting both with another human and a machine, and he is not capable of telling the difference from human to machine, that machine is then identified as intelligent.

Nonetheless, it was not until 1955 that the word "Artificial Intelligence" was officially coined. Dartmouth College, New Hampshire: a small group of scientists reunited for the *Dartmouth Summer Research Project on Artificial Intelligence*, which can be considered the birth of this field of research. John McCarthy, then a mathematics professor at the College, organized the initial meeting: as he stated in his proposal, the bedrock of the conference was that "*every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it*"(McCarthy et al., 1955, p.1).

Before delving into the chronological evolution of AI, one must first understand what artificial intelligence is. The plethora of articles about AI makes it difficult to give one single, straightforward definition, partly due to the tedious task of defining intelligence itself, and partly due to the fast, ever-changing field of artificial intelligence which may lead to certain intelligent behavior exhibited by machines as little as 5 years ago, to become quickly obsolete and barely significant (Kaplan and Haenlein, 2019).

A way commonly used to describe AI is through reference to human intelligence, which can be defined as the "biopsychological potential to process information and solve problems or create valuable products in a culture" (Gardner, 1999, pp. 33-34). In 1955, the founding fathers of AI in the Dartmouth Research Project defined it as "the science of making a machine behave in ways that would be considered intelligent if a human were to exhibit the same behavior" (McCarthy et al., 1955). Similarly, Marvin Minsky, a cognitive scientist and one of the pioneers of artificial intelligence, defined AI as "the science of making machines perform tasks that would require intelligence if performed by a human being" (Minsky, 1968).

Among the smorgasbord of definitions, I decided to use the one coined by the High-Level Expert Group on Artificial Intelligence (HLEG 2019), an independent expert group that was first set up by the European Commission in June 2018. As a testimony to the soundness of the definition, it has also been adopted by AI Watch, which deals with the monitoring of AI's development, uptake, and impact in Europe (Samoili, Lopez Cobo, et al. 2020). It reads as follows:

"*Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behavior by analyzing how the environment is affected by their previous actions.*

As a scientific discipline, AI includes several approaches and techniques, such as machine learning (of which deep learning and reinforcement learning are specific examples), machine reasoning (which includes planning, scheduling, knowledge representation,

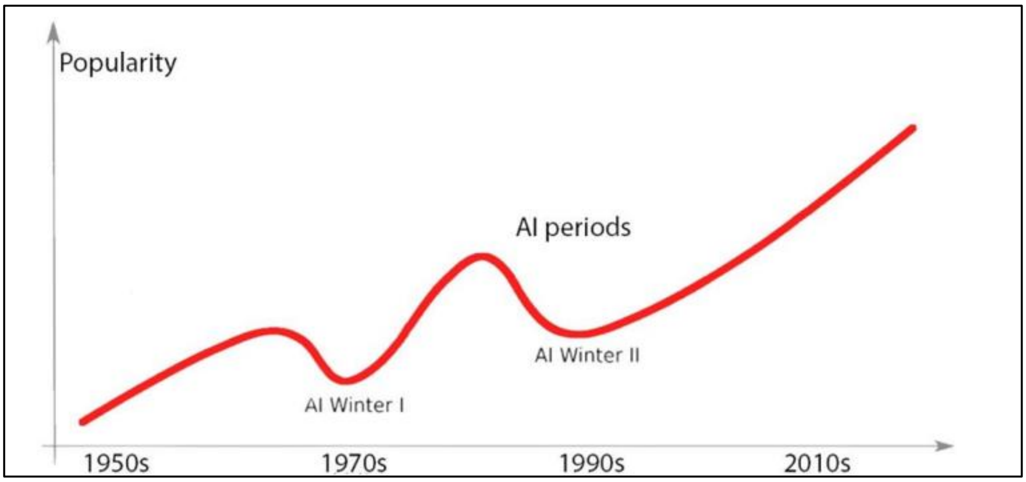
reasoning, search, and optimization), and robotics (which includes control, perception, sensors, and actuators, as well as the integration of all other techniques into cyber-physical systems)."
(HLEG, 2019)

The main objective of AI is to develop machines that can emulate human thought processes and behaviors, such as reasoning, learning, planning, predicting, and perceiving (Xu et al., 2021). Intelligence is a crucial attribute that sets humans apart from animals, and an intelligent machine strives to replicate this trait. An astounding plethora of scientists are focusing on the field of AI, and this brings about a plentiful and diverse environment of research within the field. Among the major research fields, a few stand out as the most prominent and high-potential: the likes of natural language processing, machine learning (ML), and deep learning (DL) are the AI-stemmed technologies that are raising the highest interest among scientists and businesspeople likewise.

2.2 The Seasons Of AI

The development of AI has been a rollercoaster ride with three distinct periods – seasons, where winters represent decline while springs represent growth. If we were to try and pinpoint the different stages of AI development, we would opt for a three-stage pathway. The first one, which lasted from the 1950s to the 1970s, was characterized by the inception of most of the AI algorithms. Then, from the 1970s until the 1990s, there was a second AI period which saw a paradigm shift in symbolic algorithms and the creation of expert systems, also known as knowledge-based systems. Lastly, the third period lasting from the 1990s onwards has been marked by the development of machine learning, which then led to the birth of deep learning in the 2010s (Delipetrev et al., 2020).
In this regard, **Figure 1** clearly displays the up-and-down path of AI.

Figure 1: AI periods.



Source: JRC.

During the first period, there was a great deal of excitement surrounding the fact that computers were now able to solve problems in a manner that resembled human thinking for the first time, thus giving an impression of intelligence. This initial optimism was shared by the broader AI research community, which made bold claims and helped to increase the popularity of the field (Delipetrev et al., 2020). Among the major AI breakthroughs of the period were the perceptron, the embryo of an electronic computer that gave birth to connectionism, the foundation of Neural Networks (NN), and Deep Learning (Rosenblatt, 1961). Another paramount invention of the period was ELIZA, a natural language processing system that imitated a doctor. Users believed that they were dialoguing with a human being until it reached its limitations, turning the dialogue into nonsense (Weizenenbaum, 1966).
Governments started investing massively in AI, fascinated by the optimism of the leading scientists: in 1970, Marvin Minsky released an interview stating that there were strong possibilities of developing a machine, within three to eight years, with the general intelligence of an average human being.
Nonetheless, unfulfilled promises, enormous expectations, and financial complications caused AI to go through its first winter in the 1970s. Technological advancements faced significant obstacles as AI encountered limitations in computing power, processing speed, and memory that seemed impossible to overcome (Delipetrev et al., 2020). Fundings decreased rapidly and the research on AI came to a halt.

Come 1980s, the approach to AI shifted towards symbolic AI, which led to the development of expert systems, also known as knowledge-based systems. The main objective of these systems was to convert human expertise into computer programs that could be installed on personal computers (Delipetrev et al., 2020).
Expert systems consisted of two core components: the knowledge base, which was a collection of rules, facts, and relationships that pertained to a specific domain, and the inference engine, which was responsible for manipulating and combining these symbols. The facts and rules were clearly represented and could be modified as required, with Lisp and Prolog being the primary symbolic programming languages used for developing expert systems (Delipetrev et al., 2020).
However, the expert system started to unveil several disadvantages, such as privacy technologies, lack of flexibility, and poor versatility (Xu et al., 2021). On top of that, knowledge acquisition was getting extremely problematic: namely, it was challenging to acquire the time and expertise of domain experts due to the constant demand by their respective organizations (Delipetrev et al., 2020). Eventually, funds dried up again.

Between the 1990s and 2010s, AI made significant strides in solving complex problems across various application domains such as data mining, industrial robotics, logistics, business intelligence, and so on.
AI researchers used advanced mathematical tools, realizing that many AI problems had already been tackled by researchers in other fields: such a shared mathematical language facilitated a higher level of collaboration and turned AI into a more rigorous scientific discipline.
Still, to secure funding, many AI researchers in the 1990s adopted alternative names for their work, for the failed promises continued to cast a shadow on AI research in the commercial world (Delipetrev et al., 2020).
The paradigm shift took place in 2006: Fei-Fei Li, a computer science professor at Stanford University, posited that AI's main limitation was the data quantity that failed to reflect real-world scenarios. Indeed, she stated that more data would produce better models (Delipetrev et al., 2020).
Meanwhile, in 2009, a dataset called ImageNet was published, which contained over three million labeled images, categorized into 5,427 different classes, and grouped into 12 subtrees such as "vehicle", "mammal" and "furniture" (Deng et al. 2009).

Over the past decade, the annual ImageNet Large Scale Visual Recognition Challenge (ILSVRC) has witnessed considerable progress. Initially, the average classification error rate was about 25% in 2011; even so, in 2012, a deep convolutional network called AlexNet achieved a remarkable 16% classification error rate (Krizhevski et al. 2012). With further advancements, error rates dropped to just a few percent. These breakthroughs led to the AI paradigm shift to deep learning (Delipetrev et al., 2020). Deep Learning (DL) is a subset of Machine Learning (ML) and Artificial Intelligence (AI) that rests upon the idea of leveraging multi-layer neural network architecture that can learn data representations with varying degrees of abstraction, as proposed by LeCun et al. (2015). Some of the commonly used DL neural networks are deep neural networks, deep belief networks, and convolutional neural networks (CNN).

In terms of funding, private companies are primary investors in the current AI period (Delipetrev et al., 2020): Google hired Geoffrey Hinton, Facebook hired Yann LeCun, and Microsoft invested $10 billion in OpenAI[1].

Likewise, many Chinese companies have revealed their strategic plans in AI with significant investment proposals. In addition, the State Council of China has laid out an ambitious three-stage plan to accomplish the country's objective in AI, as outlined by Ding (2018), whereby it aims to turn China into the "world's primary AI innovation center" by 2030.

The EU Member States, in collaboration with the European Commission (EC), have allocated significant funds towards AI investment. The EC has proposed to dedicate a minimum of €1 billion annually from Horizon Europe and the Digital Europe Program towards AI under the next multiannual financial framework (Delipetrev et al., 2020). However, in comparison to other parts of the world, the level of AI investments in the EU is low and fragmented.

One of AI Watch's initial reports focused on analyzing the global landscape of AI players from 2009 to 2018. The study identified 34,000 players worldwide, with the US having the highest number of players due to its strong industrial ecosystem, where 96% of US players are firms (Samoili, Righi et al., 2020). Along with the US, the EU and China are among the geographical areas with the highest number of active AI players, with the US

[1] https://www.bloomberg.com/news/articles/2023-01-23/microsoft-makes-multibillion-dollar-investment-in-openai

specializing in AI services and robotics and automation, while China leads in patent applications, particularly in computer vision, machine learning, and connected vehicles. (Delipetrev et al., 2020). The EU boasts a robust research network and ranks second in the number of research institutions active in AI worldwide and first in the number of research institutions in AI publications (Delipetrev et al., 2020): its main areas of specialization are robotics and automation and AI service.

2.3 AI Classification

When trying to categorize distinct types of AI, particularly in a business context, it can be helpful to refer to management literature and studies that have identified the skills and traits that successful managers and high-performing employees possess. Researchers such as Boyatzis (2008), Hopkins and Bilimoria (2008), Luthans et al. (1988), McClelland and Boyatzis (1982), and Stubbs Koman and Wolff (2008) have generally agreed that exceptional performance is strongly linked to three types of competencies: cognitive intelligence (e.g. skills related to pattern recognition and analytical thinking), emotional intelligence (e.g. adaptability, self-confidence, emotional self-awareness, and achievement orientation), and social intelligence (e.g. empathy, teamwork, and inspirational leadership).

Clarifying the use of cognitive intelligence for AI classification is straightforward, but explaining the applicability of emotional and social intelligence requires more detail. As Kaplan and Haenlein (2019) state in their paper, intelligence is generally deemed to be innate; in other words, something that individuals are born with instead of something that can be learned.

On the other hand, social and emotional intelligence is related to a specific set of skills that individuals can learn and that AI systems can imitate. Although AI systems and machines lack the ability to experience emotions themselves, they can undergo training to identify and discern emotions (for instance, by analyzing facial micro-expressions) and subsequently adjust their responses accordingly.

Before discussing AI systems, it is crucial to differentiate between **real AI** and **expert systems**. The latter, which can be considered as sets of guidelines written by humans in the format of if-then statements (Kaplan and Haenlein, 2019), do not belong strictly to AI since they do not possess the ability to learn from external data by themselves. In fact, they are an entirely different approach altogether. When attempting to formalize human intelligence through rules and a top-down approach, these systems often struggle with tasks that require complex, implicit forms of human intelligence, which cannot be easily transferred (Kaplan and Haenlein, 2019).

Real AI, instead, uses a bottom-up approach that mirrors the brain’s structure (neural networks) and employs such data to derive knowledge independently (Kaplan and Haenlein, 2019). Think of it like a child who learns to recognize faces: they don't do it by following rules that their parents have taught them, but rather by seeing hundreds of thousands of faces and eventually being able to distinguish between a face and a broom (Kaplan and Haenlein, 2019).

Drawing upon these characteristics, AI systems can be classified into three groups (Kaplan and Haenlein, 2019):

1) **Analytical AI**. In terms of intelligence, it is only consistent with the cognitive one. These AI systems create a mental model of the world and employ machine learning to make informed decisions based on past experiences. Within the workplace, they are commonly used for various purposes such as enabling self-driving cars to navigate safely or detecting fraudulent activities.
2) **Human-Inspired AI**. They draw elements from both cognitive and emotional intelligence. Indeed, in addition to cognitive elements, these systems can understand human emotions and consider them in their decision-making. Companies can use such systems to recognize emotions during customer interactions or while recruiting new employees. Real-life example: Affectiva, an AI company founded by MIT, uses advanced vision systems to recognize emotions like joy, surprise, and anger at the same level as humans.
3) **Humanized AI**. They possess all types of intelligence. At present, there are no systems that display self-consciousness and self-awareness in their interactions with others. Although significant progress has been made in recognizing and imitating human activities, this type of AI represents a project that may still take a while to achieve.

As we stated before, a pivotal element of AI systems is the ability to learn from data. In supervised learning, a given set of inputs for a given set of (labeled) outputs is mapped. It is usually the least scary method for managers since it includes methods many ought

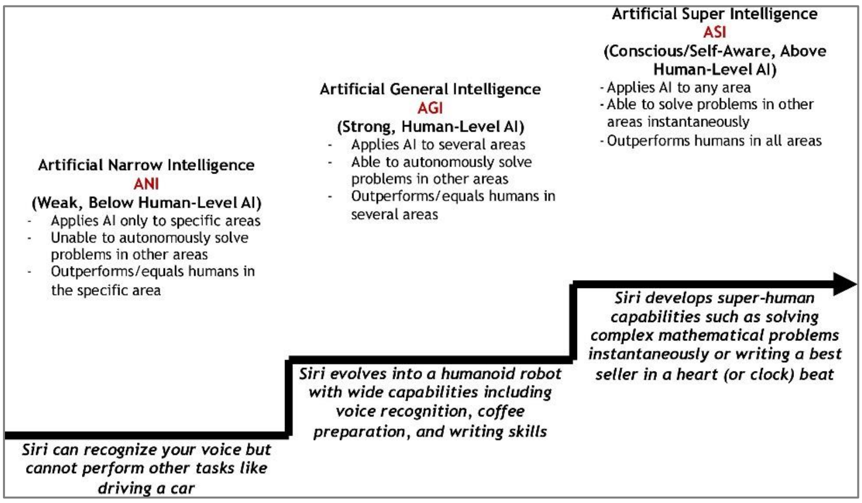
to be familiar with (linear regression, classification trees).
An example would be using a large database of labeled images to differentiate between those picturing a Chihuahua and those showing a muffin (Kaplan and Haenlein, 2019).

Regarding unsupervised learning, instead, inputs are labeled but not the outputs: this means that the underlying structure needs to be inferred from the data by the algorithm itself (Kaplan and Haenlein, 2019).
As the output is generated by the algorithm, it becomes difficult to ascertain the accuracy or correctness of the resulting output. This demands users to rely heavily on the AI system, which can quickly cause unease among managers. Amazon's Alexa or Apple's Siri run on speech recognition, which can be conducted with unsupervised learning.

Last but not least, reinforcement learning is characterized by the maximization of an output variable received by the system, together with a set of decisions that can be taken to influence the output (Kaplan and Haenlein, 2019). It is like an AI system learning to play Pac-Man, only by knowing which directions Pac-Man can move in and that the goal is to maximize the score of the game. Microsoft employs this learning process to pick headlines on MSN.com by rewarding the higher-scoring system when there are more clicks on a given link.

Artificial intelligence can also be classified into three distinct stages: looking at **Figure 2** is helpful to get a better grasp of what type of route AI is moving along.

Figure 2: Three stages of AI.



Source: Kaplan and Haenlein (2019)

Most of the AI systems we have today fall under the category of Artificial Narrow Intelligence (ANI), also known as "Weak" AI. These systems are designed to perform specific tasks within a defined environment (Delipetrev et al., 2020). ANI can process data at lightning-fast speed and boost productivity and efficiency in various practical applications: indeed, they can translate over 100 languages simultaneously or even identify faces and objects in billions of images. At the same time, ANI is capable of performing repetitive and mundane tasks that humans may prefer to avoid. Siri, Alexa, and image recognition systems are a clear example of this: they are systems designed to perform a specific task or a few tasks within a predefined environment.

On the other hand, Artificial General Intelligence (AGI), also known as "Strong" AI, refers to the development of machines that possess human-like intelligence. The goal of AGI is to enable machines to perform any intellectual task that a human can, such as reasoning, learning, and problem-solving (Delipetrev et al., 2020). Although both Kaplan and Haenlein (2019) and Delipetrev et al. (2020) discussed seeing this technology in the distant future, AGI is already here: the recent release of the generative pre-trained transformer (GPT) has taken all of the attention in the field of artificial intelligence into AGI (Peng et al., 2023). Differently from AI whose generality lies in data generalization, AGI's generality focuses on task generalization. In other words, AGI should possess the ability to acclimate and respond effectively in a constantly changing environment, where it may encounter an endless array of unforeseen circumstances (Peng et al., 2023). However, it is still rusty and needs refinement: AGI systems should target features the likes of **infinite tasks** since it should mirror human intelligence which is not limited to a specific number of tasks (Peng et al., 2023), or **self-driven task generation**, where it shows the capability to determine its next course of action and generate tasks on its own without requiring constant guidance or detailed instructions from a human operator (Peng et al., 2023). When it does, it will become impossible to tell it apart from human intelligence in any given situation.

Last but not least, Artificial Superintelligence (ASI). Bostrom (2014) considered it is any form of intelligence that surpasses human cognitive abilities in nearly all areas of interest. It is believed that ASI will outperform human intelligence in every possible way, including general wisdom, problem-solving, and inventiveness (Delipetrev et al., 2020). The potential is so big that it is expected to exhibit a level of intelligence we would not fathom: hence why it is deemed as the true artificial intelligence (Kaplan and Haenlein, 2019). As worrisome as it sounds, for now, it only belongs to science fiction.

2.4 Revolutionizing Marketing: The Power Of AI

Research on Intelligent Systems and Artificial Intelligence (AI) in marketing has been growing lately, revealing that AI can effectively imitate human behavior and carry out tasks intelligently.
From a strategic standpoint, AI is playing an increasingly crucial role in marketing (Vlačić et al., 2021). Marketing's core activities – making sense of customer needs, matching them with the right products and services, and winning them over by talking them into buying such products – can all be dramatically enhanced by AI (Davenport et al., 2021). It does not come as a surprise that, according to a McKinsey analysis in 2018, AI's greatest value contribution was predicted to be in the marketing domain, with over 400 advanced use cases analyzed.
Moreover, there is an increasing number of chief marketing officers embracing the technology: as specified by a survey conducted by the American Marketing Association in August 2019, the adoption rate of AI had increased by 27% in the previous 18 months. Furthermore, a global survey by Deloitte in 2020 revealed that three out of five objectives of early AI adopters were related to marketing: namely, improving existing products and services, developing new products and services, and strengthening customer relationships.
A growing number of companies, including Google, Rare Carat, Spotify, and Under Armor, are leveraging AI-based platforms, such as Microsoft Cognitive Services, Amazon Lex, Google Assistant, and IBM Watson (Vlačić et al., 2021). This approach enables them to improve their customer interaction across marketing channels and enhance market forecasting and automation (Vlačić et al., 2021). As a consequence, AI has been identified as the leading technology for business, with an estimated contribution of $15.7 trillion to the global economy in 2030. The latest McKinsey Global Survey also confirmed the explosive growth of AI, especially in terms of generative AI (gen AI) tools. Generative AI, an incredibly powerful technology that has been popularized by ChatGPT, can be defined as "*a technology that leverages deep learning models to generate human-like content (e.g. images, words) in response to complex and varied prompts (e.g. languages, instructions, questions)*" (Lim et al., 2023, p.2).

The findings from the McKinsey survey show that respondents are already experimenting with the nascent tools, and also expect these new capabilities to overhaul their industries. Selecting by industry, respondents working in the **technology, media, and telecom** industry are by far those that use it the most: a staggering 14% of respondents regularly use generative AI tools for work, almost double the respondents of the closest "competitor", namely financial services.

In order to present all the different ways and contexts AI is being applied, I will refer to the analysis carried out by Vlačić et al., (2021). Therein, four major research themes are presented, as identified conforming to the technological progress of AI in marketing.

