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Artificial Intelligence in Tennis. A Social Perspective

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ABSTRACT. Introduction: Artificial Intelligence (AI) is increasingly influencing professional sports, including tennis, by supporting technical analysis, training optimization, and decision-making processes. Understanding how different groups perceive AI in the sports context is essential for its effective integration. **Objective:** The study aims to explore and compare the social representations of artificial intelligence in tennis among athletes and non-athletes. **Methods:** The research employed the word association technique (Vergès, 2001) and the social representation indicator (Havârneanu, 2001). The sample included 60 participants, divided equally into two groups: 30 athletes and 30 non-athletes. The analysis focused on the frequency and order of appearance of words associated with AI in a sports context. **Results:** Distinct differences emerged between the two groups. Athletes primarily associated AI with advanced technology that enhances performance and efficiency, while aspects such as injury prevention or ethical concerns were less prominent. Non-athletes emphasized "equipment and infrastructure," reflecting a more concrete and device-oriented perception of AI in sports. **Conclusions:** The study highlights divergent perceptions of AI between athletes and non-athletes, which may influence how AI-based technologies are accepted and implemented in tennis. Understanding these differences is crucial for tailoring AI applications to meet the expectations and needs of various stakeholders in sports.

Keywords: *artificial intelligence, tennis, social representation.*

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INTRODUCTION

Artificial intelligence (AI)

Artificial Intelligence is an advanced domain within computer science dedicated to the development of systems capable of replicating cognitive processes specific to human intelligence, such as learning, reasoning, perception, planning, and decision-making. These systems rely on sophisticated algorithms and computational models that enable machines to analyze large volumes of data, identify patterns, make predictions, and act autonomously or semi-autonomously.

According to Morandín-Ahuerma (2022), artificial intelligence is defined as “the ability of a machine or computer system to simulate and perform tasks that would normally require human intelligence, such as logical reasoning, learning, and problem-solving.”

Additionally, as noted by Apoorva et al. (2018), artificial intelligence is a field within computer science focused on developing computational models designed to solve problems of complexity comparable to those addressed by human intelligence, including processes such as reasoning, planning, and perception.

Artificial intelligence in sport

In the realm of sports, artificial intelligence has become a cornerstone tool with a significant impact on transforming training, competition, and decision-making processes. AI applications are diverse and encompass performance analysis, technique and tactic evaluation, game strategy optimization, injury prevention, physiological monitoring, and even the automation of officiating decisions.

According to a bibliometric analysis by Sampaio et al. (2024), the use of artificial intelligence in tennis is continually expanding, covering areas such as biomechanical movement analysis, match outcome prediction, assessment of technical-tactical performance, physiological parameter monitoring and also the analysis of competitive economics.

Types of devices used in tennis

Artificial intelligence has brought significant innovations to professional tennis through the integration of devices that optimize training, assessment, and game strategy.

Among the most widely used technologies are video systems with automated feedback, which analyze technical executions in real time and accelerate learning (Lin et al., 2020), as well as smart rackets such as the Babolat Pure Drive, which enhance shot accuracy and efficiency by integrating sensors and advanced materials (Ozdemir, 2019). Additionally, posture estimation technology and wearable devices allow for the monitoring of biomechanics and physical condition, contributing to personalized training and injury prevention (Chatterjee et al., 2021; Wang et al., 2024).

Another area includes smart ball launchers and tactical-technical analysis platforms that provide automated training and decision-making support for coaches by adjusting drills and analyzing match data (Abid et al., 2023; Yin, 2021). Furthermore, wearable devices track physiological parameters and support injury prevention by enabling training intensity adjustments (Wang et al., 2024).

Overall, these technologies demonstrate a transformative potential for athletic practice, supported by empirical research. However, their implementation requires a balanced approach that considers technical limitations and ethical implications.

The value of artificial intelligence in tennis

Artificial intelligence has a significant impact on professional tennis, particularly by enhancing technical and tactical analysis.

An important contribution in this area comes from Chatterjee et al. (2021), who demonstrated the effectiveness of posture estimation technology through computer vision. This allows for the automatic identification of players' body positions and the classification of strokes, thereby helping to detect biomechanical imbalances and enabling timely, precise corrections.

However, these advantages come with certain limitations. Excessive reliance on technology may reduce the athlete's ability to self-correct and develop intuitive skills, while high costs can restrict access to such tools (Wang et al., 2024; Abid et al., 2023). Additionally, the accuracy of visual recognition algorithms depends on external conditions such as lighting or game speed (Wu et al., 2023), and the integration of these technologies into the sports education process requires a clearly defined methodological framework (Lin et al., 2020).