2.4.1 Marketing Channels

The first theme focuses on marketing channels, which serve as a vital link between producers and consumers, closing the gap in the buyer-seller exchange, as stated by Vlačić et al. (2021). There is a significant amount of literature on marketing channels that recognizes the potential for AI technologies and applications, such as robots, voice assistance devices, and more, to bring about endless possibilities for improvement in this area (Bock et al., 2020; Wirtz, 2018).

AI's remarkable capacity to collect and comprehend vast amounts of data accurately, derive insights, and utilize them intelligently (Kaplan and Haenlein, 2019) is reliant on various technological enablers, such as machine learning, deep learning, and neural networks.

It does not come as a surprise, then, that numerous retailers, including Amazon and North Face among others, have already integrated the latest AI-based innovations into their operations, such as social media and retail analytics tools like Pepper Robot, Conversica Sales Agent, and IBM Watson Cognitive Computing (Angus & Westbrook, 2019; Sjodin et al., 2018). These investments are driven by the belief that understanding customer demographics and psychographics will help marketers to create better customer profiles and anticipate customer choices, especially when it comes to the purchase and distribution of goods (Vlačić et al., 2021).

AI solutions are also being recognized as additional and, to a certain degree, alternative marketing assistants when it comes to comprehending customers (Wirth, 2018).

Indeed, the availability and open access to toolboxes like TensorFlow, which allows Data Scientists to leverage extremely powerful but also easy-to-use algorithms, means

that costly on-premise technology can be foregone since such cloud services can be easily scaled up (Wirth, 2018). Therefore, AI can be used to replace human expertise due to both the scale and speed at which decisions are made, something that would cause a human to feel lost, at best (Wirth, 2018).
De et al. (2020) contributed to highlighting the additional opportunities offered by AI for conversational commerce, especially for millennials, as chatbots are extremely suitable to meet their online interaction preferences. The findings also indicate that engaging in a social-focused dialogue can increase the perception that the interactant is a social creature; moreover, trust and perceived enjoyment both emerge as outcomes of social presence and catalysts for attitude toward the chatbot. This compliments Hassanein and Head (2005), whose research found that perceived enjoyment and trust towards the chatbot notably foretell a positive attitude towards the chatbots.

Modern big data analytics empower companies to track consumer behavior with a high degree of accuracy over a prolonged period (Schiessl et al., 2022). In fact, AI tools can even simulate traditional netnographic[2] methods as bots are now widely used to interact with customers in various online services. Specifically, chatbots presents the same level of effectiveness as proficient workers and a fourfold effectiveness compared to inexperienced workers to engender customer purchases (Luo et al., 2019).
Findings from Volkmar et al. (2022) also confirm AI's and ML's capabilities of increasing customer experience. They facilitate customer needs, allowing companies to address them rapidly and in a more tailor-suited way.
At the same time, however, firms ought to be aware of the tradeoff that exists between operational efficiency (inward perspective) and enhanced customer experience (outward perspective): taking chatbots as an example, they should not be considered solely as a way to reduce employees' workload. Rather, they have the potential to (1) enhance the customer experience by providing a unique communication channel and (2) improve critical in-person interactions by allowing employees to devote more time to such engagements. (Volkmar et al., 2022).
AI's contribution, in terms of marketing channels, extends to value chains. As explained by Porter (1985) in his book "Competitive Advantage: Creating And Sustaining Superior

[2] A research method that studies online communities' behavior and activities. It represents an innovative approach to ethnography, involving the systematic observation, analysis, and interpretation of online data.

Performance", a value chain represents the interrelated operating activities businesses perform during the process of converting raw materials into finished products. In the present dynamic environment, it is imperative to configure, reconfigure, shorten, simplify, and frequently adapt value chains (van Esch and Stewart Black, 2021). More often than not, this needs to happen quickly and accurately, across multiple countries and languages. Completing this task manually is a time-consuming process that leaves room for human errors. Nonetheless, with the help of AI-powered find-and-replace technology, changes and updates can be made instantaneously across all design files. By recognizing and ensuring that all content pieces are up to date, the risk of human error can be minimized.

In terms of the framework for strategic market planning, Huang and Rust (2020) propose incorporating multiple artificial intelligences to foster promotion, that can be considered as the set of marketing communications that consumers and marketers engage in (Huang and Rust, 2020).

Mechanical AI, designed for automating repetitive and routine tasks (Huang and Rust, 2018; Huang et al., 2019) can help marketers in the labor-intensive, high-time-pressure process, by robotizing promotional media planning and executions.

Thinking AI is created to analyze data and generate new conclusions or decisions, normally processing data that are unstructured (Huang and Rust, 2020). Its potential in content personalization is immense: one such example is the use of AI content writers to generate ads or post content. Recently, IBM Watson was used to create the script for the Lexus car commercial titled "Driven By Intuition."

At the last, Feeling AI has been developed to interact with humans and analyze human emotions and feelings. (Huang and Rust, 2020). Some of the current technologies used for this include sentiment analysis, natural language processing, text-to-speech technology, recurrent neural networks, or chatbots designed to mimic human speech (McDuff and Czerwinski, 2018). It can be used to track customer response to promotional messages to detect emotions such as liking, disliking, amusement, etc. This information can be used to adjust the content and delivery of promotional messages to better engage customers and provide a more satisfying interaction experience.

According to studies by Hartmann et al. (2019) and Lee et al. (2018), more accurate and real-time emotion sensing from posted messages can significantly improve customer engagement.

2.4.2 Performance

Scholarly literature on the intersection of AI and marketing explores its performance through two distinct perspectives. The first perspective compares the performance of AI tools and techniques with conventional methods, particularly in terms of accuracy and cost (Vlačić et al., 2021). AI, aided by its technological enablers, performs better in making predictions due to its ability to handle complex and nonlinear relationships between inputs and outputs (Syam and Sharma, 2018).

Additionally, AI's prowess in reducing human mistakes is unmatchable: it has been developed to prevent human interaction, thus eliminating the possibility of human error (Haleem et al., 2022).

Artificial Intelligence can also expedite data processing, ensuring accuracy and security while freeing up time for the team to focus on strategic goals to create effective AI-powered campaigns (Kumar et al., 2019a; Davenport et al., 2020). By gathering and tracking real-time tactical data, AI enables marketers to make informed and timely decisions, rather than waiting for campaigns to conclude. With the help of data-driven reports, marketers can make wiser and more objective judgments about what to do next (Haleem et al., 2022).

The second perspective views performance as an outcome variable and focuses on how AI can contribute to competitive advantage, efficiency, sales prediction, and so on. Companies can leverage AI to analyze big data and extract valuable insights, which can be used to develop effective marketing and sales strategies and gain a sustainable competitive advantage (Paschen et al., 2020).

Through the implementation of AI, marketers can create and put into effect innovative marketing strategies that are more tailored to each individual, thus much more human-centered. More often than not, these techniques bring about a spike in customers' interest, turning them into ardent brand supporters (Haleem et al., 2022).

Through the use of AI-powered marketing tools, companies can enhance their sales funnel by predicting what products or services their customers may be interested in purchasing. Recent studies by Syam and Sharma (2018) and Davenport et al. (2020) have highlighted the impact of AI on a company's sales process and performance.

Additionally, accurate forecasting of future trends can be achieved with the help of AI, aided by the development of advanced tools such as the Adaptive Neuro-Fuzzy

Inference System and the Modular Genetic-Fuzzy Forecasting System (Hadavandi et al., 2011).

2.4.3 Marketing Strategy

Marketing strategy can be defined as *"an organization's integrated pattern of decisions that specify its crucial choices…. concerning marketing activities toward the creation, communication and/or delivery of a product that offers value to customers in exchanges with the organization and thereby enables the organization to achieve specific objectives*" (Varadarajan, 2010).

Intelligent systems and their continuous evolution are fundamentally modifying the future of marketing strategies (Rust, 2020). AI can be used to gather data, create predictive models, and validate them through real customer testing (Vrontis et al., 2022). The use of AI allows for the delivery of customized emails to each customer. Moreover, it's worth noting that with the help of machine-learning algorithms, businesses can detect disengaged customer groups who may be considering switching to a competitor. By analyzing a broad range of customer interactions and observing a decline in engagement, AI-powered churn prediction can provide targeted offers, push notifications, and emails to keep customers engaged and prevent them from leaving the company. When combined with personalized content creation, AI-powered churn prediction[3] can increase customer engagement, resulting in higher lifetime value and revenue. This is crucial for companies, as research has shown that it is much more favorable business-wise to retain existing customers rather than acquire new customers (Kumar et al., 2005). Reicheld et al. (1996) have also demonstrated, numerically wise, the importance of retaining existing customers: indeed, they found that the Net Present Value (NPV) of customers for a software company and an advertising agency increased by 35 percent and 95 percent respectively, when they managed to achieve a 5 percent increase in customer retention rate.

Nowadays, some of the most relevant problems concerning marketing strategy are being solved using AI solutions. According to numerous studies, the application of AI-based marketing solutions has indeed led to improvements in multiple areas: for instance, Valter et al. (2018) reported significant improvements in business model

[3] A process where companies use AI and ML models to forecast which customers are at the highest risk of ending their patronage (Ahn et al., 2020)

decisions, while Paschen (2019) noted that AI has improved communications. Furthermore, Tong et al. (2020) reported that AI-based solutions have enabled personalized mobile marketing strategies.

With regard to improvements in marketing strategies, the implementation of AI in digital advertising cannot go unnoticed. It is used across various platforms including Facebook, Google, and Instagram to provide the best possible results (Haleem et al., 2022).

At the same time, marketers can also utilize AI technology to identify microtrends and anticipate upcoming trends, enabling them to make strategic decisions (Martínez-López and Casillas, 2013). As a result, companies can reduce digital advertising waste and ensure that their investment provides the highest returns possible. By harnessing the power of IoT[4] and connected devices, AI's role in the future of digital marketing is undisputed (Haleem et al., 2022).

2.4.4 Segmentation, Targeting, and Positioning (STP)

The main focus of recent research on segmentation, targeting, and positioning (STP) has been on finding solutions to challenges faced by businesses in managing their customer base, which is in turn crucial to leverage the support of artificial intelligence (AI) to enhance STP strategies (Vlačić et al., 2021).

Huang and Rust (2020) also discussed deploying AI for the three key strategic decisions of segmentation, targeting, and positioning. Still, before making specific decisions regarding STP, marketers must first determine the overall strategic positioning that will guide these decisions. According to Huang and Rust (2017), one approach to strategic positioning is a technology-driven approach, which considers the dimensions of standardization-personalization and transaction-relationship. For example, a firm could choose a commodity strategy that utilizes automated/robotic technology for increased efficiency, a relational strategy that focuses on maximizing the lifetime value of existing customers, and a static personalization strategy that employs cross-sectional big data analytics to personalize offerings for like-minded customers, or an adaptive personalization strategy that utilizes longitudinal customer data to dynamically

[4] a paradigm where ordinary objects can be given the ability to identify, sense, connect, and process information. This enables them to communicate with each other and other devices and services via the Internet, with the goal of achieving specific objectives (Lynn et al., 2020).

personalize offerings over time. Such strategic positioning will then guide a firm's STP decisions.

Segmentation involves dividing a market into groups according to the unique needs and wants of the customers in each group (Huang and Rust, 2020). The use of mechanical AI, especially different mining and grouping techniques, excels at identifying new patterns of data. Indeed, AI segmentation offers flexibility as it can break down the market into individual segments, where each customer becomes a segment, and also merge scattered long tails into one segment.

The process of targeting involves selecting the appropriate segment (s) to focus the firm's marketing efforts on. While market segmentation can be done automatically by AI based on relevant data, choosing the right segment instead calls for a sound combination of judgment, knowledge, and intuition in a specific domain (Huang and Rust, 2020).

Recommendation engines and predictive modeling are representative AI tools used to suggest potential targets and aid marketing managers in making final decisions (Huang and Rust, 2020).

Existing studies show that various thinking AI can be used for this purpose, such as Simester et al. (2020)'s study on the optimization of promotion targeting new customers using various machine learning methods, or Neumann et al. (2019) research on profiling digital consumers for targeting online browsing data.

Last but not least, we have positioning: as defined by Ries and Trout (1969), it is "a strategy for 'staking out turf' or 'filling a slot' in the mind of target customers" (Ries and Trout, 1969). To put it simply, the objective of positioning is to connect the characteristics of a product with the advantages it offers to customers by determining a favorable and competitive position for the product in the minds of customers (Huang and Rust, 2020). This term is closely related to brand and advertising positioning, focusing on customer perceptions and communications to maintain a positive image.

Daabes and Kharbat (2017) showed how data mining can be used to create a customer-based perceptual map, replacing traditional marketer knowledge with customer perceptions.

In comparison to mechanical segmentation and thinking-based targeting, positioning aims to connect with customers on an emotional level, often through a positioning statement or a slogan in promotional communication (Huang and Rust, 2020).

Some successful positioning statements allow brands to establish a unique position in customers' minds and achieve long-term success in the market (Huang and Rust, 2020): the likes of Nike's "Just Do it", Apple computer's "Be Different", and McDonald's "I'm loving it" are extremely proficient in resonating with customers on an emotional level, thus sticking in customers' minds, even if unconsciously. Feeling AI, such as feeling analytics, can be valuable in making this strategic decision by understanding what emotionally resonates with the target customers.

2.5 The Concept Of Engagement

The concept of engagement has been defined in several ways by different authors and disciplines, using terms such as "interaction," "participation," "co-creation," and "long-term relationships" to describe it (Kumar et al., 2010; Patterson et al., 2006). In marketing, the focus has been on actor engagement (Brodie et al., 2019), which refers to the interplay between levels of aggregation (micro, meso, and macro levels). This means that businesses have relationships with other businesses, entrepreneurs interact with other entrepreneurs, and at the lowest level, employees collaborate across businesses.

In this section, we will provide a literature review on the concept of customer engagement. Then, we will discuss the difference between fan engagement and customer engagement, as well as related constructs. Additionally, we will differentiate between non-transactional and transactional forms of fan engagement.

2.5.1 Customer Engagement

Academics in the field of marketing, including Bowden (2009), van Doorn (2010), Kumar et al. (2010), and Brodie et al. (2011), started to focus on the concept of engagement in the early 2000s. Particularly, the term 'customer engagement' gained momentum around 2005.

Until now, the study of customer engagement has been approached from four main angles: (i) as a behavioral phenomenon, following the research conducted by van Doorn et al. (2010), (ii) as a psychological state, according to Brodie et al. (2011), (iii) as a predisposition to act, as explained by Storbacka et al. (2016), and (iv) as a multistage process within the customer decision-making journey, as explored by Maslowska et al. (2016).

Customer engagement behaviors (CEB) is how literature tends to identify behavioral manifestations. According to van Doorn et al. (2010), CEB is defined as behaviors that "*go beyond transactions and may be specifically defined as a customer's behavioural manifestations that have a brand or firm focus, beyond purchase, resulting from motivational drivers*" (p.254).

While Kumar et al. (2010) argue that CE should include transactional behaviours, most scholars (Verhoef et al., 2010; Bijmolt et al., 2010, Jaakkola and Alexander, 2014; Verleye et al., 2014) concur with van Doorn et al. (2010) and the Marketing Science Institute (Marketing Science Institute 2010) that customer engagement only involves behaviour that extends beyond transactions, and thus beyond the purchase. Since behaviours can be easily observed and measured, this conceptualization is often utilized by industry practitioners in measuring CE, for example, as customer activities such as online word of mouth, customer reviews, peer-to-peer information sharing, and customer-initiated activities with firms (Bolton, 2011).

On the other hand, when CE is referred to as a psychological state, it describes a complex concept that includes the involvement of behaviors, thoughts, and emotions. According to the definition given by Brodie et al. (2011), customer engagement can be considered as a psychological state that arises from interactive and collaborative experiences between customers and a brand or service provider within a service relationship. However, the authors acknowledge that CE does not follow a linear or sequential process over time. Instead, it is influenced by the context, allowing the three dimensions of engagement to occur in different sequences. For example, a customer may first become emotionally engaged through movie advertisements or conversations with friends, before seeking more information online (involving emotional, behavioral, and cognitive engagement). This perspective of customer engagement also considers situations where customers may engage without conscious effort or intention, either cognitively or emotionally, before displaying proactive behaviors.

Thirdly, an engagement disposition is an internal state that reflects an inclination or readiness to participate (Storbacka et al., 2016; Fehrer et al., 2018). This disposition naturally leads to observable actions, indicating engagement through various behavioral expressions. Indeed, Storbacka et al. (2016) deem actor engagement as referring to both the willingness of individuals to participate and the actual process of interacting and integrating resources within the institutional framework provided by a service ecosystem.

Lastly, other researchers have acknowledged that engagement in modeling consumer behaviors or decision-making is not a singular concept or stage. In addition to cognitive, emotional, and behavioral dimensions recognized earlier, some researchers view engagement as a multi-stage process in customer decision-making. This approach encompasses various interactions and experiences, such as those with a brand or firm, rather than confining engagement to only one specific stage. Examples of such studies include Maslowska et al. (2016) and Verleye et al. (2014).

2.5.2 Customer Engagement In The Sports Context: Fan Engagement

Several research studies in the field of sports marketing have investigated the concept of fan engagement and its various elements and outcomes. In their groundbreaking study on fan engagement, Yoshida et al. (2014) defined it as a unique type of (nontransactional) customer engagement in the context of sports, focusing on fan commitment and its influence on a team. To evaluate the credibility of this concept, Yoshida et al. (2014) conducted a test to determine the theoretical validity of the construct based on sports consumption behavior.
First, the test investigated the impact of antecedents such as team identification, positive affect, and basking in reflected glory (BIRGing) on three fan engagement characteristics: management cooperation, prosocial behavior, and performance tolerance. Team identification refers to the perceived bond fans have with a team, and it is derived from the cognitive dimension of fan engagement (Ashforth & Mael, 1989; Gwinner & Swanson, 2003). Positive affect, on the other hand, is an antecedent from the affective dimension and is demonstrated through actions such as expressing joy in being a fan (Wakefield et al., 1996). BIRGing, which is derived from the behavioral dimension, was also examined as an antecedent to evaluate the validity of Yoshida et al.'s (2014) concept of fan engagement. The study conducted by Yoshida et al. (2014) discovered that both Team Identification and BIRGing played a significant role in management cooperation, prosocial behavior, and performance tolerance. Moreover, Team Identification impacted all three fan engagement characteristics, including social interaction, prosocial behavior, and positive affect, while BIRGing only influenced

prosocial behavior but to a greater extent than team identification. However, the study found that positive affect did not have a significant impact on fan engagement. Additionally, the researchers aimed to examine whether fan engagement influenced purchase intention and referral intention. The study found that fan engagement indeed had an impact on customers' likelihood to make a purchase. They also observed that engaged fans were more inclined to repeat their purchases compared to fans who were not engaged. However, the activities related to fan engagement did not have any significant effect on referral intention. It is worth mentioning that Yoshida et al. (2014) were the pioneers in proposing a method to measure fan engagement, as previous studies on this subject were focused on specific sporting contexts, such as a particular sport, team, or association, or specific technologies like social media, and failed to consider fan engagement in its entirety.

However, other studies highlighted and studied the concept of fan engagement: in their study, Jones et al. (2019) aimed to determine the factors that contribute to higher fan engagement in Formula One racing. They specifically focused on the impact of controllable service quality factors on two aspects of customer engagement behavior. The researchers found that interactions between spectators and event staff, as well as the physical environment, have a positive influence on consumers' value perceptions and ultimately lead to increased fan engagement.

In a separate study, Bernthal et al. (2015) and Doyle et al. (2016) examined sports spectator behavior. Bernthal et al. (2015) investigated the characteristics and motivations of professional bass fishing fans, with a specific emphasis on understanding factors that contribute to fan engagement. The researchers discovered that there was a positive connection between various aspects of fan engagement and spectator behavior. They also observed that fans who were engaged in each of these aspects had distinct reasons for being spectators compared to those who were not engaged. Additionally, Doyle et al. (2016) conducted a study to examine the advantages of consuming sports at an individual level. The study aimed to understand how participating in sports activates various domains of well-being, including positive emotions, engagement, relationships, meaning, and accomplishment.

Moreover, Anagnostopoulos et al. (2018) conducted a study on how professional team sports organizations utilize Instagram for branding and analyzed the significance of Instagram followers' reactions to these organizations' activities on the platform. In this study, "fan engagement" referred to the likes and comments made by Instagram users on the sports organizations' posts. Later, Yim et al. (2020) examined consumption-related decision-making, considering fan engagement as one of the five consumption traits that influence the behavior of millennial sports fans.

Still, the most interesting feature of fan engagement is its conceptualization and subsequent division into transactional and non-transactional. According to Beckers et al. (2018), an individual's level of engagement is dependent on the resources he/she invests in interacting with an organization. In the context of sports, this concept can be broken down into both transactional and non-transactional actions. Transactional fan engagement refers to the exchange of resources, such as money, effort, and time, in order to obtain a product or service (Huiszoon et al., 2018). This type of engagement often fulfills self-interest tasks, such as attending live games, watching games on TV or other media sources, purchasing season tickets, paying annual membership fees, buying team apparel, memorabilia, or other team-related products (Biscaia et al., 2016; Yoshida et al., 2014).

On the other hand, nontransactional fan engagement is something more than simple consumption and economic contribution (Jaakkola and Alexander, 2014). Indeed, it involves voluntary actions aimed at benefiting both the team and other fans. Huettermann & Kunkel (2021) and Pansari & Kumar (2017) support this definition by emphasizing that nontransactional fan engagement encompasses actions taken without any direct financial exchange. This type of fan engagement relies on interactive experiences with the brand, such as the team, as well as with other fans, making it highly context-dependent (Brodie et al., 2011). Furthermore, Yoshida et al. (2014) emphasize that nontransactional fan engagement represents a significant avenue for developing and enhancing relationships between fans and teams over time.

Table 1: Scientific articles related to Artificial Intelligence (AI) and Fan Engagement.

TITLE	AUTHORS	JOURNAL	SAMPLE	SUMMARY
Conceptualization and Measurement of Fan Engagement: Empirical Evidence from a Professional Sport Context	Masayudi Yoshida, Brian Gordon, Makoto Nakazawa, Rui Biscaia (2014)	Journal of Sport Management	Pilot study: 53 students Study 1: 431 spectators at a professional soccer game in a midsized city in East Japan Study 2: 500 spectators attending another J. League Division II game in a large city in Western Japan	Two studies were conducted to validate a scale designed to measure fan engagement. The scale comprises three defining elements, namely management cooperation, prosocial behavior, and performance tolerance. The first study found evidence supporting the three-factor model's convergent and discriminant validity. In contrast, the second study examined the antecedents and consequences of fan engagement, demonstrating its nomological validity. It revealed that team identification and basking in reflected glory are essential in increasing fan engagement's three dimensions. Moreover, the study suggested that performance tolerance has a positive impact on purchase intentions.
Consumer engagement via interactive intelligence and mixed reality	Eunyoung (Christine) Sung, Sujin Bae, Dai-In Danny Han, Ohbyung Kwon (2021)	International Journal of Information Management	322 respondents (customers) visiting the MR retail/entertainment complex who volunteered to complete an onsite survey and were compensated with a gift	The research highlights the significance of AI quality (speech recognition and synthesis) to enhance the overall customer experience. This, in turn, leads to greater intentions of consumers to engage with such technology-enabled retail environments. When incorporated into consumer engagement tactics, immersive technology experiences can effectively enhance the engagement between consumers and the brand, ultimately leading to voluntary and unpaid brand endorsements (word-of-mouth) and an increase in purchase intentions.
Fans behave as buyers? Assimilate fan-based and team-based drivers of fan engagement	Doaa Fathy, Mohamed H. Elsharnouby, Ehab Abouaish (2022)	Journal of Research in Interactive Marketing	Exploratory phase: 22 fans (in-depth interviews) Quantitative phase: 30 fans (first stage) 407 fans (second stage) Qualitative phase: 10 experts and practitioners (interviews)	The study conducted by the authors suggests that team jealousy, team competitiveness, and team morality are newly identified factors that can predict fan engagement behaviors. Moreover, the research also reveals that fan role readiness has a highly positive impact on management cooperation, while team identification is the most significant predictor of prosocial behavior. Lastly, the study finds that team morality plays a crucial role in

				enhancing performance tolerance.
Artificial intelligence in customer relationship management: literature review and future research directions	Cristina Ledro, Anna Nosella, Andrea Vinelli (2022)	Journal of Business & Industrial Marketing	212 peer-reviewed articles published between 1989 and 2020	The literature on customer relationship management (CRM) is shaped and characterized by three subfields, which are Big Data and CRM as a database, AI and ML techniques applied to CRM activities, and strategic management of AI-CRM integrations. A recent study has identified and described these subfields and proposed a conceptual model that integrates them. The authors of the study have also proposed a three-step strategy for AI implementation in CRM, which includes information management of Big Data, technology investigation of AI and ML techniques applied to CRM activities, and AI-driven business transformation.
Service Quality, Perceived Value, and Fan Engagement: Case of Shanghai Formula One Racing	Charles W. Jones,Kevin K. Byon, Haiyan Huang (2019)	Sport Marketing Quarterly	637 fans who attended the F1 Chinese Grand Prix	Findings from this study suggest that spectator interactions and with event personnel and physical environment variables can directly impact value perceptions, and lead to greater fan engagement.
Customer Engagement: Conceptual Domain, Fundamental Propositions, and Implications for Research	Roderick J. Brodie, Linda D. Hollebeek, Ana Ilic (2011)	Journal of Service Research	n.a.	This article delves into the theoretical underpinnings of customer engagement by leveraging the principles of relationship marketing theory and the service-dominant logic. The analysis scrutinizes the usage of the term "engagement" across social science, management, and marketing academic literature. Finally, the analysis derives five fundamental propositions to establish a comprehensive definition of customer engagement.
Customer Engagement Behavior: Theoretical Foundations and Research Directions	Jenny van Doorn, Katherine N. Lemon, Peter C. Verhoef (2010)	Journal of Service Research	n.a.	The concept of customer engagement behaviors (CEB) has been developed and discussed by the authors. They define it as the actions exhibited by customers towards a brand or firm which encompass a wide range of behaviors such as word-of-mouth, recommendations, assisting other customers, and

				so on. After defining CEB, the authors go on to create a conceptual model of the factors that influence it - including those related to the customer, firm, and society - as well as the outcomes of CEBs.
Undervalued or Overvalued Customers: Capturing Total Customer Engagement Value	V. Kumar, Lerzan Aksoy, Sebastian Tillmanns (2010)	Journal of Service Research	n.a.	The proposal suggests that a customer's engagement value (CEV) with a company depends on four factors: their customer lifetime value (i.e., their past purchase behavior), customer referral value (i.e., their potential to refer new customers), customer influencer value (i.e., their ability to influence other customers), and customer knowledge value (i.e., the value added to the company through their feedback).
A conceptual approach to classifying sports fans	Kenneth A. Hunt, Terry Bristol, R. Edward Bashaw	Journal of Service Marketing	n.a.	This article provides the reader with a definition of fans, along with the development of a classification or typology of sports fans. Specifically, it contends that five different types of sports fans exist: temporary, local, devoted, fanatical, and dysfunctional.
The Psychological Continuum Model: A Conceptual Framework for Understanding an Individual's Psychological Connection to Sport	Daniel C. Funk, Jeff James (2001)	Sport Management Review	n.a.	The article discusses the concept of sports fans and spectators, and proposes a model called the Psychological Continuum Model (PCM) that explains the mental connections individuals can have towards a particular sport or team. The PCM outlines four distinct levels: awareness, attraction, attachment, and allegiance, each of which represents a deeper level of psychological connection. The model suggests that the strength of an individual's connection with a sports team is determined by the complexity and reinforcement of their mental associations with the sport.
Consumer satisfaction and identity theory: A model of sport spectator conative loyalty	Galen Trail, D.F. Anderson, J.S. Fink (2005)	Sport Marketing Quarterly	1279 students attending intercollegiate basketball games	The study aimed to evaluate three different conative loyalty models based on identity theory and consumer satisfaction theory. These models explored the relationships between team identification, disconfirmation/confirmation of expectancies, mood, self-esteem responses, and conative loyalty. Both models were found to be statistically

				equivalent and fit well. In terms of marketing, the study highlights the importance of fostering self-esteem responses to generate conative loyalty, which in turn leads to increased attendance at future games and purchases of team merchandise.
Enhancing Fan Engagement in a 5G stadium with AI-based technologies and live streaming	Wu et al. (2022)	IEEE Systems Journal	n.a.	This paper finds that AI, through the analysis of data, can curate a customized selection of articles, videos, highlights, and other content that is more likely to resonate with each fan. This personalized approach ensures that fans receive content that aligns with their specific interests, increasing their engagement.
The diffusion of natural language processing in professional sport	Wanless et al. (2022)	Sport Management Review	91 teams from the "Big Four" North American professional sports league	The adoption of NLP in the professional sports industry has been thoroughly studied using multiple methods such as a discrete derivative of the Bass model, integrative literature review, and qualitative description. The research helped uncover the timing, mechanisms, and key influences surrounding the diffusion of NLP. The findings suggest that NLP is currently at near-peak adoption in the industry, and shed light on the organizational factors that catalyzed its adoption timing. This research provides valuable context for both academics and practitioners to better understand and embrace NLP in the sports industry.
Artificial intelligence empowered conversational agents: A systematic literature review and research agenda	Marcello M. Mariani, Novin Hashemi, Jochen Wirtz (2023)	Journal of Business Research	n.a.	The authors conducted a systematic literature review to illustrate and map out research in the field of conversational agents (CAs). Among the findings, they found that chatbots' presence affects positively consumer engagement outcomes.
Does artificial intelligence satisfy you? A meta-analysis of user gratification with AI-powered chatbots	Chenxing Xie, Yanding Wang, Yang Cheng (2022)	International Journal of Human Computer Interaction	12 studies	This study found that user satisfaction is positively correlated with four categories of gratification (utilitarian, hedonic, technology, and social), which encourages designers to consider user-centered design to fulfill users' gratification better when designing AI-powered chatbots.

Symbiosis and Substitution in Spectator Sport	Mark P. Pritchard, Daniel C. Funk (2006)	Journal of Sport Management	308 baseball game spectators	The study employs a dual-route framework (DRF) to describe symbiotic and substitution behaviors (between the consumption of sport via media and its more active counterpart, attendance). The DRF modes suggest that plotting media use in conjunction with attendance offers a more accurate account of spectator involvement.
Psychological connection to a new sports team: Building or maintaining the consumer base?	Jeffrey D. James, R.H. Kolbe, Galen T. Trail (2002)	Sport Marketing Quarterly	507 season ticket holders of a new Major League Basketball franchise	The researchers carried out a survey via mail to determine if customers had a psychological attachment to a team before having any direct contact with it. The study found notable discrepancies among the groups of participants in terms of the quantity and impact of the factors that influenced their decision to purchase season tickets. The outcomes revealed that a considerable proportion of sports fans can form deep, emotional bonds with a team without having any personal experience with it.
Relationship Marketing and Interactive Fan Festivals: The Women's United Soccer Association's "Soccer Sensation"	Elizabeth Jowdy, Mark McDonald (2002)	International Journal of Sports Marketing	n.a.	The following example showcases how the Women's United Soccer Association (WUSA), a newly established professional sports league, effectively integrated an engaging fan festival into its first Championship Weekend. As per the authors, passionate sports enthusiasts consume sports content with a strong desire to establish long-term connections with their favorite teams and actively engage in initiatives that foster such relationships..
Machine learning and artificial intelligence use in marketing: a general taxonomy	Andrea De Mauro, Andrea Sestino, Andrea Bacconi (2022)	Italian Journal of Marketing	A collection of 40 use cases of Machine Learning (ML) and Artificial Intelligence (AI) in Marketing	The authors build a structured taxonomy of 11 typical application scenarios, grouped into four categories; two being on the consumer-facing side (improve shopping fundamentals, improve consumption experience) and the other two on the business-facing side (improve decision-making, improve financial applications).
Good, better, engaged? The effect of company-initiated customer engagement behavior on shareholder value	Sander F.M. Beckers, Jenny van Doorn, Peter C. Verhoef (2018)	Journal of the Academy of Marketing Science	n.a.	The authors investigate the financial consequences of firm-initiated customer engagement, i.e., explicit company strategies to stimulate customer engagement behavior. They find support for the mechanism that customer engagement

				initiatives can strengthen customer relationships.
Investigating the role of fan club membership on the perception of team brand equity in football	Rui Biscaia, Stephen Ross, Masayuki Yoshida, Abel Correia, Antonio Fernando Boleto Rosado, Joao Maroco (2016)	Sport Management Review	2287 fans of a professional football league	The authors deployed a multi-group SE analysis that revealed that social interaction, team success, and internalization were significant positive predictors of behavioral intentions among the overall sample.
Sport governing bodies' influence on non-transactional fan behaviors	Paul Huiszoon, Guillaume Martinent, Guillaume Bodet (2018)	Managing Sport and Leisure	501 individuals	The purpose of the paper is to capture a sports governing body's influence on non-transactional fan behaviors. A partial least squares (PLS) path modeling approach was used to test the global model. It shows that non-transactional engagement often contributes to increased transactional behaviors.
Examining fan engagement through social networking sites	Thiago Oliveira Santos, Abel Correia, Rui Biscaia, Ann Pegoraro (2019)	International Journal of Sports Marketing and Sponsorship	139 randomly selected students from a mid-sized Portuguese university	The authors found that social networking sites (SNS) represent an important entertainment tool available for fans that contributes to enhancing their interaction and knowledge of the team. The article also found that the second-order construct of fan engagement through SNS construct was a positive predictor of both online and offline behavioral intentions.
Customer engagement: Exploring customer relationships beyond purchase	Shiri D. Vivek, Sharon E. Beatty, Robert M. Morgan (2012)	Journal of Marketing Theory and Practice	n.a.	The research delves into the significance and extent of customer engagement, which is an essential aspect of relationship marketing. The authors suggest that it is made up of cognitive, emotional, behavioral, and social factors. They also present a model of customer engagement, where the involvement and participation of existing or potential customers act as precursors, whereas value, trust, emotional attachment, word of mouth, loyalty, and engagement with the brand community are possible outcomes.

A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence	Michael Haenlein, Andreas Kaplan (2019)	California Management Review	n.a.	It summarizes seven articles published in this that present a wide variety of perspectives on AI, authored by several of the world's leading experts and specialists in AI. It concludes by offering a comprehensive outlook on the future of AI, drawing on micro-, meso- ---, and macro-perspectives.
A Descriptive Model of Managerial Effectiveness	Fred Luthans, Dianne H.B. Welsh, Lewis A. Taylor III (1988)	Group & Organization Management	n.a.	This study was designed to help understand what effective managers really do. Using canonical correlation analysis, a descriptive model of managerial effectiveness was derived. This empirically derived descriptive model helps identify needed managerial activities and skills for quantity and quality performance in today's organizations.
Journey of customers in this digital era: Understanding the role of artificial intelligence technologies in user engagement and conversion	Surajit Bag, Gautam Srivastava, Md Mamoon Al Bashir, Sushma Kumari, Mihalis Giannakis, Abdul Hannan (2021)	Benchmarking: An International Journal	n.a.	This research study confirms that the implementation of AI technologies has a beneficial impact on user engagement and conversion rates. Additionally, it is shown that increased conversion rates result in a more fulfilling user experience. Moreover, there is a significant connection between a satisfying user experience and the intention of customers to make repeat purchase
The impact of artificial intelligence on event experiences: a scenario technique approach	Barbara Neuhofer, Bianca Magnus, Krzysztof Celuch (2021)	Electronic Markets	n.a.	Using the service-dominant (SD) logic framework and a scenario technique approach, this research investigates the influence of artificial intelligence as a dynamic resource on event experiences. By examining the role of AI in the digitally advanced events industry, it reveals that AI functions as a comprehensive system that bridges customer and business technologies, enabling customized human experiences down to the smallest detail. Ultimately, the study demonstrates that AI's primary value lies in its ability to co-create and personalize experiences in the events context.
Transforming the Fan Experience through Livestreaming: A Conceptual Model	Sarah Wymer, Michael L. Naraine, Ashleigh-Jane Thompson,	Journal of Interactive Advertising	Study 1: 443 Facebook posts Study 2: two semi-structured interviews with the organization's digital staff	The findings revealed that live streaming can be an engaging proposition when it provides exclusive content that allows fans to experience authentic insights into the rituals and traditions of their favorite

	Andrew J. Martin (2021)			sports team and athletes in real-time.
A Framework for Collaborative Artificial Intelligence in Marketing	Ming-Hu Huang, Roland T. Rust (2022)	Journal of Retailing	n.a.	A conceptual framework for collaborative artificial intelligence (AI) in marketing is developed, providing systematic guidance for how human marketers and consumers can team up with AI, which has profound implications for retailing, which is the interface between marketers and consumers. Drawing from the multiple intelligences view that AI advances from mechanical, to thinking, to feeling intelligence (based on how difficult for AI to mimic human intelligences), the framework posits that collaboration between AI and HI (human marketers and consumers) can be achieved by 1) recognizing the respective strengths of AI and HI, 2) having lower-level AI augmenting higher-level HI, and 3) moving HI to a higher intelligence level when AI automates the lower level.
A strategic framework for artificial intelligence in marketing	Ming-Hu Huang, Roland T. Rust (2020)	Journal of the Academy of Marketing Science	n.a.	The authors have created a strategic marketing planning framework consisting of three stages, which leverage various benefits of artificial intelligence (AI): mechanical AI for automating repetitive marketing tasks, thinking AI for analyzing data to make decisions, and feeling AI for evaluating interactions and emotions. This framework highlights the potential applications of AI in marketing research, strategy development (including segmentation, targeting, positioning), and implementation.
Artificial intelligence (AI) applications for marketing: A literature-based study	Abid Haleem, Mohd Javaid, Mohd Asim Qadri, Ravi Pratap Singh, Rajiv Suman (2022)	International Journal of Intelligent Networks	n.a.	Relevant articles on AI in marketing are identified from Scopus, Google Scholar, researchGate, and other platforms for this research. Afterwards, the articles are read, and the theme of the paper is developed. The objective of this paper is to review the role of AI in marketing by examining the

				specific applications of AI in various marketing segments and their transformations for marketing sectors. Lastly, critical applications of AI for marketing are recognized and analyzed.
Artificial Intelligence (AI): Revolutionizing Digital Marketing	Patrick van Esch, J. Stewart Black (2021)	Australasian Marketing Journal	n.a.	The study analyzes the evolution of AI when applied to digital marketing, it focuses on the level of personalization and mass-customization that AI can bring about, while also underlining the uncaptured value chain efficiencies and the breadth and depth of AI application in marketing.
Artificial intelligence: A powerful paradigm for scientific research	Yongjun Xu et al. (2021)	The Innovation	n.a.	The article explores the different sectors AI can be applied to, while also providing the reader with the history of artificial intelligence throughout its phases.
Historical Evolution Of Artificial Intelligence	Blagoj Delipetrev, Chrysi Tsinaraki, Uros Kostic (2020)	Publications Office of the European Union	n.a.	This report provides an overview of the progress of AI, highlighting the concept of "seasons" in AI development (such as winters representing decline and springs representing growth). It outlines the current surge in interest in AI and discusses the uncertainty surrounding its future, including the possibility of another AI winter or a significant AI spring.
The evolving role of artificial intelligence in marketing: A review and research agenda	Bozidar Vlacic, Leonardo Corbo, Susana Costa e Silva, Marina Dabic (2021)	Journal of Business Research	n.a.	This review offers a comprehensive examination of the evolution of marketing and AI research areas. By analyzing 164 articles from Web of Science and Scopus-indexed journals, the article proposes a specialized research agenda to further advance these fields.
Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence	Andreas Kaplan, Michael Haenlein (2019)	Business Horizons	n.a.	The article delves into the distinction between AI, the Internet of Things (IoT), and big data, emphasizing the need for a nuanced understanding of AI. It explores the developmental phases of AI (narrow, general, super) and delves into various categories of AI systems (analytical, human-inspired, humanized). Additionally, it introduces the Three C Model of Confidence, Change, and Control as a tool for organizations to consider

				the internal and external impacts of AI.
Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators	Weng Marc Lim, Asanka Gunasekara, Jessica Leigh Pallant, Jason Ian Pallant, Ekaterina Pechenkina (2023)	The International Journal of Management Education	n.a.	By employing critical analysis as a methodology and utilizing paradox theory as a theoretical framework, the article aims to (i) clarify the concepts of Generative AI and transformative education, (ii) identify the inherent paradoxes within Generative AI, and (iii) offer insights on the implications for the evolution of education, particularly from the standpoint of management educators.
Artificial intelligence: disrupting what we know about services	Dora E. Bock, Jeremy S. Wolter, O.C. Ferrell (2020)	Journal of Services Marketing	n.a.	In this paper, the dominant service theories and their implications for AI in service encounters are examined. Through this analysis, a comprehensive definition of service AI is proposed, highlighting the theoretical challenges it presents and the numerous research avenues it opens up.
Hello marketing, what can artificial intelligence help you with?	Norbert Wirth (2018)	International Journal of Market Research	n.a.	This article provides the reader with a definition of artificial intelligence and its different forms: narrow AI, hybrid AI, and strong AI. The author concludes his reflection on the question of whether it is feasible to develop AI-based solutions by stating that it is high time that we embrace AI.
Smart Factory Implementation and Process Innovation	David R. Sjodin, Vinit Parida, Markus Leksell, Aleksandar Petrovic (2018)	Research-Technology Management	69,800 employees unevenly spread across five factories operated by two leading manufacturers (Truckcorp, and Carcorp) widely recognized as frontrunners in process innovation and smart factory implementation	The article delves into the progression of innovative digital technologies associated with the Internet of Things, as well as advancements in artificial intelligence and automation. The authors examine the obstacles that companies encounter when integrating these technologies and outline the essential measures required to bring the smart factory concept to fruition. This involves compiling data from thorough investigations of five factories within two prominent automotive manufacturers.