Artificial intelligence offers considerable benefits in improving training efficiency and refining sport-specific technique in tennis, but it also involves risks that call for a critical and balanced approach. The effectiveness of these systems depends on their contextualized integration, economic accessibility, and the capacity of coaches and athletes to use them reflectively and adaptively.

The associative technique in the current context

Using the associative technique from social psychology, this section explores how artificial intelligence shapes perceptions of technique in tennis.

The associative technique involves forming stable mental connections between stimuli and responses. In sports, this process is manifested through repeated pairings between a specific technical execution and the feedback received. Artificial intelligence-based devices amplify this association by providing immediate, accurate, and personalized feedback. Associativity thus functions as a cross-cutting principle that helps explain the effectiveness of AI-based interventions in tennis.

Smart devices not only record and analyze data but also facilitate the development of cognitive networks that link action, feedback, and adjustment (key components in motor learning and technical refinement). In this regard, artificial intelligence becomes a catalyst for associative learning, transforming each execution into an opportunity for cognitive and motor reinforcement.

HYPOTHESIS

Research question

In the context of the accelerated digitalization of sports, analyzing perceptions of artificial intelligence in tennis has become a timely and relevant topic with both theoretical and practical implications. As AI is increasingly used in training, evaluation, and technical optimization, it becomes essential to understand how different user groups, namely athletes and non-athletes, perceive these technologies. This understanding can support the development of effective implementation strategies that are tailored to users' real needs.

Accordingly, the *research question centers on identifying the social representations held by athletes and non-athletes regarding the use of artificial intelligence in tennis, and potentially, the differences in their cognitive association patterns between the two groups*.

It is hypothesized that athletes and non-athletes differ significantly in their social representations and perceptions of artificial intelligence in tennis, both in terms of the content of their cognitive associations and the depth of their engagement with the technology.

MATERIALS AND METHODS

Methodology

To explore perceptions of artificial intelligence in tennis from a social perspective, a qualitative research design with an exploratory component was used. The study included a total of 60 participants, selected based on variability in sports experience, ranging from 0 to 18 years.

The group of active athletes consisted of 30 participants aged between 16 and 25 years, including 17 male and 13 female athletes. The group of non-athletes was composed of 30 participants aged between 18 and 30 years, evenly split between 15 male and 15 female individuals. This diversity in participant profiles was considered essential to capture potential differences in perception and symbolic associations between the two categories.

The study variables included independent variables: namely, the status of being an athlete or non-athlete; and the dependent variable, which was the social representation of artificial intelligence in tennis.

Instrument

The research employed a questionnaire based on the word association technique (Vergès, 2001) and an alternative method for determining the structure and organization of the elements within a social representation, as proposed by Professor C. Havârneanu (2001). The first technique relied on the frequency of mentions and the average order of appearance, while the second technique used the frequency of occurrence and the average importance rankings. The formula used for the latter is:

Social Representation Indicator (SR) =
frequency of mentions × mean rank scores

The use of the Social Representation Indicator (SR) has proven essential in revealing not only the salience but also the structural positioning of elements within participants' cognitive frameworks regarding artificial intelligence in tennis, in this case. By combining frequency of mentions with perceived importance, the SR index allows for a more nuanced understanding of how deeply rooted certain concepts are within the shared social knowledge of both athletes and non-athletes. This indicator does more than highlight popular associations. It identifies the core components of the social representation, distinguishing central, stable beliefs from more peripheral, flexible ones. Such insight is important when aiming to design targeted communication strategies or technology implementation policies that resonate with users' actual cognitive structures.

The data collection process involved the physical distribution of the questionnaire to each participant, who completed it individually in the presence of the researcher. This ensured clarity of the instructions and adherence to standardization conditions. Upon completion, the questionnaires were collected to ensure the integrity of the data.

Questionnaire 1. ***Questions related to identifying the social representation of artificial intelligence in tennis***

I. What comes to mind when you think of artificial intelligence in tennis? Please list 5 representative words or ideas.
II. Rank these words or ideas in order of importance (from 1 = most important to 5 = least important).

Procedure

The data analysis was carried out in two stages. In the first phase, the responses were thematically coded by identifying semantic recurrences, symbolic variations, and metaphorical uses. Subsequently, the frequencies and rankings of each word/association were extracted, forming the basis for constructing the structural framework proposed by Vergès (2001), including the delineation of the central core and peripheral zones.

RESULTS

Associative Technique

Following the application of the word association technique, content analysis enabled the identification of 96 distinct terms, grouped together with their semantic synonyms and equivalent expressions. These terms were then categorized into thematic groups based on the similarity of their meanings and usage context. The classification process was conducted separately for the two participant groups: athletes (see Appendix 1); and non-athletes (see Appendix 2). The following thematic categories emerged for each of these groups:

Table 1. Categories, Frequencies, and Mean Ranks (Mean Rank of Appearance and Mean Rank of Importance), Social Representation Indicator – Specific to Athletes
Athletes – N = 30

No.	Category	Frequency	Rank of appearance	Rank of importance	Social representation indicator (RS)
1	Advanced technology	56	2.5	2.625	143.5
2	Training	18	3.66	3.61	65.43
3	Social and ethical aspects	14	3.78	3.51	51.03
4	Tactics	15	3.2	3.4	49.5
5	Injury prevention and physical monitoring	15	3.6	3	49.5
6	Video analysis	12	2.41	2.91	31.92
7	Officiating	7	3	3.28	21.98
8	Equipment and infrastructure	6	2.66	3.33	17.97
9	Feed-back	7	1.85	1.71	12.46

Table 2. Categories, Frequencies, and Mean Ranks (Mean Rank of Appearance and Mean Rank of Importance), Social Representation Indicator – Specific to Non-Athletes
Non-Athletes – N = 30

No.	Category	Frequency	Rank of appearance	Rank of importance	Social representation indicator (RS)
1	Training	35	3.25	2.48	100.3
2	Advanced technology	17	3.52	3.7	61.3
3	Officiating	15	3.33	3.66	52.4
4	Tactics	20	2.6	2.5	51
5	Video analysis	18	2.66	2.94	50.4
6	Equipment and infrastructure	17	2.47	2.7	43.9
7	Social and ethical aspects	13	2.61	3.15	37.4
8	Injury prevention and physical monitoring	9	3.55	2.66	27.9
9	Feed-back	6	2.66	3.33	17.9

The application of the technique developed by P. Vergès (2001) allowed for the identification of both the central core and the peripheral system of the social representation of artificial intelligence in the context of tennis, differentiated for the two categories of independent variables: athletes and non-athletes.

The analysis was based on two main indicators: the frequency with which an element was mentioned and its rank of appearance within the individual lists. In constructing the analytical quadrant, frequency was represented on the vertical axis, while order of appearance was plotted on the horizontal axis. A convenient threshold was established to distinguish elements with both high frequency and low rank of appearance (indicating high cognitive salience) from other categories of terms.

Thus, the upper left quadrant was interpreted as representing the central core of the social representation (the most stable and widely shared elements), while the lower right quadrant included peripheral elements, characterized by low frequency and high order of appearance, and therefore reflecting more contextual or individualized components of the representation.

Data analysis reveals clear differences between athletes and non-athletes in how artificial intelligence is socially represented in the context of tennis. These differences suggest that AI is understood and valued differently depending on one's direct experience with sport and their orientation toward technological phenomena.

In the case of athletes (Table 3), the central core of the representation is occupied by the category "Advanced Technology," which has a significant frequency (56) and a low mean rank of appearance (2.5). This reflects a dominant perception that AI is primarily a performance tool, associated with efficiency, innovation, and precision in athletic practice. This category is situated in a strong consensus zone, being considered essential for the advancement of professional sports.

Table 3. Tabular Matrix for Athletes

		Rank of appearance	
		≤2,5	**>2,5**
Frequency	≥28	Advanced technology (56)	Training (18)
	<28	Video analysis (12)	Social and ethical aspects (14)
		Feedback (7)	Tactics (15)
			Injury prevention and physical monitoring (15)
			Officiating (7)
			Equipment and infrastructure (6)

At the opposite end, in the peripheral quadrant, we find categories such as "Training," "Tactics," "Social and Ethical Aspects," "Injury Prevention and Physical Monitoring," "Equipment and Infrastructure," and "Officiating." Although these elements appear in athletes' discourse, they do so with lower frequency and in less prominent positions, suggesting a secondary role in the structure of the representation. These elements seem to be perceived more as complementary or contextual functions, rather than defining characteristics of AI in tennis.