				Subsequently, a preliminary maturity model for smart factory implementation is proposed, centered on three fundamental principles: fostering digital talent, implementing flexible processes, and integrating modular technologies.
Millennials' attitude toward chatbots: an experimental study in a social relationship perspective	Roberta De Cicco, Susana C. Silva, Francesca Romana Alparone (2020)	International Journal of Retail & Distribution Management	193 Italian millennials	Utilizing a between-participants factorial design, this study explores the impact of visual cues (avatar presence or absence) and interaction styles (social-oriented or task-oriented) on social presence, and subsequently how this influences millennials' perceived enjoyment, trust, and attitude towards the chatbot. The findings indicate that employing a social-oriented interaction style heightens users' perception of social presence, whereas the presence of an avatar had minimal effect.
The Impact of Infusing Social Presence in the Web Interface: An Investigation Across Product Types	Khaled Hassanein, Milena M. Head (2005)	International Journal of Electronic Commerce	First study: 78 participants Second study: 90 participants	This paper investigates the impact of infusing social presence via the interface across commercial Websites selling various product types. It was found that perceived usefulness, trust, and enjoyment are important antecedents to online shoppers' attitudes. However, higher levels of social presence have varying effects on these attitudinal antecedents according to the product being sold online.
Artificial intelligence in marketing: a network analysis and future agenda	Djonata Schiessl, Helison Bertoli Alves Dias, José Carlos Korelo (2022)	Journal of Marketing Analytics	n.a.	The researchers carried out a thorough review and network analysis to fill the knowledge gap on AI's role in leveraging consumer data and generating strategic insights. Out of the initial 672 papers reviewed, 74 were included in the final sample. The study identifies three key clusters from the data: brand function, interaction elements, and outcomes of customer engagement.
Frontiers: Machines vs. Humans: The Impact of Artificial Intelligence Chatbot Disclosure on Customer Purchase	Xueming Luo, Siliang Tong, Zheng Fang, Zhe Qu (2019)	Marketing Science	More than 6,200 customers	The research utilized real-world data from a field experiment where customers were randomly assigned to receive outbound sales calls from either chatbots or human workers. Findings indicate that anonymous chatbots are just as effective as skilled workers and are four times more successful

				than novices at prompting customer purchases. Interestingly, revealing the chatbot's identity led to a significant decrease in purchase rates, dropping by over 79.7%. However, introducing the disclosure later in the conversation and considering the customer's previous experience with AI technology can help alleviate this negative impact.
Artificial Intelligence and Machine Learning: Exploring drivers, barriers, and future developments in marketing management	Gioia Volkmar, Peter M. FIscher, Sven Reinecke (2022)	Journal of Business Research	Delphi Study, round 1: 39 AI experts Delphi Study, round 2: 34 AI experts Quantitative survey: 204 managers Focus groups: 11 managers	The authors delve into the factors that influence the adoption of AI and ML in marketing, taking into account both strategic and behavioral aspects. They offer insights from both the perspective of marketers and customers. Through a combination of qualitative and quantitative research methods, the authors propose various research ideas that shed light on the obstacles marketing managers encounter in three key areas: (1) Culture, Strategy, and Implementation; (2) Decision-Making and Ethics; (3) Customer Management.
Comparing automated text classification methods	Jochen Hartmann, Mark Heitmann, Christina Patricia Schamp (2018)	International Journal of Research in Marketing	1000 and 3000	The results of the study show that machine learning algorithms outperform lexicon-based approaches in terms of accurately capturing human intuition and text classification.
Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook	Dokun Lee, Kartik Hosanagar, Harikesh S. Nair (2018)	Management Science	106,316 Facebook messages across 782 companies	The researchers explore how different types of social media marketing content impact user engagement with messages. They discover that incorporating popular content related to brand personality (such as humor and emotion) leads to increased consumer engagement with a message. On the other hand, directly informative content (like price and deals) tends to result in lower levels of engagement when presented alone, but higher levels of engagement when combined with brand personality-related characteristics.
Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in	Niladry Siam, Arun Sharma (2018)	Industrial Marketing Management	n.a.	The authors analyze the impact of AI and ML on improving marketing effectiveness in all stages of the B2B sales funnel, including prospecting, pre-approach, approach, presentation, objection

sales research and practice				handling, closing, and follow-up. They also highlight potential research avenues for further exploration in the sales process.
Understanding the Role of Artificial Intelligence in Personalized Engagement Marketing	V. Kumar, Bharath Rajan, Rajkumar Venkatesan, Jim Lecinski (2019)	California Management Review	n.a.	The article delves into the impact of artificial intelligence (AI) on enhancing personalized engagement marketing. It suggests that businesses can utilize both individual customer data and AI tools to offer tailored products and services. Through AI technology, companies can continuously learn in real-time and enhance their customer value proposition. By implementing a strategy of personalized products that deliver growing value to customers, firms can foster customer loyalty and maintain a sustainable competitive edge.
How artificial intelligence will change the future of marketing	Thomas Davenport, Abhijit Guha, Dhruv Grewal, Timna Bressgott (2020)	Journal of the Academy of Marketing Science	n.a.	The authors propose an interdisciplinary framework that combines insights from marketing, social sciences, and computer science/robotics to help customers and businesses anticipate the future impact of AI. This framework considers three crucial factors: the sophistication of AI intelligence, the range of tasks it can accomplish, and its integration into robotic systems. Through this analysis, the authors uncover the potential advantages of adopting AI, including reduced costs and enhanced customer experiences.
Collaborative intelligence: How human and artificial intelligence create value along the B2B sales funnel	Jeannette Paschen, Matthew Wilson, Joao J. Ferreira (2020)	Business Horizons	n.a.	The authors explain the impact of AI on the B2B sales process, detailing the key sales tasks at each stage of the funnel. They highlight the specific advantages AI brings and the role of humans in these tasks. Additionally, they provide insights on how managers can optimize the collaboration between AI and human resources in B2B sales.
The future of marketing	Roland T. Rust	International Journal of Research in Marketing	n.a.	Changes in three significant forces, namely technological trends, socioeconomic trends, and geopolitical trends, have a significant impact on the future of marketing. AI algorithms have the potential to revolutionize all aspects of

				marketing research, education, and practice.
Artificial intelligence, robotics, advanced technologies, and human resource management: a systematic review	Demetris Vrontis, Michael Christofi, Vijay Pereira, Shlomo Tarba, Anna Makrides, Eleni Trichina (2022)	The International Journal of Human Resource Management	n.a.	The article focuses on 45 articles studying AI, robotics, and other advanced technologies within HRM settings. It states that the impact of these technologies has been identified to focus on HRM strategies (human-robot/AI collaboration, decision-making) and HRM activities (recruiting, training).
Advanced Business Model Innovation Supported by Artificial Intelligence and Deep Learning	Per Valter, Peter Lindgren, Ramjee Prasad (2018)	Wireless Personal Communications	n.a.	The paper describes the relationship between humans, machines, and business models (BMs) embedded with advanced technologies. It proposes that advanced technologies are and will be increasingly integrated into business models, thereby creating a completely new agenda of business model innovation (BMI).
Investigating the emotional appeal of fake news using artificial intelligence and human contributions	Jeannette Paschen (2019)	Journal of Product & Brand Management	n.a.	The paper suggests that titles are a strong differentiator in emotions between fake and real news and that fake news titles are more negative. Moreover, the study reveals that the text body of fake news is higher in displaying specific negative emotions.
Personalized mobile marketing strategies	Siliang Tong, Xueming Luo, Bo Xu (2020)	Journal of the Academy of Marketing Science	n.a.	The authors construct a framework to review extant efforts on mobile marketing and discuss relevant applications in business practices. The paper focuses on personalization, and how mobile marketing fosters it.
Artificial intelligence-based systems applied in industrial marketing: a historical overview, current, and future insights	Francisco J. Martinez -Lopez, Jorge Casillas (2013)	Industrial Marketing Management	50 articles	There is limited and unexplored research on the convergence of AI and industrial marketing. The majority of existing research has occurred in the past ten years and focuses on various AI approaches like fuzzy logic, neural networks, dynamic programming, and optimization algorithms for developing ad-hoc intelligent systems.
Technology-driven service society	Ming-Hui Huang Roland T. Rust (2017)	Journal of the Academy of Marketing Science	n.a.	In their study, the authors create a typology and positioning map for service strategy, emphasizing the importance of technology in the process. They provide guidelines for firms to position or reposition their service strategies, showing how

				technology is crucial in this aspect. The positioning map connects marketing strategies with the evolution of service literature, highlighting the shift towards customer relationships and co-productive activities.
Targeting Prospective Customers: Robustness of Machine-Learning Methods to Typical Data Challenges	Duncan Simester, Artem Timoshenko, Spyros I. Zoumpoulis (2020)	Management Science	n.a.	The authors investigate how firms can use the results of field experiments to optimize the targeting of promotions when prospecting for new customers. The first field experiment creates a common pool of training data for each of the seven methods; then, they validate the seven optimized policies provided by each method together with uniform benchmark policies in a second field experiment. Results reveal that when the training data are ideal, model-driven methods perform better than distance-driven methods and classification methods.
Frontiers: How Effective is Third-Party Consumer Profiling? Evidence from Field Studies	Nico Neumann, Catherine E. Tucker, Timothy Whitfield (2019)	Marketing Science	More than 90 third-party audiences across 19 data brokers	Data brokers often use online browsing records to create digital consumer profiles, which are then sold to marketers as predefined audiences for ad targeting. In this paper, the authors investigate using three fields to assess the accuracy of a variety of demographic and audience-interest segments. Results show that audience identification can be improved, on average, by 123% when combined with optimization software.
Customer-based perceptual map as a marketing intelligence source	Ajayeb Abu Daabes Faten F. Kharbat (2017)	International Journal of Economics and Business Research	n.a.	The utilization of information systems in processing and analyzing the extensive volume of available data has been demonstrated as a critical component for achieving effective Management Intelligence (MI). This study introduces a practical and continuous intelligence framework to digest the massive amount of information and convert it into a valuable graphical mental map (PM).

III. Hypothesis Development

Although Yoshida et al. (2014) conceptualized fan engagement as a nontransactional construct, I decided to broaden the definition and, for the purpose of my study, to focus on the transactional aspects of fan engagement.
I decided to follow this path because, as McCaffrey et al. (2018) points out, sports clubs' primary revenue streams are media rights, sales, sponsorship, and merchandising: as it can be inferred, many of these streams rely upon transactional behaviors. Hence, coming to terms with different applications of Artificial Intelligence (AI), and understanding if and how these could influence fan engagement in its transactional behaviors, could provide sports teams' marketers and managers with valuable insights to increase their financial potential.

3.1 Research Gap

The literature on the *trait d'union* between artificial intelligence and fan engagement is, to a certain degree, non-existent. Indeed, researchers have been exploring the potential impact of Artificial Intelligence (AI) on both customers' willingness to adopt it and subsequent engagement under a more general lense (Chung et al., 2018; Kowalczuk, 2018; Gursoy et al., 2019; Lu et al., 2019; Liang et al., 2020).
In terms of sports and fan engagement, on the other hand, the applications of artificial intelligence are at the very beginning of their study process: for example, Stavros et al. (2021) discuss the notion of enhanced viewing as characterized by the coming together of the observational dimension and an enhanced cognitive process, that "digs deeper into the action to make sense of what is going on during a sporting event" (Stavros et al., 2021). In particular, it is artificial intelligence and machine learning algorithms that generate sophisticated analytical statistics, precise timing tools, and measurement systems that significantly improve the rudimentary mechanical tools previously used to monitor games on TV (Stavros et al., 2021).
In addition, Zadeh (2021) explores the role of sentiment analysis for fan engagement in the sports industry, showing that the use of text mining and sentiment analysis can provide athletic departments with more effective data understanding, which in turn will bring about an improvement in fan engagement to scale with no further costs.

Additionally, Wanless et al. (2022) examine the integration of natural language processing (NPL) in professional sports, with a specific emphasis on the four major North American professional sports leagues: the National Football League (NFL), the National Basketball Association (NBA), the Major League Baseball (MLB), and the National Hockey League (NHL). NPL, defined as "the ability for computer algorithms to be trained for pattern recognition in text data" (Wanless et al., 2022), is one of the most promising AI-powered technologies to hit the market and is of key interest considering the increase in text data available for sport business use. Through a multiple methods approach comprised of a discrete derivative of the Bass model, an integrative literature review, and a qualitative description, NPL was found to be implemented in different domains, including customer relationships, partnerships, the sports industry, and the sport experience.

Therefore, with my research I would like to have at least a rural understanding of the level of relationship between these two topics, especially considering that AI technologies are already being used to provide fans with a better experience overall: see, for example, IBM technologies at the US Open[5] and the Masters[6]. Similarly, LaLiga, Spain's premier football division, employs artificial intelligence (AI) and machine learning (ML) technologies to provide novel insights to athletes and trainers, as well as to revolutionize the way spectators watch and comprehend the game.[7]

[5] "IBM at the US Open", accessible at https://www.youtube.com/watch?v=ruyNj90NEdM.
[6] "IBM technology at the 2023 Masters", accessible at https://www.youtube.com/watch?v=t7oOxw3v_0c.
[12] "LaLiga boosts fan engagement with conversational AI on Azure", accessible at https://www.youtube.com/watch?v=M3lLbg_wVHY.

3.2 Formulation Of Hypotheses

3.2.1. AI Technologies: Chatbots

Chatbots are one the most prominent AI-powered technologies to have entered the markets, and they are employed in almost every business context. They are being adopted by numerous renowned brands and government agencies to improve operational effectiveness and offer on-demand customer services. A significant portion, estimated to be one-third of all online interactions, involves the use of chatbots. This trend is projected to persist as conversations initiated through messaging apps now surpass those occurring on social networks (Sweezey, 2019).

The majority of advantages related to chatbots stems from enhancements in efficiency, including reduced costs for the company, shorter waiting periods for customers, and conformity with customer preferences for digital rather than voice-based interactions (Shumanov et al., 2021). A systematic literature review by Mariani et al. (2023) proved that chatbots' presence positively affects consumer engagement outcomes, in the same way as Xie et al. (2022) proposed that consumers are satisfied with AI-powered chatbots when utility is put at the core of the chatbots' design. Additionally, Tsai et al. (2021) showed that the high level of social presence communication exhibited by chatbots has a positive impact on consumer engagement outcomes. Therefore, applying it to the sports context, we can hypothesize the following:

H1: AI-powered chatbots have a positive effect on fan engagement.

3.2.2 AI Technologies: Sentiment Analysis

Understanding the emotions and opinions expressed by customers is extremely important for companies trying to ameliorate their offerings. This is because these sentiments have a significant impact on the relationship between customers and brands (Xu et al., 2021), and it is exactly this spot that sentiment analysis fills: it is a technique used to process and analyze the attitudes, opinions, sentiments, and subjectivity expressed in the text (Lui, 2012). It offers numerous benefits and can help achieve various goals, the most notable being measuring customer satisfaction (Jiang et al., 2010; Rui et al., 2013; Kang and Park, 2014).

A compelling study by Annamalai et al. (2021) explored the implementation of sentiment analysis in a sports context: based on a netnography study on the Facebook platform among six cricket clubs of the Indian Premier League, the authors used sentiment analysis to capture the feelings of fans through comments. In the context of the study, sentiment analysis proved to be an extremely useful tool to indicate which directions to take in terms of online content communication strategies (from the perspective of sports clubs), so as to drive fan engagement to new heights.

In a similar fashion, Wunderlich & Memmert (2020) examined the practicality of employing lexicon-based sentiment analysis tools for football-related text on Twitter. The sentiment of 10,000 tweets concerning ten high-level football matches was assessed through manual evaluation by individuals and automated analysis using publicly accessible sentiment analysis tools. The study found that the general sentiment of reality sets (1000-tweet sets with 60% having the same polarity) is accurately classified with over 95% accuracy. This study highlights the potential of sentiment analysis as a useful tool for sports-related content. Thus, we can formulate the following hypothesis:

H2: AI-powered sentiment analysis has a positive effect on fan engagement.

3.2.3 AI Technologies: Digital Personal Assistants

When it comes to marketing, personalization, and customization are often discussed together, as they share a similar concept but have different approaches. Personalization occurs when a firm analyzes collected customer data in order to determine the most suitable marketing mix for each individual (Arora et al., 2008). On the other hand, customization takes place when a customer actively specifies one or more elements of their marketing mix. There is a general consensus that personalization is primarily controlled by the firm and relies on customer-level data, while customization is driven by the customer and focuses on the design and delivery of the offering (Murthi and Sarkar, 2003). Abbott (2008) also discusses the notion of curation, to be conceived as "the management and preservation of digital material to ensure accessibility over the long term" (Abbott, 2008). The process of curation involves the selection, maintenance, and management of information (Kumar et al., 2019). For example, Intel utilized an AI tool to collect, select, synthesize, and maintain social media information related to the purchase of a PC, alongside human involvement. Similarly, HealthifyMe, an Indian health and fitness app, possessed a vast database consisting of the food habits, workout routines, and interactions between users and human nutritionists[8]. To harness the value of this data, the company introduced Ria, an AI bot, in 2017: it is capable of monitoring and managing daily calorie requirements and workout plans, as well as providing suggestions for adopting healthy lifestyle habits.

In the realm of personalized engagement marketing, the concept of curation refers to the automated process of selecting tailored products, prices, website content, and advertising messages that cater to an individual customer's unique preferences, courtesy of machine algorithms (Kumar et al., 2019). In this scenario, the AI system utilizes various data points to predict the preferred type, timing, and purchase behavior of customers towards the firm's offerings, all without human intervention (Kumar et al., 2019).

Bag et al. (2021) conducted a study wherein they tested and further established that deploying AI technologies has a positive relationship with user engagement and conversion. Further, conversion leads to a satisfying user experience. Finally, the

[8] https://qz.com/india/1279254/healthifyme-has-an-artificial-intelligence-led-nutritionist-for-fitness-freaks.

relationship between satisfying user experience and repurchase intention is also found to be significant (Bag et al., 2021).

Wu et al. (2022) explored the enhancement of fan engagement with AI-based technologies: they found that, through the analysis of data, AI can curate a customized selection of articles, videos, highlights, and other content that is more likely to resonate with each fan. Such a personalized approach ensures that fans receive content that aligns with their specific interests, increasing their engagement (Wu et al., 2022).

As a consequence, we can hypothesize the following:

H3: AI-powered personal assistants have a positive effect on fan engagement.

3.2.4 The Moderators: Perceived Risk & Trust In AI Technologies

The use of AI technology has been surrounded by promises of benefits, but it also has a hidden dark side. To uncover this side, I referred to the literature on relationship marketing which has identified a lack of trust as a major factor that can negatively affect the quality of the relationship between customers and businesses, especially in B2C contexts.

According to Davenport et al. (2020) and Guha et al. (2021), in B2C settings, the main advantage of AI lies in its ability to provide customized offers through eliciting deep insights about customers. However, customization also raises concerns among customers, leading to issues related to privacy, bias, and uniqueness neglect (Granulo et al., 2021; Guha et al., 2021; Longoni et al., 2019; Puntoni et al., 2021).

One of the main concerns regarding AI technology is privacy. Due to the deep customer insights that AI can provide, customers may have heightened privacy concerns (Grewal et al., 2021). In case of a data breach, the kind of insights that AI can capture can be damaging, and thus, customers are likely to have stronger privacy concerns when they know AI is in use.

Another concern is bias. If the AI solution is not clearly explained and feels like a black box, it is likely to engender lower levels of trust and lower levels of adoption and engagement. The greater the solution is explained, the higher the trust levels they will likely engender, viewed as being unbiased (Rai, 2020).

The third concern is empathy. Lack of trust raises concerns that the AI may not account for a customer's unique preferences, circumstances, and identities (Granulo et al., 2021; Longoni et al., 2019). Customers prefer human recommendations even if it has been made explicit that the AI providers are superior to the human providers. When the customers' uniqueness is a factor for the product choice, AI solutions are less trusted.

Perceived privacy risk and trust play a crucial role in consumer behavior, especially when it comes to sharing sensitive personal information while adopting and using information technology. With AI being a recent, emerging, and sophisticated technology, it is reasonable to assume that the average individual may not entirely comprehend how it works, which puts the consumer in a vulnerable position of blindly trusting a provider. This phenomenon has been confirmed by recent studies, which have found that a lack of trust and understanding can slow down the adoption of new technology[9]. Therefore, it is essential to consider these factors when trying to understand the adoption of intelligent voice assistants.

Apart from consumer concerns over trust and privacy, the complexity of governing these technologies from regulatory bodies exacerbates the problem. Lohr (2019)[10] acknowledges that policymakers, who lack a working knowledge of how AI is developed, may struggle to create effective rules and regulations to protect individuals from the potential misuse of personal information.

As a consequence, it is feasible to hypothesize the following:

H4: Trust will negatively moderate the relationship between AI technologies and fan engagement.

H5: Perceived risk will negatively moderate the relationship between AI technologies and fan engagement.