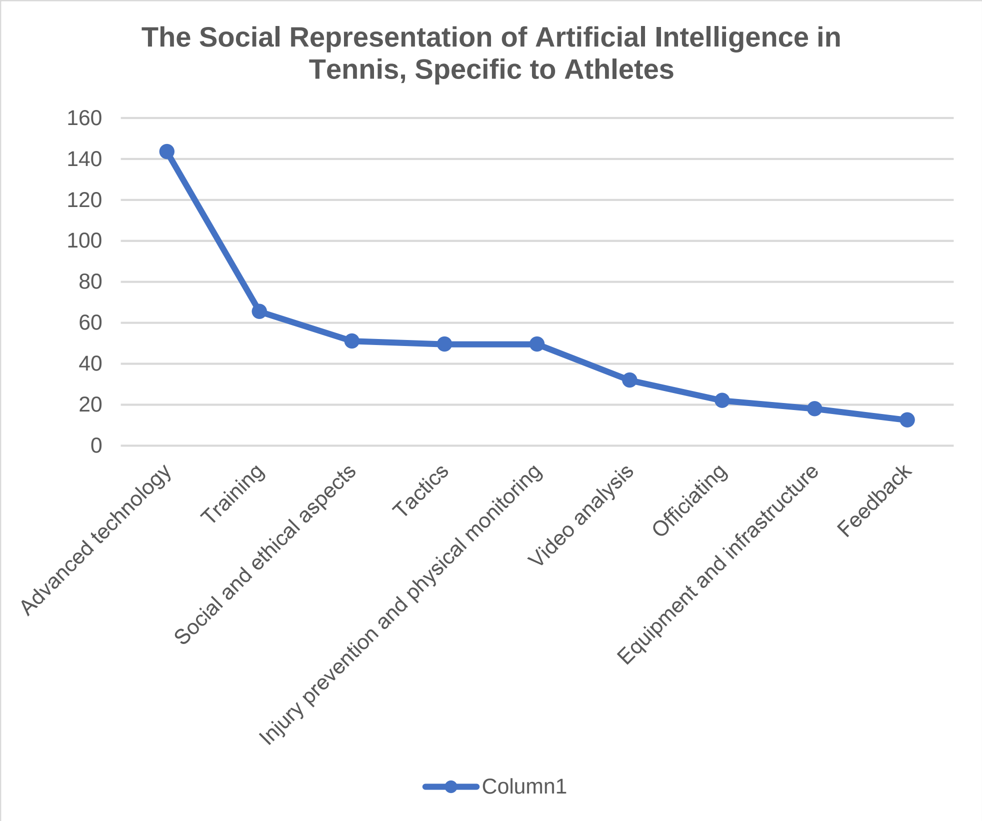
For non-athletes (Table 4), the configuration of AI's social representation is distinct, with a central core dominated by the category "Equipment and Infrastructure." This is the only category that meets both a high frequency (17) and a low mean rank of appearance (2.47). The result suggests that, for non-athletes, artificial intelligence is primarily perceived as an extension of tangible technology (e.g., sporting infrastructure, smart equipment, and logistical support).

Table 4. Tabular Matrix for Non-Athletes

		Rank of appearance	
		≤2,5	**>2,5**
Frequency	≥17	Equipment and infrastructure (17)	Training (35)
			Advanced technology (17)
			Tactics (20)
			Video analysis (18)
	<17		Officiating (15)
			Social and ethical aspects (13)
			Injury prevention and physical monitoring (9)
			Feedback (6)

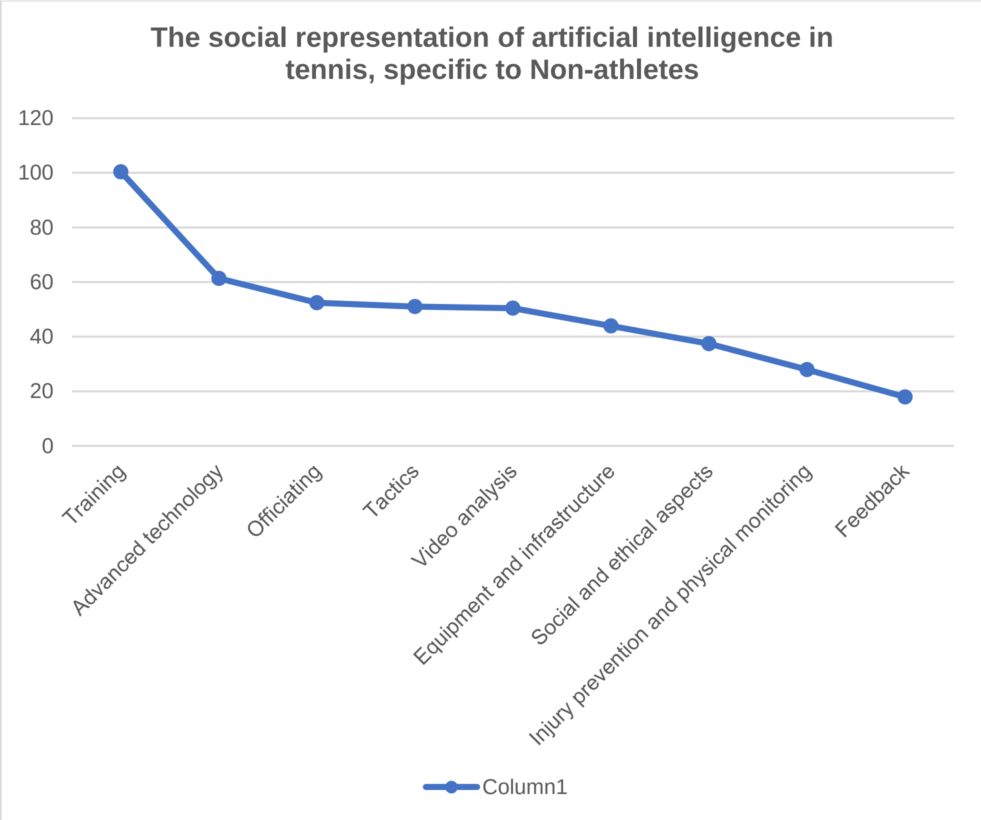
Other categories such as "Training," "Advanced Technology," "Tactics," and "Video Analysis," while frequently cited, appear with higher cognitive positioning ranks and are thus included in the peripheral system. These indicate sustained interest in the functionalities of AI in sport, though not yet integrated into a collective consensus. Their perception remains relevant but more individualized and situational.

In the lower peripheral zone, categories such as "Feedback," "Injury Prevention," and "Social and Ethical Aspects" are found, which appear rarely and in delayed positions. This positioning indicates that non-athletes do not associate these elements with a central role in AI-assisted sports practice but rather perceive them as less relevant or visible within their experience.



The Social Representation Indicator Technique (Havârneanu, 2001)

Figure 1. The social representation of artificial intelligence in tennis - Athletes



The Social Representation Indicator Technique (Havârneanu, 2001)

Figure 2. The social representation of artificial intelligence in tennis – Non-athletes

Therefore, the social representation of artificial intelligence in tennis among non-athlete's centers on technical and infrastructural dimensions, suggesting a more external and mechanical perception of the technology. Compared to athletes, who perceive AI in terms of performance and practical efficiency, non-athletes construct a more concrete and object-focused representation, anchored in what can be directly seen and used.

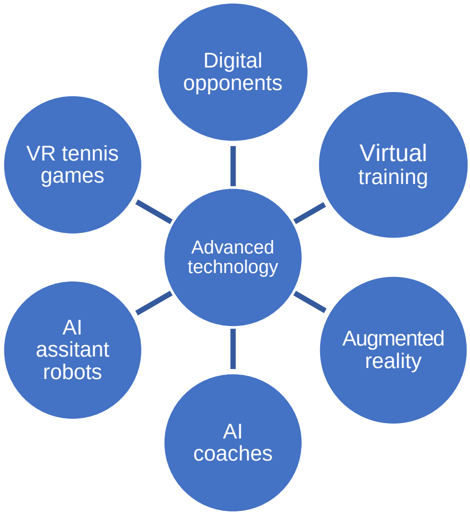


Figure 3. The social representation of artificial intelligence in tennis - Athletes

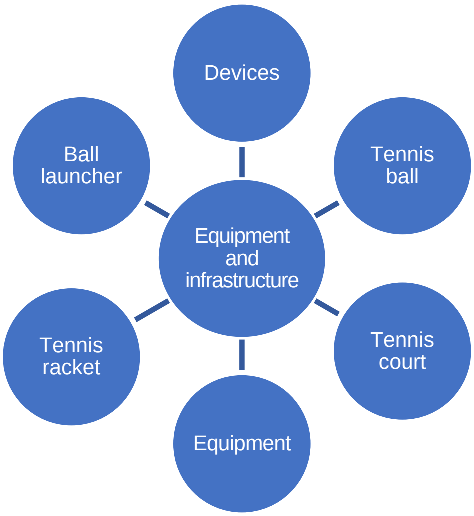


Figure 4. The social representation of artificial intelligence in tennis – Non-athletes

DISCUSSION

The results reveal substantial differences in the social representation of artificial intelligence in tennis between athletes and non-athletes. These differences are nuanced and reflect the distinct experiential positioning of each group toward technological phenomena.