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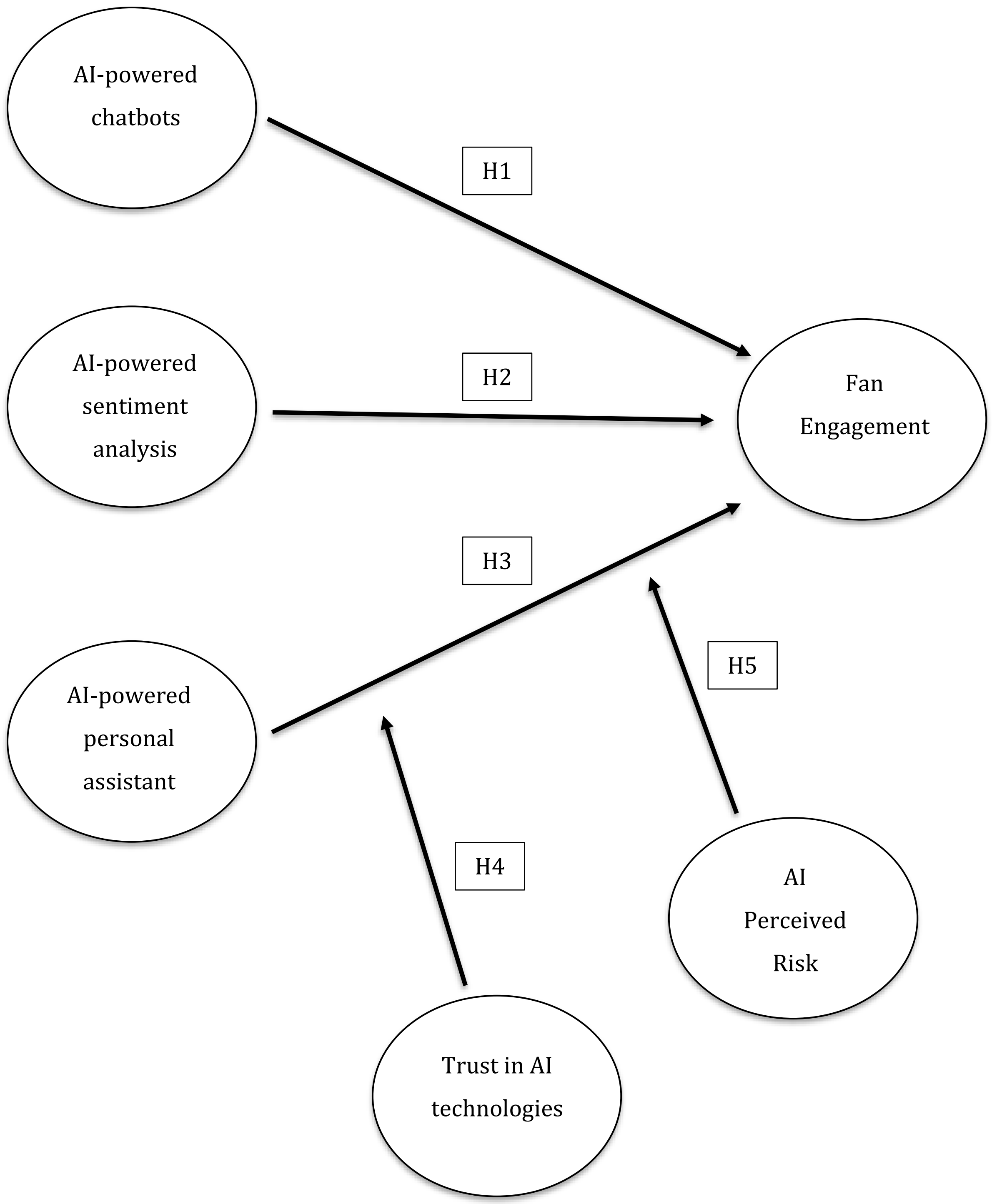
[9] Trust in Technology, HSBC (2018). Available at https://www.hsbc.com/-/files/hsbc/media/media-release/2017/170609-updated-trust-in-technology-final-report.pdf.
[10] Available at https://www.nytimes.com/2019/01/20/technology/artificial-intelligence-policy-world.html.

Hypothesized research model



IV. Methodology And Data Collection

4.1 Research Method

In terms of research design, there are two different paths to follow: qualitative and quantitative research. The process of data collection in qualitative and quantitative studies differs significantly owing to the distinctive nature of the data they collect. While quantitative studies are inclined towards numerical or measurable data, qualitative studies seek personal accounts or documents that provide a detailed insight into individuals' thoughts and responses within a societal framework.

Qualitative research methods include gathering and interpreting non-numerical data. During the course of a qualitative study, the researcher may engage in interviews or focus groups to gather information that is not readily available in pre-existing documents or records. To enable the participants to provide varied and unexpected answers, the interviews and focus groups may be conducted in an unstructured or semi-structured format. This approach allows the researcher to pose open-ended questions and explore the responses in detail, providing a comprehensive perspective on each individual's experiences. These findings are further analyzed and compared with those of other participants in the study to draw inferences and conclusions.

On the other hand, quantitative studies require a different approach to data collection. In such studies, numerical data is compiled to test causal relationships among variables. To generate countable answers which can be turned into quantifiable data, questionnaires with a multiple-choice format are used. This method allows for an objective and standardized approach to data collection, which can be analyzed using statistical methods to draw conclusions.

Qualitative and quantitative research are two distinct approaches to studying a phenomenon, correlation, or behavior. While qualitative research delves into the details of the testimonies of those being studied, quantitative research focuses on numerical analysis to develop a statistical picture of a trend or connection. The conclusions drawn from qualitative research are based on compiling, comparing, and evaluating participants' feedback and input, while quantitative research aims to shed light on cause-and-effect relationships through statistical results. By answering the questions of

"why", qualitative research enriches understanding of a subject and may spark action, while quantitative research aims to answer the questions of "what" or "how".
Within this research, a quantitative study was considered to be more suitable to analyze and examine the hypotheses that were created, especially considering the degree of newness which pertains to the realm of artificial intelligence.

4.2 Survey Structure

This study examines the impact of different applications of AI technology (namely, AI-powered Chatbots, AI-powered Sentiment Analysis, and AI-powered Virtual Assistant) on Fan Engagement. In order to do this, a questionnaire was launched in Qualtrics, a software that enables you to generate surveys and reports without requiring any advanced programming knowledge whatsoever. The data collection took place in December 2023/January 2024, with the questionnaire being opened on the 24th of December and closed on the 20th of January. Participants were recruited through different channels, such as Facebook, Instagram, LinkedIn, and WhatsApp. A technique known as “snowball sampling” was used to increase the number of participants by utilizing personal connections. To increase the survey’s reach, all respondents were asked to forward it to their friends and acquaintances. The online survey was selected because it is effective in gathering rich and diverse information in a short amount of time, even if this recruitment method does not guarantee a fully representative sample.

The questionnaire was composed of four different blocks:

- 1st block = focused on the control variables (age, gender, education, etc..).
- 2nd block = focused on fan engagement.
- 3rd block = focused on the perceived usefulness of AI technologies.
- 4th block = focused on moderators (trust in AI technologies and perceived risk of AI technologies).

In total, 196 answers were collected for my research. Out of them, 150 were identified as sports consumers (or enjoyers), and their questionnaires were considered valid. The final valid sample consisted of 136 answers since 14 out of the valid 150 questionnaires were either incomplete or failed the attention checks.

In **Table 2**, all the demographic characteristics of respondents are presented. This table only presents the characteristics of respondents of the 136 valid questionnaires.

Table 2: Demographic Characteristics.

Questions	Percentage (%)	Count
How old are you?		
15-18	4%	5
19-24	18%	25
25-34	27%	37
35-44	9%	12
45-54	16%	22
55-64	20%	27
65 or older	6%	8
What is your gender?		
Male	55%	75
Female	44%	60
Non-binary/third gender	1%	1
Prefer not to say	0%	0
What is your education?		
Elementary school	1%	1
Middle school	7%	9
High school	40%	54
University (Bachelor's Degree)	14%	19
University (Master's Degree)	37%	50

University (Doctorate)	0%	0
Other	2%	3
What is your job position?		
Employed full time	50%	68
Employed part-time	13%	18
Unemployed looking for work	4%	5
Unemployed not looking for work	0%	0
Retired	7%	10
Student	13%	18
Other	13%	17
What is your annual income?		
Less than €10,000	21%	28
€10,000 - €19,999	21%	28
€20,000 - €29,999	29%	39
€30,000 - €39,999	17%	23
€40,000 - €49,999	4%	5
€50,000 - €59,999	4%	6
€60,000 - 69,999	2%	3
€70,000 - €79,999	2%	3
€80,000 - €89,999	0%	0
€90,000 - €99,999	0%	0
€100,000 - €149,999	1%	1
More than €150,000	0%	0

Source: *SmartPLS 4*

In terms of age, the respondents are clustered around two different groups: the youngsters (19-34), as they represent 45% of the population, and the middle age/older strata (45-64), representing 36% of the population. This ought to provide for interesting insights, considering the different attitudes towards technology that pertain to these groups.

Moreover, half the population (51%) possesses a higher education (university degree), whilst the remaining 48% stops at high school. Again, an interesting split in the data.

4.3 Scale Development

All of the different applications of AI that I explored in my study, namely chatbots, virtual assistants, and sentiment analysis, although the latter to a smaller degree, can be considered as Artificial Intelligence Service Agents (AISAs).
Service quality is commonly viewed as a consumer's overall evaluation of a service provider's performance, which is measured at an attitude level over a long-term period (Parasuraman et al., 1994a, Cronin Jr and Taylor, 1994). The dimensions of service quality have been extensively researched, discussed, and validated across different service contexts.
The construct of service quality has been a topic of debate among scholars, with some arguing that it is reflective, as suggested by the majority of service quality scale development literature (Parasuraman et al., 2005), and others suggesting that it contains formative higher orders constructs (Ladhari, 2009; Ladhari, 2010; Martínez and Martínez, 2010). Nonetheless, it is worth noting that some scholars have advised caution in considering the formative specification (Caro and Garcia, 2008).
In terms of AISA service quality, however, there is limited research.
There are three studies worth mentioning - Prentice et al. (2020), Noor et al. (2021b), and Noor et al (2022). Prentice et al. (2020) conducted a study in the hospitality and hotel industry, where they used five constructs to measure the quality of AI services. These constructs included services from concierge robots, digital assistance, voice-activated services, travel experience enhancers, and automatic data processing. However, the authors did not provide any evidence of rigorous development and validation of the constructs and 15 items used, which were sourced from Makadia (2018).
In contrast, Noor et al. (2021b) proposed 12 dimensions that represent the perceived service quality of AISA. They used a two-stage approach, which involved a comprehensive review of service quality and information systems literature, followed by a qualitative validation stage. This approach aimed to both validate the identified dimensions and identify new dimensions that might be applicable to AISA service quality.

Noor et al. (2022)'s scale is the most recent one, and also the one that conveys into a single scale what the previous two started exploring.
Nonetheless, I decided not to use this scale since it deals with AISAs that are already present within the marketplace, as it can be easily deduced by the items used to measure constructs: for example, to measure *efficiency*, Noor et al. (2022) used "The AISA works correctly at first attempt (EFF1)" or "The AISA interface design provides information clearly (EFF3)"; likewise, "Using the AISA is fun (ENJ1)" or "Using the AISA is entertaining (ENJ4)" were proposed to measure *enjoyment*. Since my study is focused on AI technologies that are still in an embryonal state and following a development path, not so much considering the technology in itself but regarding the context they are applied to (namely, sports), I preferred to adapt Froehle (2004)'s scale to evaluate **perceptions** of technology-mediated customer service experience, since we are still dealing with Artificial Intelligence Service Agents (AISA), as stated before. As a consequence, I decided to measure the **perceived usefulness** of these AI technologies. Additionally, before answering those questions, respondents were presented with a brief presentation of the three technologies (chatbots, sentiment analysis, and virtual assistant), so as to make sure that they had at least an understanding of what they were asked about. In terms of measurement scales, I adapted all scales to fit either fan engagement or artificial intelligence. Aside from the construct "Media Consumption," which was measured following a 5-point Likert scale for frequency, where 1 stands for "Never" and 5 for "Always", all of the other constructs were measured using a 7-point Likert scale, where 1 stands for "Strongly Disagree" while 7 for "Strongly Agree".

In the following **Table 3**, all of the constructs, items, and sources are resumed.

Table 3: Constructs, Items, Source.

CONSTRUCT	ITEMS	SOURCE
Merchandise consumption intention (*subset of fan engagement)*	I will continue buying the products of this brand (favorite sports team) in the future. My purchases with this brand (favorite sports team) make me content. I do not get my money's worth when I purchase products from this brand (favorite sports team). ***REVERSED*** Owning the product of this brand (favorite sports team) makes me happy.	Kumar, V., and Anita Pansari (2016), "Competitive Advantage Through Engagement," Journal of Marketing Research, 53 (4), 497-514.

Relationship equity *(subset of fan engagement)*	I have the feeling that the (favorite sports team) knows exactly what I want. I feel at home with (favorite sports team). I feel committed to (favorite sports team).	Ou, Yi-Chun, Peter C. Verhoef, and Thorsten Wiesel (2017), "The Effects of Customer Equity Drivers on Loyalty Across Services Industries and Firms," Journal of the Academy of Marketing Science, 45 (3), 336–356.
Media consumption *(subset of fan engagement)*	How often do you do each of these activities? 1. Watch events of (favorite sports team) on TV, computer, or mobile phone. 2. Watch video clips about (favorite sports team) on TV, computer, or mobile phone. 3. Search the Internet for news about (favorite sports team). 4. Read articles, online or on paper, about (favorite sports team).	L.D. Rosen, K. Whaling, L.M. Carrier, N.A. Cheever, J. Rokkum, (2013), "The Media and Technology Usage and Attitudes Scale: An empirical investigation," Computers in Human Behavior, Volume 29, Issue 6, 2013, 2501-2511.
Attendance intention *(subset of fan engagement)*	I intend to attend the (Favorite Sports Team)'s event (s). The likelihood that I will attend the (Favorite Sports Team)'s event (s) in the future is high. I will attend the (Favorite Sports Team)'s event (s) in the future.	B. Paek, A. Morse, S. Hutchinson & C. H. Lim (2021), "Examining the relationship for sport motives, relationship quality, and sport consumption intention," Sport Management Review, 24:2, 322-344.
Perceived Usefulness of AI technologies	I believe that having this technology will be a useful experience. I believe that having this technology will add additional value to my experience. I believe that having this technology will add value to the overall service. where technology (AI) is: • *Automated Customer Service (Chatbots)*: voice activation or text prompted response to event participant and customer event inquiries (details and fixture list of ongoing and upcoming matches, answer simple queries like match details or sports news or any information about the players or teams (e.g., statistics), check for the tickets of a specific match, and even purchase it).	Froehle, Craig M., and Aleda V. Roth (2004), "New Measurement Scales for Evaluating Perceptions of the Technology-Mediated Customer Service Experience," Journal of Operations Management, 22 (1), 1–21. L. Wanless, C. Seifried, A. Bouchet, A. Valeant & M. L. Naraine (2022), "The diffusion of natural language processing in

	• *Real-Time Sentiment Analysis*: analyzing conversation surrounding certain industry topics in the public narrative by sentiment (analysis of social networks and/or live spectators during a sports event to monitor fans' level of engagement and emotional reactivity, to adjust strategies and create a more captivating experience). • *Digital Personal Assistants*: to support the in-game and off-game experience (**off-game**: analysis of data such as past viewing habits, favorite teams or athletes, and social media interactions to curate a customized selection of articles, videos, highlights, and other content; **in-game**: a digital arena assistant that guides fans around it and provides them with information about the game).	professional sport", Sport Management Review, 25:3, 522-545
Trust in AI technologies	AI technologies that can perform this kind of task better than humans make me uncomfortable. AI technologies that can perform this kind of task go against what I believe computers should be used for. AI technologies that can perform this kind of task are unsettling.	Castelo, Noah, Maarten W. Bos, and Donald R. Lehmann (2019), "Task-Dependent Algorithm Aversion," Journal of Marketing Research, 56 (5), 809–825.
Perceived Risk	It is risky to provide personal information to AI technologies. There will be much uncertainty associated with providing personal information to AI technologies. There will be much potential loss associated with providing personal information to AI technologies.	Rajibul Hasan, Riad Shams, Mizan Rahman (2021), "Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri," Journal of Business Research, Volume 131, 591-597.

4.4 Data Analysis Procedure

For more than a century, social science researchers have been relying on statistical analysis as a crucial tool in their work. With the advent of computer hardware and software, the applications of statistical methods have expanded dramatically. Particularly in recent years, user-friendly interfaces and technology-delivered knowledge have made many more methods widely accessible. As current social science research directions involve more complex relationships, it has become increasingly necessary to use more sophisticated multivariate data analysis methods.

Multivariate analysis involves the simultaneous analysis of multiple variables, typically representing measurements associated with individuals, companies, events, activities, situations, etc. These measurements are often obtained from surveys or observations to collect primary data but may also come from databases containing secondary data. The statistical methods used by social scientists are called first-generation techniques (Fornell, 1982, 1987), including regression-based approaches such as multiple regression, logistic regression, and analysis of variance, as well as exploratory and confirmatory factor analysis, cluster analysis, and multidimensional scaling. These methods can confirm a priori established theory or identify data patterns and relationships when applied to a research question. Specifically, they are confirmatory when testing hypotheses of existing theories and concepts and exploratory when searching for patterns in the data with little or no prior knowledge of how the variables are related.

Researchers in the social sciences have been utilizing first-generation techniques widely. However, over the last two decades, lots of researchers have been turning to second-generation techniques to overcome the limitations of first-generation methods. Structural equation modeling (SEM) is a second-generation technique that allows researchers to include unobservable variables that are measured indirectly by indicator variables. SEM also helps in accounting for measurement errors in observed variables. There are two types of SEM: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). CB-SEM is used primarily to validate or reject theories, while PLS-SEM is mainly used for exploratory research to develop theories by explaining the variance in dependent variables when examining the model.

For my analysis, PLS-SEM is the most fitting one for exploratory research, as it focuses on the explanation of the variance in dependent variables within the examined model.

The rationale for selecting PLS-SEM over CB-SEM is due to the suggestion by Hair et al. (2017) that PLS-SEM is more efficient in predicting exogenous variables. Moreover, PLS-SEM employs the data to determine the path relationships, thereby reducing the error terms. Furthermore, PLS-SEM does not require any assumptions regarding the data distribution, and as a result, it allows us to incorporate most of the measurement items (Hair et al., 2017). Last but not least, the goal is to assess the relationship between reflective-formative constructs (hierarchical latent variables) that cannot be analyzed through CB-SEM, justifying the use of PLS-SEM. When constructing constructs, researchers must consider reflective and formative measurement models (Hair et al., 2017). Reflective measurement models, also known as Mode A measurement in PLS-

SEM, are grounded in classical test theory and suggest that measures represent the effects of an underlying construct (Hair et al., 2017). Reflective indicators are considered representative samples of all possible items within a construct's conceptual domain and should be highly correlated with each other (Nunnally & Bernstein, 1994). It is important that individual items can be interchangeable and that any single item can be excluded without altering the construct's meaning, provided that the construct remains reliable (Hair et al., 2017). On the other hand, formative measurement models, also known as Mode B measurement in PLS-SEM, differ from reflective measurement models by assuming that causal indicators create the construct through linear combinations. They are often called formative indexes, and unlike reflective indicators, they are not interchangeable (Hair et al., 2017). Each indicator captures a specific aspect of the construct's domain, and together, they define the meaning of the construct. Omitting an indicator can potentially change the nature of the construct, so it is crucial to ensure that the breadth of coverage of the construct domain is adequate to capture the content of the focal construct accurately, as emphasized by Diamantopoulos and Winklhofer (2001).

4.4.1 Reflective-Formative Higher-Order Construct

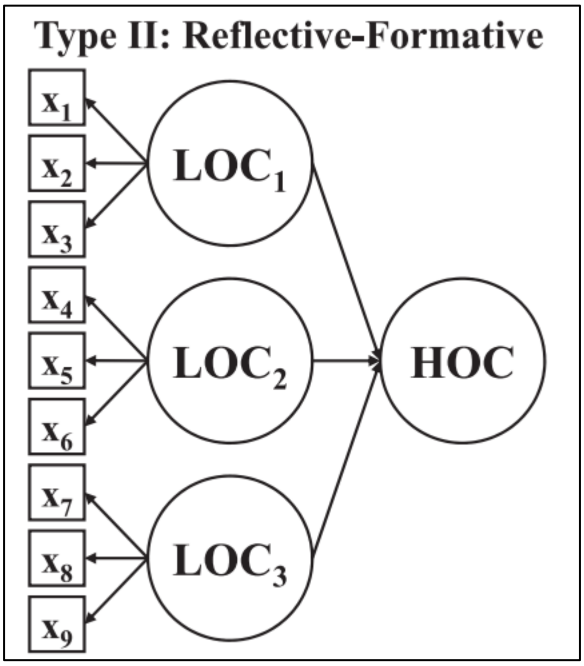
During the course of my research, I realized that the construct of fan engagement was difficult to frame: aside from the difference between transactional and non-transactional, it also emerged how it comprised a plethora of different sub-constructs, as I have previously explored in my research. As a consequence, I decided to consider it as a second-order construct within my research model, thus putting forward a hierarchical component model.

In the field of PLS-SEM, higher-order constructs (also known as hierarchical component models) provide researchers with a way to model a construct on a more abstract level (known as the higher-order component) and its more concrete subdimensions (known as the lower-order components). As Lohmöller (1989) notes,this approach extends standard construct conceptualizations, which typically rely on a single layer of abstraction. Higher-order constructs have several advantages, including reducing the number of path model relationships, which leads to model parsimony (Edwards, 2001; Johnson et al., 2011; Polites et al., 2012). They also help overcome the bandwidthfidelity dilemma, which refers to the tradeoff between a variety of information and thoroughness of testing to obtain more certain information (Cronbach & Gleser, 1965, p. 100).Finally, higher-order constructs provide a means for reducing collinearity among formative indicators by offering a vehicle to re-arrange the indicators and/or constructs across different concrete subdimensions of the more abstract construct (Hair et al., 2018).

It is important to understand that hierarchical component models (HCMs) consist of two elements: the higher-order component (HOC), which represents the more abstract entity, and the lower-order components (LOCs), which capture the subdimensions of the HOC (Hair et al., 2017). Different types of HCMs can be distinguished based on the relationships between the HOC and LOCs, as well as between constructs and their indicators. For instance, the reflective-reflective HCM type involves a reflective relationship between the HOC and LOCs, and all first-order constructs are measured by reflective indicators. On the other hand, the reflective-formative HCM type involves formative relationships between the LOCs and the HOC, and all first-order constructs are measured by reflective indicators. Additionally, researchers may use other alternative HCMs such as formative-reflective and formative-formative HCMs.

As per my study, I opted for a reflective-formative higher-order construct, where the lower-order constructs are **reflective** while the higher-order construct is **formative**. To clarify, the higher-order construct is fan engagement, and the lower-order constructs are media consumption, attendance intention, merchandise purchase intention, and relationship equity. **Figure 3** provides a clear graphical representation of the model under scrutiny.

Figure 3: Reflective-formative HOC.



Source: Sarstedt et al (2019).

I decided to opt for this measurement model since the literature on FE (fan engagement) presents it as a combination of many distinct components, which have been gradually formed or shaped by individual experiences, and that do not necessarily correlate one with the other: for example, a fan could be extremely proficient in terms of attendance intention and media consumption, while at the same time not caring about purchasing official merchandise. I drew inspiration from Ho et al. (2021) which refuted the largely accepted conceptualization of customer engagement as a reflectively measured construct since such a generic gauging fails to capture the “specific experiential qualities that underlie CEBs” (Ho et al., 2021). Although their study was applied to a social media context, many parallels can be drawn, and as such the reflective-formative measurement model is perceived to be the best-fitting one.

Moreover, to give an additional layer of robustness to my decision, a confirmatory tetrad analysis (CTA-PLS) was carried out in PLS-SEM (Gudergan et al., 2008). This PLS-SEM-based statistical test helps in deciding whether a latent variable should be measured reflectively or formatively, thus assisting in avoiding the incorrect specification of a measurement model. As stated by Hair et al. (2017), “CTA-PLS builds on the concept of tetrads (t), which describe the relationship between pairs of covariances". A tetrad is the result of subtracting the product of one pair of covariances from the product of another pair of covariances. Supposing we had a reflectively measured latent variable with four indicators, we would obtain three tetrads thus formed:

Formula 1: *Tetrads*

$$\tau_{1234} = \sigma_{12} \cdot \sigma_{34} - \sigma_{13} \cdot \sigma_{24},$$
$$\tau_{1342} = \sigma_{13} \cdot \sigma_{42} - \sigma_{14} \cdot \sigma_{32},$$
$$\tau_{1423} = \sigma_{14} \cdot \sigma_{23} - \sigma_{12} \cdot \sigma_{43}.$$

Source: *Hair, J. et al. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (2^{nd} ed.).*

The reflective measurement model expects each tetrad to have a value of zero and disappear. This is because reflective indicators represent one specific concept or trait equally well according to the domain sampling model. However, tetrads are rarely exactly zero and often have a residual value. Therefore, if one tetrad's residual value is significantly different from zero, it suggests that the reflective measurement model specification should be rejected in favor of the alternative formative specification. The CTA is a statistical test that evaluates the hypothesis H0: t = 0 (the tetrad equals zero and disappears) and the alternative hypothesis H1: t ≠ 0 (the tetrad does not equal zero). The CTA initially assumes a reflective measurement specification (Hair et al., 2017). A non-significant test statistic supports H0, implying that the tetrads vanish as expected in a reflective measurement model. On the other hand, a significant test statistic that supports H1 suggests that the reflective model specification is doubtful in favor of the alternative formative specification.

Bollen and Ting (2000) provide the five steps that are involved in CTA-PLS, and they are as follow:

1. Form and compute all vanishing tetrads for the measurement model of a latent variable.
2. Identify model-implied vanishing tetrads.
3. Eliminate model-implied redundant vanishing tetrads.
4. Perform a statistical significance test for each vanishing tetrad.
5. Evaluate the results for all model-implied nonredundant vanishing tetrads per measurement model.

The CTA-PLS method involves five steps: the first three steps focus on selecting nonredundant vanishing tetrads per measurement model, while the latter two address their significance testing (Hair et al., 2017). In the fourth step, the CTA-PLS uses bootstrapping to test whether the tetrads' residual values differ significantly from zero. However, testing each tetrad individually poses a multiple testing problem. If the measurement model has a large number of nonredundant vanishing tetrads, it increases the chance of rejecting the null hypothesis by chance (Hair et al., 2017). Therefore, in the fifth step, the Bonferroni correction is applied to adjust for the multiple testing problem. This step calculates the confidence intervals of the nonredundant vanishing tetrads for a prespecified error level. A nonredundant tetrad is considered significantly different from zero if its confidence interval does not include zero. If none of the tetrads are significantly different from zero, a reflective measurement model specification is assumed. However, if only one tetrad is significantly different from zero, a formative measurement model specification should be considered (Hair et al., 2017).
Insofar as SmartPLS 4 does all of the calculations by itself, it allows us to only check for the last step of significance testing. To provide a greater degree of clarity, this analysis was carried out in the second step of the PLS-SEM analysis, where the higher-order construct of fan engagement was actually inserted into the model (a more in-depth explanation of the entire process will be presented in the next section). The results of the CTA-PLS are as shown in the Table below.

Table 4: Confirmatory Tetrad Analysis.

Fan Engagement	**CI low adj.**	**CI up adj.**
1: Attendance Intention, Media Consumption, Merch Purch Intention, Relationship Equity	-0.001	0.168
2: Attendance Intention, Media Consumption, Relationship Equity, Merch Purch Intention	0.086	0.240

Source: *SmartPLS 4*

As **Table 4** shows, one tetrad is actually significantly different from zero, as its confidence interval does not include zero (0.086 – 0.240). Hence, following Hair et al. (2017)'s guidelines stated before, we can consider fan engagement as a formative construct.

4.4.2 Estimation Of Hierarchical Latent Variable Models In PLS-SEM

PLS-SEM requires the computation of construct scores for each latent variable in the path model (Ringle et al., 2015). However, when it comes to modeling hierarchical latent variables in PLS-SEM, three approaches have been proposed in the literature to estimate the construct scores of a higher-order construct. These are: (1) the repeated indicator approach (Lohmöller, 1989; Wold, 1982), (2) the sequential latent variable score method or two-stage approach (Ringle et al., 2012; Wetzels et al., 2009), and (3) the hybrid approach (Wilson and Henseler, 2007).

The repeated indicator approach involves constructing a higher-order latent variable by specifying a latent variable that represents all the manifest variables of the underlying lower-order latent variables (Lohmöller, 1989; Noonan and Wold, 1993; Wold, 1982). This method involves using the manifest variables twice - once for the first-order latent variable ("primary" loadings/weights) and once for the second-order latent variable ("secondary" loadings/weights). The outer model (measurement model) is specified in this way, and the inner model (structural model) accounts for the hierarchical component of the model, as the path coefficients between the first-order and second-order constructs represent the loadings/weights of the second-order latent variable. This approach can easily be extended to higher-order hierarchical models (e.g., Noonan and Wold, 1983; Wetzels et al., 2009).

The two-stage approach, also known as the sequential latent variable score method, offers the advantage of determining latent variable scores in PLS-SEM, allowing the acquisition of scores for lower-order latent variables (Chin, 1998a; Lohmöller, 1989; Tenenhaus et al., 2005). In the first stage, the construct scores of the first-order constructs are estimated without the presence of the second-order construct. These first-stage construct scores are then used as indicators for the higher-order latent variable in a separate second-stage analysis (Agarwal and Karahanna, 2000; Wetzels et al., 2009; Wilson and Henseler, 2007). Alternatively, a repeated indicator model can be estimated in the first stage, and the first-order construct scores can be used in a separate second-stage analysis (Ringle et al., 2012; Wilson, 2010).

According to Wilson and Henseler (2007), the hybrid approach is a technique that is similar to the repeated indicator approach. However, unlike the repeated indicator approach, the hybrid approach uses each indicator (manifest variable) only once in a model to avoid artificially correlated residuals. To achieve this, the hybrid approach splits the indicators of each first-order construct and uses one half to estimate the first-order construct while using the other half to estimate the second-order construct. By doing so, the hybrid approach avoids the repeated use of indicators in the model.

The repeated indicator approach has the advantage of estimating all constructs simultaneously, rather than estimating lower-order and higher-order dimensions separately. This approach considers the entire nomological network, avoiding interpretational confounding. When using the repeated indicator approach, researchers must make decisions regarding the measurement mode for the higher-order construct and the inner weighting scheme. Reflective constructs are typically associated with Mode A measurement, while formative constructs are associated with Mode B, according to Henseler et al. (2009) and Tenenhaus et al. (2005). The most commonly used approach for repeated indicators on a hierarchical latent variable is to use Mode A, which is well-suited for reflective-reflective type models, as recommended by Wold (1982). However, Mode A is also used for estimating formative type models, especially when the first-order constructs are reflective, as in the case of reflective-formative type models, as suggested by Chin (2010) and Ringle et al. (2012).In contrast, the formative nature of the higher-order construct might suggest Mode B measurement, making it more appropriate to use Mode B for the repeated indicators of a formative type hierarchical latent variable model (i.e., reflective-formative and formative-formative types). However, research papers presenting the repeated indicator approach usually do not discuss the importance of the mode of measurement, but only indirectly infer it from the direction of arrows in the path diagram (Chin, 2010; Ringle et al., 2012).

One of the drawbacks of using the repeated indicator approach is that the same indicators are used repeatedly, which can lead to artificially correlated residuals. To avoid this issue, the hybrid approach randomly splits the indicators and uses them only once either on the first-order construct or on the second-order construct. However, this approach results in reduced reliability of measures due to the use of only half the number of indicators. This could be problematic because PLS-SEM is known for being consistent at large, meaning estimates are consistent when the sample size and number of indicators increase (Lohmöller, 1989). There are no clear guidelines on whether

Mode A or Mode B should be used for the formative second-order construct when using the hybrid approach. In contrast, the two-stage approach estimates a more parsimonious model on the higher-level analysis without requiring the lower-order constructs. However, the separate estimation of the lower and higher-order level models might cause interpretational confounding because it does not take the whole nomological network into account. (Wilson and Henseler, 2007).

According to Ringle et al. (2012), it is worth noting that there is a significant difference between the approaches when using hierarchical latent variables in a nomological network of latent variables. This is particularly apparent when the higher-order construct is formative, and the repeated indicator approach is used. In this case, the lower-order constructs already account for all the variance of the higher-order construct. Therefore, other antecedent constructs cannot explain any variance of the higher-order construct, leading to zero paths to the higher-order construct (Wetzels et al., 2009). However, this problem can be avoided by using the two-stage approach for formative hierarchical constructs (Ringle et al., 2012). Therefore, it is recommended to use the two-stage approach when the PLS-SEM model involves a formative hierarchical latent variable model in an endogenous position.

V. Empirical Findings

5.1 Validating Higher-Order Constructs

This chapter entails a comprehensive presentation of the findings obtained from the data analysis. It covers an evaluation of the measurement and structural model, wherein the former establishes the construct's reliability and validity, while the latter confirms the hypothesized relationships' significance. To summarize, let us revisit the proposed hypotheses:

H1: there is a significantly positive impact of AI-powered Chatbots on Fan Engagement.
H2: there is a significantly positive impact of AI-powered Sentiment Analysis on Fan Engagement.
H3: there is a significantly positive impact of AI-powered Personal Assistants on Fan Engagement.
H4: there is a significantly negative moderating impact of AI Trust on the relationship between AI technologies and Fan Engagement.
H5: there is a significantly negative moderating impact of AI Perceived Risk on the relationship between AI technologies and Fan Engagement.

As Becker et al. (2012) proposed, I used the two-stage approach to evaluate my reflective-formative higher-order model, since fan engagement is a formative latent variable in an endogenous position; that is, it is the dependent variable of the model.

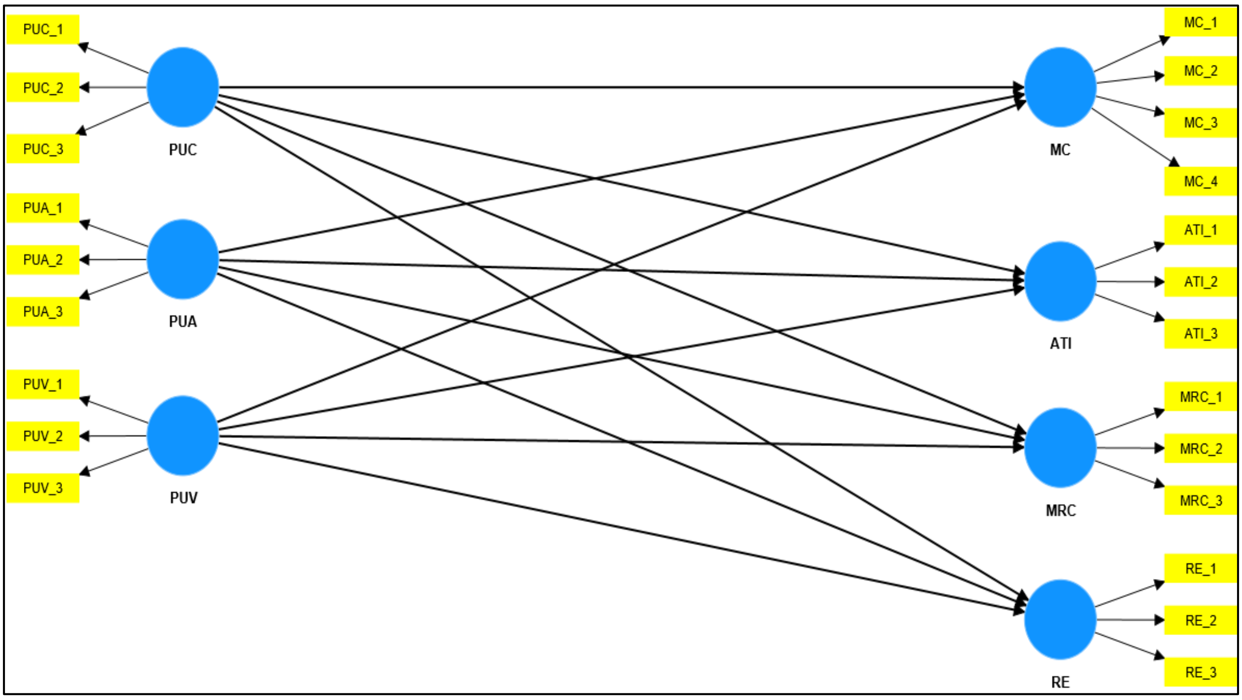
Following guidelines provided by Sarstedt et al. (2019), stage one was characterized by the estimation and measurement model assessment for the lower-order components as based on the standard model, which draws direct relationship between the constructs. At this stage, the higher-order component is not yet included in the PLS path model.

Then, in stage two, the latent variable scores from the stage one results allow the creation and estimation of the model.

5.2 Measurement Model

To assess the quality of the study’s construct, the measurement model is evaluated. This evaluation begins with an assessment of the factor loadings, followed by establishing the construct’s reliability and validity. This is the **first stage** of the analysis, and the model was graphically represented in SmartPLS 4 as **Figure 4** shows.

Figure 4: Structural Model - First Stage Analysis.



Source: *SmartPLS 4*

5.2.1 LOCs - Factor Loadings

According to Pett et al. (2003), factor loadings are the measure of the correlation between each item in the correlation matrix and the given principal component. The range of factor loadings is from -1.0 to +1.0, with higher absolute values indicating a stronger correlation of the item with the underlying factor. Hair et al. (2017) recommend that the outer loadings should ideally be 0.708 or higher. Since all the factor loadings in the present study exceeded this threshold, none of them were eliminated. The values are reported in **Table 5**, as it can be seen in the next page.

Table 5: Factor Loadings.

	ATI	MC	MRC	PUA	PUC	PUV	RE
ATI_1	0.937						
ATI_2	0.959						
ATI_3	0.965						
MC_1		0.814					
MC_2		0.883					
MC_3		0.904					
MC_4		0.852					
MRC_1			0.972				
MRC_2			0.972				
MRC_3			0.978				
PUA_1				0.965			
PUA_2				0.958			
PUA_3				0.966			
PUC_1					0.908		
PUC_2					0.938		
PUC_3					0.934		
PUV_1						0.963	
PUV_2						0.936	
PUV_3						0.935	
RE_1							0.785
RE_2							0.907
RE_3							0.834

Source: *SmartPLS4*

5.2.2 Reliability Analysis

After having examined outer loadings, the analysis continues by assessing the reliability of the measuring instrument. Reliability is defined as the degree to which a measurement tool remains constant and dependable.

One way to measure this is through internal consistency, which refers to how well the items on an instrument are related to each other and reflect the same underlying construct (Cooper & Schindler, 2014). Traditionally, Cronbach's Alpha (α) coefficient has been used to determine internal consistency. However, recent studies have suggested that the reliability of individual indicators is equally important, especially in PLS-SEM (Hair et al., 2017). Therefore, instead of relying solely on Cronbach's Alpha, researchers now consider composite reliability, which takes into account the reliability of individual indicators and the extent to which they indicate the latent variable (Hair et al., 2017). **Table 6** presents the results for both Cronbach's Alpha and Composite

Reliability: since they both exceed the recommended threshold of 0.7, as suggested by Hair et al. (2011), the reliability of the construct is established.

Table 6: *Construct Reliability Analysis (Cronbach's Alpha and Composite Reliability)*

	Cronbach's alpha	Composite reliability
ATI	0.950	0.968
MC	0.889	0.922
MRC	0.973	0.982
PUA	0.961	0.975
PUC	0.919	0.948
PUV	0.940	0.962
RE	0.795	0.880

Source: *SmartPLS 4*

5.2.3 LOCs - Construct Validity

Validity is another crucial aspect to take into consideration when measuring a model in SmartPLS. The two types of validity to consider are convergent and discriminant validity; establishing both is fundamental to constitute construct validity.

To assess convergent validity, we look at the average variance extracted (AVE): this metric tells us how much variance is captured by the construct compared to measurement error. On the other hand, discriminant validity, which examines the degree of distinctiveness of different constructs, can be measured via other methods such as the Fornell-Larcker criterion or by analyzing cross loadings and heterotrait-monotrait (HTMT) ratio of correlations.

Convergent validity

According to Bagozzi et al. (1991), convergent validity is "the degree to which multiple attempts to measure the same concept are in agreement". In other words, if two or more measures of the same thing covary highly, then they are valid measures of the concept (Bagozzi et al., 1991). If the AVE value is greater than or equal to the recommended value of 0.50, items converge to the underlying construct and thus convergent validity is established (Fornell & Lacker, 1981). As it can be seen from **Table 7**, all AVEs are above the recommended threshold, hence convergent validity is established.

Table 7: *Construct Convergent Validity (AVE)*

	Average variance extracted (AVE)
ATI	**0.910**
MC	**0.746**
MRC	**0.948**
PUA	**0.928**
PUC	**0.859**
PUV	**0.893**
RE	**0.711**

Source: *SmartPLS 4*

Discriminant validity

Discriminant validity refers to the degree to which different constructs can be clearly differentiated from one another based on empirical evidence. It determines whether a construct is truly unique and distinct from others. It is paramount to ensure that each construct is not only concept-wise, but also statistics-wise unique, maintaining its individual identity. The three most commonly used method to assess discriminant validity are:

- Fornell-Lacker criterion.
- Heterotrait-monotrait (HTMT) ratio of correlations.
- Cross loadings.

One of the most common approaches is the one developed by Fornell and Lacker (1981). This method involves comparing the correlations among latent variables with the square root of the Average Variance Extracted (AVE). Discriminant validity can be established if the square root of AVE for a construct is greater than its correlation with all other constructs. **Table 8** presents the results, with the square roof of AVE being marked in green. Strong support for the establishment of discriminant validity is provided since each square root of AVE was found to be greater than its correlation with other constructs.

Through the employment of these methods, researchers can assess whether a construct is distinguishable from others and the extent to which it differs, thus ensuring discriminant validity is respected. It is necessary to establish such differentiation in order to prevent overlap and maintain each construct's uniqueness.

Table 8: *Discriminant Validity – Fornell & Larcker Criterion*

	ATI	MC	MRC	PUA	PUC	PUV	RE
ATI	**0.954**						
MC	0.732	**0.864**					
MRC	0.710	0.521	**0.974**				
PUA	0.264	0.220	0.230	**0.963**			
PUC	0.201	0.154	0.224	0.624	**0.927**		
PUV	0.207	0.214	0.213	0.569	0.697	**0.945**	
RE	0.684	0.612	0.705	0.472	0.360	0.398	**0.843**

Source: *SmartPLS 4*

According to Voorhees et al. (2016), the Fornell-Larcker criterion is more effective in identifying discriminant validity problems when there is greater variability in the indicator loadings. However, it still has some limitations overall.

In order to tackle this, Henseler et al. (2015) recommended using the heterotrait-monotrait (HTMT) ratio of the correlations. According to Hair et al. (2017), this method gives the true estimate of the correlation between variables if the variables are perfectly reliable. The correlation estimated using this method is also referred to as the disattenuated correlation. It is suggested that the HTMT ratio of the correlations should be less than 1, as per Henseler et al. (2015).