For athletes, AI is primarily associated with "advanced technology," indicating a representation focused on functionality, efficiency, and performance optimization. This aligns with the academic literature, which emphasizes AI's role in personalized training, real-time biomechanical feedback, and automated movement analysis (Ma, 2020). Furthermore, the integration of AI into sports equipment such as smart rackets or ball-tracking cameras is perceived as a natural extension of professional training (Ozdemir, 2019).

Athletes appear to assign a secondary role to categories like "ethical aspects," "feedback," or "injury prevention." While these dimensions are present in their discourse, they are not central. This outcome can be interpreted in light of Moscovici's theory of social representations, which posits that direct experience influences the cognitive salience of elements. Thus, what is directly useful in enhancing performance gains greater prominence in their representation.

In the case of non-athletes, the core of the representation is occupied by the category "equipment and infrastructure," suggesting a concrete and visual understanding of AI as a collection of tangible technologies (courts, rackets, balls, sensors, automated interfaces). Although terms like "training" or "advanced technology" are frequently mentioned, their higher rank of appearance indicates lower cognitive salience.

This perception is consistent with research showing that individuals without direct experience in sport relate to AI in terms of general technological potential rather than specific functionality (Lv et al., 2021). Moreover, the concerns of non-athletes regarding elements such as "feedback," "injury prevention," or "ethics" remain peripheral, indicating a more fragmented and less integrated representation.

CONCLUSIONS

The study revealed significant differences in the social representation of artificial intelligence in tennis between athletes and non-athletes. For athletes, AI is predominantly perceived as a technological tool for optimizing performance, whereas non-athletes primarily associate it with equipment and infrastructure. These findings confirm the influence of direct experience on the structure of social representations and highlight the need to tailor the implementation of AI technologies according to the profile of their users.

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Annex 1
Mentions by Athletes

No.	Category	Mentions
1	Advanced technology	Advanced technology, correction algorithms, AI coach, opponent simulation, technology, technological progress, computer vision, 3D visualization, augmented coaching, augmented reality, AI assistant robots, training with cutting-edge machines
2	Training	Training personalization, execution consistency, technical rigor, personalized training
3	Social and ethical aspects	Impact on employment, enhancing fan experience, reduction of human effort, trust, time-saving
4	Tactics	Tactical optimization, tactical prediction, game forecasts, personalized tactics, gameplay strategies, score prediction, tactics
5	Injury prevention and physical monitoring	Posture correction, physiological parameter control, physical wear reduction, injury protection, correlation of physiological indicators
6	Video analysis	Video analysis, stroke analysis, service analysis, video cameras for motion capture, shot timing via video cameras
7	Officiating	Automated decisions, automatic umpiring, error detection/automatic officiating
8	Equipment and infrastructure	Smart racket, equipment development, equipment optimization, equipment management
9	Feedback	Instant feedback, immediate correction, precise feedback, voice feedback

Annex 2
Mentions by Non-Athletes

No.	Category	Mentions
1	Training	Helps with training, personalized training, practice, speed, better speed and reactions, performance improvement
2	Advanced technology	Simulates a playing partner, tennis games on PC/mobile, smart ball, smart racket, sensor-equipped court
3	Officiating	Umpire assistance, referee decision-making, error correction by referees, automated umpiring decisions, officiating
4	Tactics	Teaches new tactics, strategy, prediction, game tactics, tactical foresight, strategies, tactical analysis
5	Video analysis	Video analysis, ball tracking, stroke analysis, video assistance, video recognition
6	Equipment and infrastructure	Ball launcher, stopwatch, rackets, court, ball, equipment, equipment management
7	Social and ethical aspects	Inspiration, motivation, confidence building, game improvement, reassurance
8	Injury prevention and physical monitoring	Injury prevention, real-time biometric monitoring, nutrition
9	Feedback	Precision, accuracy