Table 9: *Discriminant Validity – HTMT*

	ATI	MC	MRC	PUA	PUC	PUV	RE
ATI							
MC	**0.798**						
MRC	**0.738**	**0.555**					
PUA	**0.273**	**0.230**	**0.234**				
PUC	**0.209**	**0.166**	**0.231**	**0.664**			
PUV	**0.218**	**0.224**	**0.221**	**0.599**	**0.753**		
RE	**0.784**	**0.720**	**0.799**	**0.537**	**0.416**	**0.460**	

Source: *SmartPLS 4*

In **Table 9** we can see the final measurement. Thus, we can confirm that the condition for discriminant validity is upheld, since the HTMT values for the construct do not surpass 1, meaning that the constructs differ from each other and show discriminant validity.

Last but not least, cross-loadings are also used as a method to evaluate whether indicators have discriminant validity. Essentially, an indicator's correlation with its own construct should be higher than its correlation with any other construct, for discriminant validity to be established (Hair et al., 2017).

Table 10: *Cross loadings*

	ATI	MC	MRC	PUA	PUC	PUV	RE
ATI_1	**0.937**	0.743	0.682	0.243	0.194	0.225	0.696
ATI_2	**0.959**	0.654	0.655	0.275	0.196	0.194	0.632
ATI_3	**0.965**	0.700	0.696	0.233	0.185	0.172	0.629
MC_1	0.633	**0.814**	0.449	0.178	0.202	0.152	0.527
MC_2	0.603	**0.883**	0.470	0.196	0.167	0.241	0.537
MC_3	0.682	**0.904**	0.477	0.225	0.088	0.193	0.566
MC_4	0.621	**0.852**	0.390	0.143	0.083	0.124	0.476
MRC_1	0.690	0.508	**0.972**	0.206	0.209	0.215	0.668
MRC_2	0.679	0.501	**0.972**	0.201	0.202	0.182	0.659
MRC_3	0.703	0.512	**0.978**	0.258	0.239	0.222	0.726
PUA_1	0.254	0.220	0.229	**0.965**	0.585	0.517	0.422
PUA_2	0.225	0.181	0.191	**0.958**	0.621	0.575	0.446
PUA_3	0.278	0.231	0.240	**0.966**	0.598	0.554	0.491
PUC_1	0.147	0.106	0.170	0.563	**0.908**	0.650	0.285
PUC_2	0.231	0.189	0.238	0.578	**0.938**	0.624	0.371
PUC_3	0.167	0.118	0.204	0.595	**0.934**	0.674	0.331
PUV_1	0.190	0.198	0.202	0.561	0.665	**0.963**	0.381
PUV_2	0.209	0.224	0.206	0.533	0.654	**0.936**	0.375
PUV_3	0.189	0.183	0.195	0.520	0.658	**0.935**	0.372
RE_1	0.505	0.439	0.552	0.354	0.303	0.311	**0.785**
RE_2	0.677	0.556	0.648	0.420	0.324	0.341	**0.907**
RE_3	0.542	0.545	0.581	0.416	0.283	0.353	**0.834**

Note: ***Green*** *represents the items on their respective parent construct.* **Source**: *SmartPLS 4*

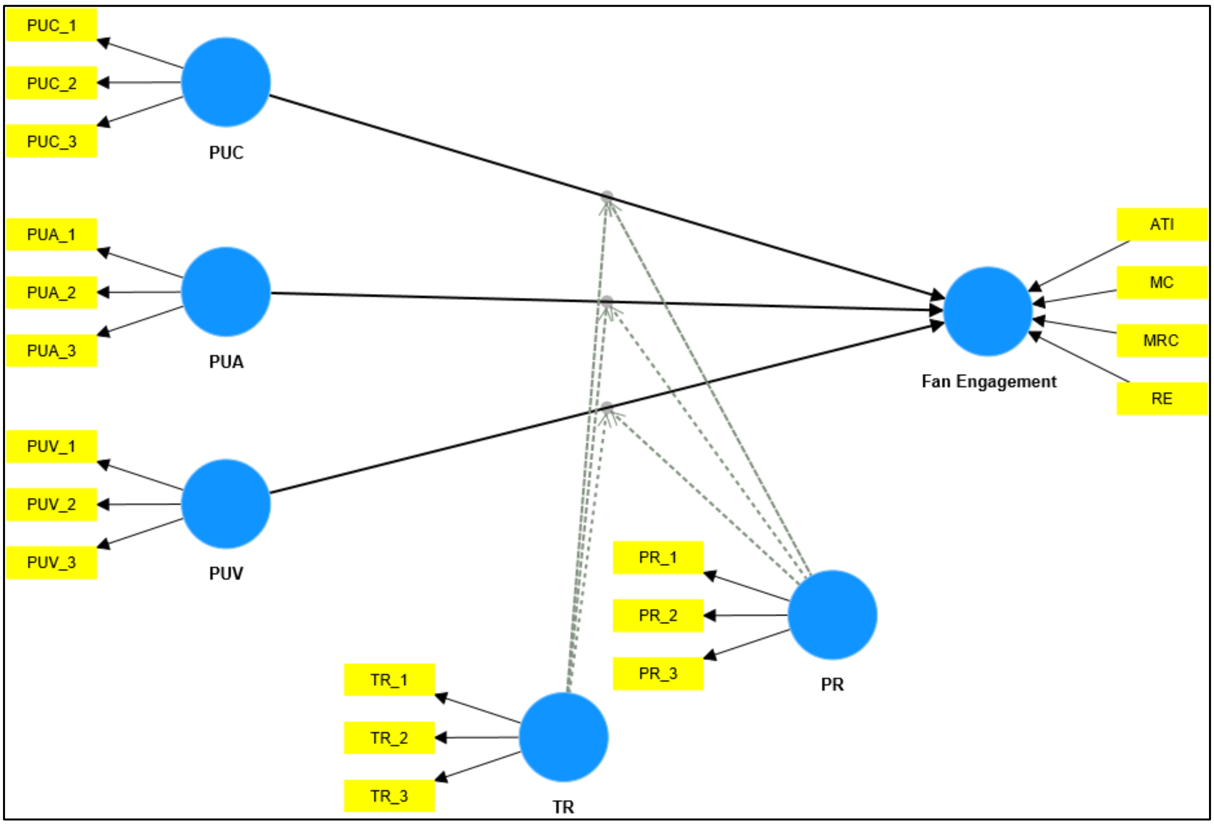
Table 10 presents the cross loadings of the constructs. The constructs are placed on the horizontal line of the table, and we would expect the items that measure each construct to demonstrate higher loadings on their designated parent construct; if so, we are in presence of discriminant validity. Once again, the conditions are respected, which provides us with another proof of respected discriminant validity.

5.2.4 Higher-Order Construct Validation

Now, we move on to the second stage of our analysis: namely, the assessment of the higher-order construct. **Figure 5** gives a graphical representation of the model in the second stage: as it can be seen, the lower-order constructs Media Consumption (MC), Attendance Intention (ATI), Merchandise Purchase Intention (MRC), and Relationship Equity (RE) have been removed. Meanwhile, the higher-order construct Fan Engagement (FE) is introduced together with the two moderators of the study: AI Perceived Risk and AI Trust.

As proposed by Becker et al. (2012) in their two-stage approach, I used the latent variable scores of the lower-order components *MC, ATI, MRC,* and *RE* as indicators of the formative higher-order construct *FE*.

Figure 5: Structural Model – Second Stage Analysis.



Source: *SmartPLS 4*

The first thing to do to validate our higher-order construct is to check for collinearity of the formative indicators. It is important to note that unlike reflective indicators, which can be used interchangeably, formative measurement models do not typically exhibit high correlations between their items (Hair et al., 2017). In fact, when two formative indicators are highly correlated, this can create issues in terms of interpretation and methodology. The worst-case scenario, when there are more than two indicators involved, is referred to as multicollinearity (Hair et al., 2017).

When formative indicators are highly correlated, it can cause significant issues in weight estimation and statistical significance (Hair et al., 2017). This is especially problematic in PLS-SEM analyses with smaller sample sizes where standard errors are generally larger due to sampling error. High collinearity can lead to incorrect weight estimation and even reverse their signs. Additionally, it can boost the standard errors, which reduces the ability to demonstrate that the estimated weights are significantly different from zero (Hair et al., 2017).

A measure of collinearity is the variance inflation factor (VIF), considered as the reciprocal of the tolerance, which represents the "amount of variance of one formative indicator not explained by the other indicators in the same block" (Hair et al., 2017). Within PLS-SEM, a VIF value of 5 or higher indicates a potential collinearity problem (Hair et al., 2011). In other words, if an indicator presents a VIF value of 5, it means that the remaining formative indicators of the same construct account for 80% of its variance. In case the collinearity level is remarkably high, with a VIF value of 5 or above, it may be necessary to eliminate one of the related indicators. However, this should only be done if the remaining indicators still effectively represent the content of the construct from a theoretical standpoint (Hair et al., 2017).

Additionally, according to Hair et al. (2017), in order to validate formative constructs, it is necessary to report the weights of the indicators and the significance of those weights. An issue that could arise when evaluating formatively specified higher-order constructs is having to deal with nonsignificant LOC weights. However, it is not recommended for researchers to immediately assume that this finding indicates poor measurement model quality and remove certain variables from the higher-order construct (HOC).

This is because by doing so, the content validity can be negatively impacted. As opposed to simply deleting the LOC with nonsignificant weights, researchers should evaluate its loading, which is "equivalent to its bivariate correlation with the HOC" (Becker et al., 2023). This value represents the LOC's absolute contribution and ought to be greater than 0.50, supposing that the weight is nonsignificant (Hair et al., 2022).

As shown by **Table 11**, all of the outer weights were found significant; additionally, outer loadings were also found significant for each of the lower-order constructs as they were all greater than 0.50. Lastly, VIF values of the formative indicators were assessed to check for collinearity, and they were all lower than the recommended value of 5 (Hair et al., 2017). Therefore, since all criteria were met, the HOC validity is established.

Table 11: *Higher-Order Construct Validity*

HOC	LOCs	Outer Weights	T Statistic	P Value	Outer Loadings	VIF
FE	ATI	0.247	5.867	0.000	0.880	3.261
	MC	0.220	3.882	0.000	0.797	2.296
	MRC	0.228	5.225	0.000	0.838	2.496
	RE	0.452	6.608	0.000	0.918	2.451

Source: *SmartPLS 4*

5.3 Structural Model

Once we have run the PLS-SEM algorithm, we will obtain estimates for the structural model relationships. These estimates represent the hypothesized relationships among the constructs and are known as path coefficients. The standardized values of path coefficients range between -1 and +1, although at times (very rarely though) they can be higher or lower. Path coefficients close to +1 indicate strong positive relationships (and the opposite for negative values) which are typically statistically significant. On the other hand, path coefficients closer to 0 suggest weaker relationships (Hair et al., 2017).

To do this, we will run a bootstrapping analysis. When conducting bootstrapping, a large number of samples are generated by randomly drawing observations from the original sample with replacement. To guarantee accurate results, it is recommended to create at least 5,000 bootstrap samples. A distribution is formed from the estimated coefficients from these samples, which approximates the original distribution. These samples are then utilized to estimate the PLS path model, so as to verify the validity of the model set for the research.

As Hair et al. (2017) proposed, marketing researchers tend to assume a significance level of 5%. Nonetheless, in the presence of a study which is exploratory in nature, researchers are more nuanced and often assume a significance level of 10%. Since my study is quite exploratory, I decided to opt for a 10% significance level.
For the coefficients to be significant, the **p value** must be lower than **0.1** and the **T Statistics** coefficients must be greater than **1.65**.

5.3.1 Hypothesis Testing

H1: There is a significantly positive impact of AI-powered Chatbots on Fan Engagement.

H1 evaluates whether (the perceived usefulness of) AI-powered Chatbots has a significant, positive impact on Fan Engagement. The results revealed that PUC does not have a significant effect on FE ($\beta = .010$, $t = .079$, $p > 0.1$).

H2: There is a significantly positive impact of AI-powered Sentiment Analysis on Fan Engagement.

H2 evaluates whether (the perceived usefulness of) AI-powered Sentiment Analysis has a significant, positive impact on Fan Engagement. The results revealed that PUA has a significant effect on FE ($\beta = .283$, $t = 2.917$, $p < 0.1$).

H3: there is a significantly positive impact of AI-powered Personal Assistants on Fan Engagement.

H3 evaluates whether (the perceived usefulness of) AI-powered Personal Assistants has a significant, positive impact on Fan Engagement. The results revealed that PUV does not have a significant effect on FE ($\beta = .159$, $t = 1.367$, $p > 0.1$).

The summary of the structural model is summarized in **Table 12**, as it can be seen below.

Table 12: *Summary of the structural model*

	Std. Beta	P-Value	T statistic	Decision
PUA -> Fan Engagement	0.283	**0.004**	2.917	Supported
PUC -> Fan Engagement	0.010	**0.937**	0.079	Rejected
PUV -> Fan Engagement	0.159	**0.172**	1.367	Rejected

Source: *SmartPLS 4*

5.3.2 Coefficient Of Determination (R^2 Value)

The R^2 value, also known as the coefficient of determination, is widely used to evaluate the structural model.

It measures the model's predictive ability by calculating the squared correlation between the predicted and actual values of a specific endogenous construct (Hair et al., 2017). This coefficient represents how the exogenous latent variables collectively affect the endogenous latent variable; in other words, it shows how much of the variance in endogenous constructs is explained by all the exogenous constructs linked to it.

Since the R^2 value includes all the data used for model estimation, it provides a measure of in-sample predictive power, indicating the model's predictive strength (Rigdon, 2012; Sarstedt, Ringle, Henseler, & Hair, 2014).

It ranges from 0 to 1, the closer to 1 the higher the level of predictive accuracy. Providing a precise benchmark for acceptable R^2 values is challenging since it depends on the complexity of the model and the field of study. Nonetheless, as a rule of thumb, scholarly research focusing on marketing issues considers R^2 values of 0.75, 0.50, or 0.25 as respectively substantial, moderate, or weak. Additionally, Falk and Miller (1992) recommended that R^2 values should be equal to or greater than 0.10 for the variance explained of a particular endogenous construct to be deemed adequate.

In our analysis, the coefficient of determination is 0.272, meaning that (the perceived usefulness of) AI-powered technologies approximately explains 27,2% of the variance in Fan Engagement.

5.3.3 Effect Size f^2

The f^2 effect size, an increasingly encouraged measure by journal editors and reviewers, is used to measure the difference in the R^2 value after removing a particular independent variable from the model. It helps to determine whether the exclusion of this variable significantly affects the dependent variable.

In terms of values, it is recommended to use the following guidelines: effect size values of 0.02, 0.15, and 0.35 are considered small, medium, and large effects respectively, as per Cohen (1998). Anything below 0.02 is considered to have no effect.
Table 13 presents the results in a more organized way: as it can be seen, PUC has no effect on the dependent variable as its *f square* is lower than 0.02, meaning that its elimination would have no effect on the dependent construct. PUV is slightly above the minimum threshold of 0.02, thus having a small effect on FE, whilst PUA is tilted towards a medium effect on FE, as its value of 0.129 is closer to 0.15 than to 0.02.

Table 13: *f square*

	Fan Engagement	PUA	PUC	PUV
Fan Engagement				
PUA	0.129			
PUC	**0.001**			
PUV	0.026			

Source: *SmartPLS 4*

5.3.4 Predictive Power

Shmueli et al. (2016) have developed a method using training and holdout samples to assess a model's predictive power through PLS path model estimations. The researchers suggest using several prediction statistics to quantify the amount of prediction error in indicators of a particular endogenous construct, with root-mean-square error (RMSE) being the most popular metric and mean absolute error (MAE) following closely behind. According to Danks and Ray (2018), researchers should usually use the RMSE to evaluate a model's predictive power, unless the prediction error's distribution is highly nonsymmetric, evidenced by either a long left or right tail in the distribution. In such cases, Shmueli et al. (2019) suggest that researchers opt for the MAE as a more appropriate prediction statistic.

In practical terms, the predictive power of the model can be measured by comparing the RMSE (or MAE) value with the LM values. The LM, also known as the linear regression model, "*offers prediction errors and summary statistics that ignore the specified PLS path model*" (Ringle et al., 2024). By comparing the results obtained from PLS-SEM with those of LM, we can determine if using a path model that is established based on theory enhances or at least maintains the predictive accuracy of the available indicator data. Ideally, the PLS-SEM results should show a lower prediction error (either RMSE or MAE) than the LM outcomes.

Another benchmark to test the predictive performance of the model is to check for the Q^2 value. Essentially, it "*compares the prediction errors of the PLS path model against simple mean predictions, employing the mean value of the training sample to predict the outcomes of the holdout sample*" (Ringle et al., 2024). The interpretation of its value results is alike to the assessment of Q^2 values obtained by the blindfolding procedure in PLS-SEM: substantially speaking, the Q^2 value predict ought to be above 0. Additionally, values of 0.02, 0.15, and 0.35 indicate a weak, moderate, or strong degree of predictive relevance for each effect respectively (Hair et al., 2017).

In our case, since the distribution of the prediction error was symmetrical for all indicators, we used the RMSE as a prediction statistic. As it can be seen from **Table 14**, all PLS-SEM values are lower than LM values, thus fostering the prediction power of the model for our manifest variables (indicators of FE). Moreover, it can be stated that RE is pretty successful in predicting FE.

Table 14: *MV Prediction*

	Q^2predict	PLS-SEM_RMSE	LM_RMSE
ATI	**0.056**	**0.979**	1.049
MC	**0.043**	**0.986**	1.044
MRC	**0.044**	**0.986**	1.055
RE	**0.208**	**0.897**	0.939

Source: *SmartPLS 4*

At the same time, regarding latent variables, FE presents a Q^2 value of **0.192**, thus further supporting the predictive power of the model.

The other exogenous constructs (PUA, PUC, PUV) do not have a Q^2 value since they are not being predicted by any other latent factor.

5.4 Moderator Analysis

The concept of cause-and-effect relationships in PLS path models implies that certain constructs have a direct effect on other constructs without any influence from other variables. However, this assumption may not hold true in many instances, and including a third variable in the analysis can alter our understanding of the model relationships. Two noteworthy examples of such extensions include moderation and mediation (Hair et al., 2017).

Mediation is a process where a third variable, known as mediator variable, comes in between two related constructs. In simpler terms, a change in the exogenous construct leads to a change in the mediator variable, which, in turn, affects the endogenous construct. By analyzing the strength of the mediator variable's relationships with other constructs, we can establish the mechanisms underlying the cause-effect relationship between an exogenous and endogenous construct. While the simplest form of analysis considers only one mediator variable, the path model can include multiple mediator variables simultaneously.

Moderation, on other hand, occurs when the strength or direction of a relationship between two constructs depends on a third variable. According to Hair et al. (2017), a moderator variable can alter the degree or even the orientation of the relationship between two constructs within a model. For example, the relationship between two constructs is not the same for all customers but differs based on their income. Therefore, moderation can serve as a mean to account for heterogeneity in the data.

In structural model, moderators can take on different forms: they can represent observable traits like age, gender, or income, but they can also represent unobservable traits such as risk attitude, brand preference, or ad liking (Hair et al., 2017).

The measurement of moderators can be done using a single item or multiple items, and through reflective or formative indicators. The most important differentiation in moderators, however, is related to their measurement scale, which involves distinguishing between categorical (usually dichotomous) and continuous moderators (Hair et al., 2017). As per the categorical moderator variables, they are usually dummy coded (i.e., 0/1), with the zero representing the reference category. Still, it does not follow that they must represent only two groups; indeed, in the case of three groups, the moderator could be split up in two dummy variables, both of them simultaneously included in the model. The other two categories would then be indicated by the value 1 in the corresponding dummy variable.

On the other hand, continuous moderator variables are a continuously changing type of variable. What happens with this type of moderator is that the relationship between two variables depends on the fluctuation and movement of the third variable (income is a perfect example). Generally, continuous moderators are measured with multiple items but can, in principle, be measured using a single item too (Hair et al., 2017).

5.4.1 Hypothesis Testing

H4: Perceived Risk will negatively moderate the relationship between AI-powered technologies and fan engagement.

H4 evaluates whether Perceived Risk has a significant, negative moderating impact on the relationship between (the perceived usefulness of) AI-powered technologies and Fan Engagement. The results revealed that PR does not have a significant, negative moderating effect (**PR x PUA:** $\beta = .034$, $t = .229$, $p > 0.1$; **PR x PUC**: $\beta = -.166$, $t = .846$, $p > 0.1$; **PR x PUV**: $\beta = -.016$, $t = .112$, $p > 0.1$).

H5: Trust will negatively moderate the relationship between AI-powered technologies and fan engagement.

H5 evaluates whether Trust has a significant, negative moderating impact on the relationship between (the perceived usefulness of) AI-powered technologies and Fan Engagement. The results revealed that TR does not have a significant, negative moderating effect (**TR x PUA**: $\beta = .126$, $t = .649$, $p > 0.1$; **TR x PUC**: $\beta = .097$, $t = .596$, $p > 0.1$; **TR x PUV**: $\beta = -.044$, $t = .295$, $p > 0.1$).

Table 13: *Moderator Analysis*

	Std. Beta	P values	T statistics	Decision
PR x PUA -> Fan Engagement	0.034	**0.819**	0.229	Rejected
PR x PUC -> Fan Engagement	-0.166	**0.398**	0.846	Rejected
PR x PUV -> Fan Engagement	-0.016	**0.910**	0.112	Rejected
TR x PUA -> Fan Engagement	0.126	**0.516**	0.649	Rejected
TR x PUC -> Fan Engagement	0.097	**0.551**	0.596	Rejected
TR x PUV -> Fan Engagement	-0.044	**0.768**	0.295	Rejected

Source: *SmartPLS 4*

As it can be seen from **Table 13**, neither PR nor TR were found to be significant in influencing the relationship between the study constructs. As a consequence, it can be stated that this research did not present any moderation effects.

VI. Findings

6.1 Discussion

Once all of the results from the quantitative research have been presented, it is fundamental to discuss and interpret the outcomes that emerged in relation to the research model. As a quick reminder, the AI-powered technologies were examined and analyzed in terms of their perceived usefulness, since it is the most common way of measuring the acceptance of an innovative technology, as proposed by Davis (1989) with his technology acceptance model (TAM).

6.1.1 AI Chatbots – Fan Engagement (H1)

Hypothesis 1 about AI-powered chatbots was rejected, meaning that it was not found to have a significantly positive influence on fan engagement. This is in contrast with what the literature tells us: although the role of chatbots is only recently starting to be acknowledged, different studies discovered that chatbots can actually help in increasing customer engagement (Kull et al., 2021; Jiang et al., 2022). Similarly, Mariani et al. (2023) proved that chatbots positively affect consumer engagement. Moreover, in the world of professional sports, AI-powered chatbots have revolutionized the way sports teams interact with their audience. They can be integrated into various platforms and provide personalized interactions with fans, thanks to their use of natural language processing and machine learning algorithms. A clear example of this is NBA's Golden State Warriors' implementation of an AI chatbot named "Rakuten"[11]. This chatbot enables fans to ask queries and get instant replies, providing a smooth and engaging experience. A possible explanation for this discrepancy could be attributed to the fact that the existing literature is yet to focus on the effect of chatbots on fan engagement, as it has rather been dealing with customer engagement. As per my research, fan engagement is a peculiar type of customer engagement, and thus may encounter some differences when the applications of AI technologies are being tested on it. Needless to say, there is a crucial need for further empirical research.

[11] Available at https://www.sportsbusinessjournal.com/Daily/Issues/2018/02/28/Technology/golden-state-warriors-launch-multi-language-rakuten-viber-chatbot.aspx.

6.1.2 AI Sentiment Analysis – Fan Engagement (H2)

Hypothesis 2 about AI-powered sentiment analysis was confirmed, meaning that it was found to have a significantly positive impact on fan engagement. This finding is in line with what was derived from the literature review: Annamalai et al. (2021) went on to understand how implementing sentiment analysis in a sport context can bring about favorable results marketing-wise; it was found that sentiment analysis was a valuable tool for identifying which direction to take in terms of online content communication strategies. Likewise, findings from Wunderlich & Memmert (2020) highlighted the potential of sentiment analysis as a useful tool for sports-related content, revealing its precision in classifying the general sentiment of the population. In this regard, this study further extends the validity of sentiment analysis as an instrument to understand the emotions and opinions of customers, deriving useful insights from it and paving the way for a better fan experience overall.

6.1.3 AI Virtual Assistant – Fan Engagement (H3)

Hypothesis 3 about AI-powered virtual assistant was rejected, meaning that it was not found to have a significantly positive impact on fan engagement. Again, this finding contradicts the literature: Wu et al. (2022) found that a personalized approach through a customized selection of articles, videos, and other content increased fan engagement, as the content was more likely to resonate with each fan. In addition, this result proves to moves in the opposite direction the sports world is walking in. For instance, let us look at what is going on in Spain: LaLiga, the Spanish national football soccer league, is working wonders in this regard. Acknowledging the digital transformation imperative, it has developed the LaLiga virtual assistant, a personal digital assistant that aims at delivering a consistent, high-quality fan experience[12]. It is available on Google Assistant and Skype, with plans to expand to other channels such as Cortana, Facebook Messenger, Alexa, and Slack. Moreover, for addicted fans, it can help to manage their fantasy league teams by analyzing their roster and providing suggestions on which players to add or drop using machine learning. Additionally, the assistant can link to third-party data to promote tie-ins with sponsorship partners, such as footwear and apparel manufacturers, if a fan enquiries about a player's attire.

[12] Available at https://customers.microsoft.com/es-es/story/laliga-media-entertainment-azure.

Nonetheless, our findings suggest otherwise: a plausible reason for this discrepancy is that, aside from the off-game support that virtual assistants can provide, little to no research has been put into the on-game experience that can be provided by virtual assistants. However, it must also be noted that this specific type of technology is at the pilot stages of its development, thus it ought to be further investigated once it has started becoming more commonplace, so as that fans could also express a sounder opinion based on actual, real-life experience.

6.1.4 AI Trust (H4) and AI Perceived Risk (H5)

Both hypothesis 4 and hypothesis 5 were rejected, as neither trust nor perceived risk of AI were found to moderate the relationship between AI technologies and fan engagement. This is quite peculiar since perceived risk and trust are known to play a crucial role in consumer behavior, especially when it comes to sharing personal information. If we consider that AI is a recent and sophisticated technology, it should not come as a surprise that the consumer may feel vulnerable and at AI's mercy, in a sense, as put forward by Longoni et al. (2019) or Granulo et al. (2021), among the others. This, in turn, should negatively affect the willingness to accept such technology, consequently hampering the relationship between AI technologies and fan engagement, as per my study. However, this was not the case since both variables' moderation effect was found to be nonsignificant.

6.1.5 General Discussion

In light of the findings from each hypothesis, let us now discuss them more generally in comparison with the literature on customer engagement and new technologies.

As research shows, the advancement of digital technologies in recent years has enabled brands to gather and process large amounts of customer engagement (CE) data in a more agile manner (Letheren et al., 2019, Ng et al., 2020, Storbacka et al., 2016). Brands can leverage artificial intelligence (AI) to tap into valuable insights from big data through machine learning. This can help them gain a better understanding of their customers, including their profiles, preferences, and behaviors. By doing so, they can improve customer engagement by delivering marketing messages and recommendations that align with customer preferences, on the right platform, and at the right time. (Kumar, Rajan, Gupta, & Pozza, et al., 2019). This is confirmed by the findings of this study, where AI-powered sentiment analysis was found to be significant in influencing fan engagement, as it enables sports companies to understand their customers more profoundly and it also provides the tools to increase their level of engagement. Nonetheless, caution is recommended: in fact, several brands are struggling to effectively utilize AI-powered solutions to generate and implement insights from CE data (Kumar, Rajan, Venkatesan, & Lecinski, 2019).

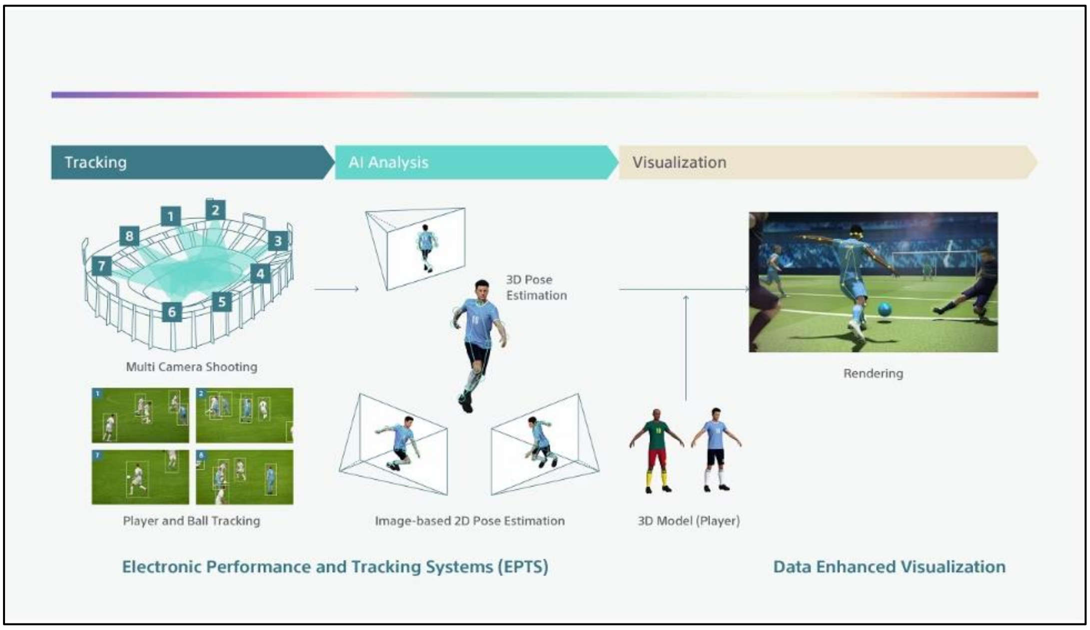
To improve customer experience through AI-enabled tools such as self-service technologies, advanced robotics, intelligent agents, voice and image recognition, smartphone apps, and the internet of things, more research is necessary (Ho et al., 2020, Larivière et al., 2017, Lin and Hsieh, 2012, Perez-Vega et al., 2020, Prentice et al., 2020). Furthermore, there is a lack of longitudinal AI-focused research in the current CE literature, which is needed to determine the benefits, costs, efficiency, and effectiveness of AI. This type of research is essential due to the nature of AI, a modern digital technology that can simulate human intelligence and continuously track, process, and record the conversion of customer data into information (Lim et al., 2022).

Additionally, another promising technology powered by AI is Augmented Reality/Virtual Reality/Mixed Reality. Even though it was not directly addressed in this research, it still offers interesting insights into how customers react to new technologies. AR/VR/MR technologies enhance the existing real-life experiences by adding more informational capabilities and interactive experiences (Hoyer et al., 2020). AR achieves this by generating computer displays that create an interactive and immersive experience of a real-world environment, providing consumers with richer, more vivid experiences (Hilken et al., 2017, Yim et al., 2017). Usually, such experiences are created on handheld devices or smartphones where additional information, presented in textual, visual, or sensory form, can be displayed.

The concept of Augmented Reality (AR) involves blending the virtual and real worlds while Virtual Reality (VR) simulates an entirely new environment, blocking out the real world. VR is experienced through a wearable device such as a headset which immerses users in virtual environments, often for entertainment purposes (Huang & Liao, 2015). In contrast, Mixed Reality (MR) combines physical and virtual elements to produce new visual environments where real and digital objects can coexist and interact in real-time (Milgram & Kishino, 1994). Unlike AR, MR integrates virtual objects with the physical world, including the use of wearable devices.

A real-life example of the implementation of these technologies to foster fan engagement is the recent partnership between Sony and Manchester City Football Club[13]. To test the potential of online fan engagement experiences, Sony and Manchester City are teaming up to conduct a proof of concept (PoC) with the aim of creating exciting and engaging digital content and services that merge the physical and virtual worlds. The focus of this PoC is to develop a global online fan community where fans can come together to interact with each other and the team, and establish new levels of connectivity with the club through a virtual recreation of the Etihad Stadium. This Virtual Etihad Stadium will provide fans with unique virtual experiences, including fully customizable avatars and next-generation interactive loyalty programs that allow them to express their fandom. To achieve this, Sony will leverage the latest image analysis and sensing technologies, along with the advanced Electronic Performance Tracking Systems of Sony's Hawk-Eye Innovations (see **Figure 6** for additional information). The ultimate goal of this collaboration is to explore new ways of engaging sports fans from anywhere in the world.

Figure 6: Sony's Technologies Virtual Fan Engagement.



Source: Sony (2021)

Furthermore, AR/VR/MR can enhance a consumer's imagination, extend beyond the physical, and elevate the consumption experience (Hoyer et al., 2020). The cognitive

[13] Available at https://www.sony.com/en/SonyInfo/News/Press/202111/21-055E/.

value of AR/VR/MR technology can prompt action by allowing individuals to mentally visualize things, engaging in pre-factual thinking that may lead to actual engagement (Epstude, Scholl, & Roese, 2016). Firms can leverage this situation by utilizing appropriate visualization techniques.

In addition, AR/VR/MR technology can create sensory and emotional connections that complement the physical world, resulting in a more enriched sensory experience for consumers (Hoyer et al., 2020). However, it is crucial that firms provide multi-sensory stimulation, not just visual and auditory experiences. The simulation must also be tailored to the physical capabilities of humans, taking our evolutionary physicality into account.

Finally, AR/VR/MR can provide social value by allowing individuals to imagine new worlds and escape from reality, as seen in gaming and entertainment (Hoyer et al., 2020). However, firms must act responsibly in creating these immersive experiences, ensuring that customers can distinguish between reality and augmented or virtual reality. The goal should be to increase the value of each reality type while maintaining clear boundaries.

To summarize, AR/VR/MR technology offers consumers quick and convenient access to relevant information and imagination before, during, and after purchasing products. These technologies also have the potential to transform the product trial experience and create new ways to imagine product usage and the overall consumption experience. Additionally, they enable improved omnichannel experiences across different online and offline touchpoints for consumers (Hilken et al., 2018).

Notwithstanding, these technologies are still suffering from numerous limitations: as per VR, there is still much to be explored when it comes to the antecedents and consequences of customer experience (CE) in relation to different stages of virtual reality (VR) interactions, such as pre-VR, intra-VR, and post-VR (Voorhees et al., 2017; Harrigan et al., 2018; Manis and Choi, 2019; Pengnate et al., 2020; Hollebeek et al., 2020). Existing research in this area is limited, making it essential to gain a more comprehensive understanding of customers' multifaceted experience with VR. This is particularly important as Lim et al. (2022) suggest that customers do not use VR headsets all the time, so it's crucial for marketers to have more detailed insights into how to manage the customer experience effectively across different interaction stages. Similarly, research on the embedded CE of augmented reality (AR) is still in its infancy, with a lack of integrated conceptual frameworks and empirical evidence providing comprehensive explanations about AR for CE (McLean and Wilson, 2019; Heller et al., 2021). Although some studies have reported that AR can enhance CE (Hollebeek et al., 2017; Hilken et al., 2017; Jessen et al., 2020; Hilken et al., 2020; Heller et al., 2021), the causality and generalizability of these findings are still questionable due to limited insights across different contexts, such as application areas, cultural perspectives, sensory richness, situational characteristics, and social scope (Lim et al., 2022). Thus, further research is necessary to gain more insights into AR for CE.

As it can be derived from this discussion, the new digital revolution entails extremely promising and exciting technologies, some of which are already between us, but it still needs further development and research to help us gauge the real impact of above-mentioned technologies. Due to the limited literature on such topics, managerial implications and conclusions ought to be taken with a pinch of salt.

6.2 Managerial Implications

Although, as previously stated, the findings from this study tend to be largely in contrast with the direction that the sports world is taking, it is still possible to derive interesting insights from this research.

Above all, managers of the sports world should really take into consideration a further development of sentiment analysis: since sport is something that deals with a lot of emotions on the fans' side, understanding them is crucial in order for companies to better their offering and provide an even more immersive experience.
Aside from doubling down on the analysis of social networks, a broader perspective should also include the analysis of live spectators during a sports event to monitor their level of engagement and emotional reactivity, so as to adjust strategies and create a more captivating experience in real time. This goes hand in hand with findings from Yoshida & James (2010), which stated that by promoting game atmosphere together with the peculiar characteristics of the product itself (i.e., player performance, rivalry, community prestige), sports marketers can satisfy and retain their customers (fans, indeed).

A perfect example is the smart stadium: integrating a host of cameras, sensors, and other digital technologies, they are the answer that managers need to offer fans a complete experience. These stadiums' pivotal feature is its Wi-Fi connectivity: having a strong Wi-Fi network throughout the stadium is crucial to enable innovative technologies, engage fans and run promotional activities. A combination of cameras and sensors coupled together with AI-powered sentiment analysis of fans' emotional innuendo could very well prove to be a strong asset to create a more fulfilling experience for fans, increasing their level of engagement. Alongside this, fans could be encouraged to connect via the stadium's Wi-Fi to a state-of-the-art mobile app, wherein they can both leave their comments in real-time and also review salient actions of the match, thus allowing them to live the match to a fuller degree while making them feel even more part of a community with a shared interest. In the meanwhile, AI-powered technologies would analyze spectators' behavior to turn it into useful data. This, in turn, is likely to deepen the relationship between fans and sport team, while at the same time increasing revenues for the teams.

The best thing about this is that it is not as far-fetched as it might sound: indeed, a couple of smart stadiums already exist. The United States is home to two of the most advanced stadiums of the world, namely the SoFi Stadium and the AT&T Stadium.
The former, home of the Los Angeles Rams (American football team), boasts impressive quality and functionality, featuring a massive double-sided Samsung 4k video board, spanning over 6,500 square meters, and suspended from the ceiling, as well as around 2,600 smaller panels distributed throughout the venue. As a result, it has become the first major US sports facility to incorporate digital twin technology.
The latter, on the other hand, is the home base of the Dallas Cowboys (American football team) and it also boasts a huge video screen about 55 meters long that can rotate 360 degrees. Although Europe is a bit behind compared to the US, it is catching up as technology is increasingly being incorporated into stadium to enhance the experience of fans. Real Madrid's home, El Santiago Bernabeu, is set to become one the most technologically advanced stadiums in the world after its renovation, mainly thanks to its Wi-Fi 6 technology. In other words, more than 1,200 Wi-Fi 6 access points will be installed, offering fans a level of speed, reliability, and bandwidth unlike anything they have ever experienced.

Smart stadiums represent the future of sports, and arguably the best perspective for managers to implement sentiment analysis to a further degree, capturing fans' engagement and subsequent emotions more precisely. The potential benefits are noticeable, and sports managers should dig deeper into it and take advantage of such technologies.

On the other hand, the results on AI-powered chatbots and AI-powered virtual assistants were negative, suggesting that these technologies do not present the same level of utility as compared to sentiment analysis. This study would suggest that managers ought to be more careful when delving into these technologies, as the results did not show them to bear any influence on fan engagement. Nonetheless, the sports world is indeed employing such technologies, specifically chatbots, which means that these findings are, to a certain degree, clashing with the real-world experience. It could also mean that the perceived usefulness of these technologies is not as strong as sentiment analysis' in relation to fan engagement, which could give food for thought to sports marketers. Still, there is the need for further research on the topic.

Overall, this research can provide managers with useful insights as to where to focus their efforts in the realm of AI technologies, with the aim of creating a more fulfilling and engaging experience overall for the fans.

VII. Limitations And Future Research Directions

As with the majority of studies, the empirical results reported herein should be considered in the light of some limitations.

In terms of methodology limitations, the major limitation is the lack of prior research studies on this specific topic. While fan engagement is indeed a peculiar declination of customer engagement, the literature has mostly focused on customer engagement only, while fan engagement in itself has never really been thought through. The exception is represented by Yoshida et al. (2014)'s breakthrough work, as they were the first to conceptualize and measure fan engagement. Later on, McDonald et al. (2022) reviewed the concept and further developed it. Nonetheless, the literature is relatively scarce, hence why there is the need for additional research and a more profound understanding of fan engagement. Specifically, considering the ever-changing landscape of the sports business and the potential revolution that could be brought about by new technologies, as we discussed in this study.

Concerning research process limitations, on the other hand, the study is culturally biased as it was mainly filled in by Italian people, since it was distributed online mainly via snowball sampling. Hence, it would be interesting to broaden the reach of the theme and understand if cultural differences have an impact on engagement levels and attitude toward artificial intelligence. At the same time, access to information is another potential limitation of this research: in fact, when it came to answering questions about AI-powered technologies applied to sports, I needed to specify what respondents were asked about. Due to the emerging and developing nature of the technology itself, there is limited knowledge at the public level, and thus it might have also been difficult for some respondents to actually picture the type of technological services that I highlighted in my study. As a consequence, this might have influenced the answers that were provided, also considering that different respondents reached out to me to manifest their benevolent ignorance of the matter.

In conclusion, research should focus on the development of these tools and, once the majority of fans has been exposed to them, gauge the actual benefits and outcomes of such technologies.

VIII. Conclusions

This thesis has delved into the relationship between AI-powered technologies and fan engagement. More specifically, the research aimed at uncovering the possible influence that new technologies, in this case artificial intelligence (AI), could have when applied to a sport context.

The relevance of this study lies in its contribution to a field that is almost non-existent in literature. Even though the study of AI technologies has seen a rapid surge in recent years, it has often been limited to the broader perspective of customer engagement. Fan engagement, on the other hand, has rarely been considered. This study builds on previous research on fan engagement and explores the connection between the world of AI and the world of sports, drawing interesting insights.

AI-powered sentiment analysis was found to be significant in influencing fan engagement, suggesting that a lot of potential is there to be brought to fans and exploited, both to fans and sports managers' benefit. Even though the other two technologies under scrutiny, AI-powered chatbots and virtual assistants, were not found significant, it must be acknowledged that many different sports teams are actually using and implementing them for their marketing operations. As a consequence, even though such technologies are in their early development stage, sports organizations may consider a cautious approach to them, without a complete rejection as this study would suggest.

Overall, this study is extremely exploratory as it tries to capture the relationship between AI and fan engagement on very concrete terms, even though such terms are either still being developed or slowly being turned into reality. Nonetheless, this research aims at providing the sports business with a rural understanding of such an impactful merge between the worlds of advanced technology and sports.

To conclude, considering the incredible developments that are expected technology-wise in the next decades, it is only right for sports managers and alike to start considering seriously what the potential impact of these technologies could be on their business. Being able to understand this could grant a leap start in the next-gen sports business, with a clear perspective of turning into the dominant player of the industry.

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