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Identifying the Key Drivers of Media Transformation and Artificial Intelligence: Opportunities for the Sports Industry

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ABSTRACT

This study examines the main factors influencing media transformation and artificial intelligence (AI), with particular emphasis on identifying major challenges and opportunities within the sports industry. Media transformation in the age of AI is not merely the outcome of technological advancements; rather, it results from the complex interaction of economic, social, cultural, and legal forces that shape the future of media through nonlinear and multiple-scenario pathways. Accordingly, this study employs a foresight methodology by integrating the Delphi method with cross-impact analysis and MICMAC structural analysis to identify fundamental drivers across the political, economic, social, technological, environmental, and legal (PESTEL) dimensions. In terms of its objective, the study is applied and developmental, while its methodological approach is mixed-methods (qualitative and quantitative). Initially, a range of factors influencing AI-driven transformation in the media industry was identified through environmental scanning and a systematic review of the scientific literature. These factors were subsequently refined through three Delphi rounds involving experts in media, communication, and information technology, ultimately resulting in consensus on 18 key drivers. In the next stage, structural analysis and MICMAC software were employed to examine the interrelationships among these drivers. The results of direct and indirect influence analyses indicated that drivers such as the concentration of capital and market power among AI-based media platforms, public policy and regulatory orientations, data and algorithmic infrastructures, and the degree of technological independence constitute key influential variables within the system. In contrast, variables such as legal requirements for algorithmic transparency, public trust in AI-generated content, and the professional competencies of media personnel were primarily identified as dependent variables.

Focusing on the sports industry as one of the most important sectors of the media landscape, the findings provide opportunities and practical recommendations for sports media development and offer insights that can support managers in this sector in leveraging the potential of artificial intelligence.

KEYWORDS :Artificial Intelligence, Media Transformation, Sports Industry

Introduction

Approaches to shaping the future and consciously engaging with future developments are relatively emerging phenomena in the history of human society. During the eighteenth century, humanity's relationship with the future underwent a fundamental transformation, and the future became an inseparable component of human life [1]. Foresight studies are recognized as an interdisciplinary field [2], encompassing a broad range of perspectives concerning probable, possible, and desirable futures [3]. To date, more than seventeen methodological approaches have been identified in this field, most of which are employed as complementary and coordinated techniques. These methods include time-series analysis, modeling, brainstorming, scenario development, simulation, historical analogy, the Delphi method, cross-impact analysis, causal modeling, genealogy, gaming, and text mapping [4].

Researchers emphasize that foresight is not simply the linear prediction of trends; rather, it is a systematic process for understanding the interactions among technological, economic, institutional, and cultural forces in shaping alternative futures [5,6]. Within this framework, tools such as cross-impact analysis, scenario planning, and the Delphi method facilitate the identification of key drivers, critical uncertainties, and potential turning points within systems [7,8]. Studies indicate that organizations employing structured foresight approaches demonstrate greater adaptive capacity when confronted with environmental shocks and unexpected developments [9].

Over the past decade, artificial intelligence has emerged as one of the transformative forces reshaping the infrastructure of the media industry. AI has not only transformed content production and distribution tools but has also redefined the underlying logic of decision-making, value creation, and audience engagement. Increasingly, media structures are emerging in which algorithms play a prominent role in selecting, prioritizing, and distributing content [10,11].

Over the next five years, the dominant trends in artificial intelligence within the media industry are expected to be closely associated with cognitive automation, advanced personalization, and the increasing concentration of technological power. Studies indicate that recommendation algorithms and systems designed to predict audience behavior constitute some of the most important economic and technological drivers, directing media consumption patterns toward individualized and platform-oriented content [12,13].

At the same time, reductions in content production costs through artificial intelligence, combined with the high scalability of digital platforms, have strengthened the concentration of capital and market power among major technology players. This trend is transforming the competitive structure of the media industry and placing the roles of traditional media organizations under increasing pressure to adapt and redefine themselves.

Research indicates that the integrated application of qualitative and quantitative foresight methods, particularly the Delphi method, structural analysis, and scenario planning, can reduce the gap

between future uncertainties and strategic decision-making, ultimately generating practical knowledge for future-oriented management [14,15].

Sports media can undoubtedly be considered one of the most important sectors of the broader media industry. Awareness of future developments has the potential to bring about substantial transformations in both sports and media. Sport represents a universal language, and achieving technological advantages in this field can generate significant transformations in both the sports industry and the media sector. The present study aims to provide practical strategies that can facilitate the dynamic exploitation of artificial intelligence opportunities in sports media.

Material and Methods

This study employed a structural analysis approach to examine the driving forces shaping artificial intelligence and media, with particular emphasis on the sports industry. The research design combined a literature- and document-based preliminary phase with expert-based foresight techniques, consisting of a three-round Delphi process followed by MICMAC cross-impact analysis.

Initially, a comprehensive review of the academic literature on artificial intelligence, foresight, media, and the sports industry was conducted to identify an initial set of potential drivers. These candidate drivers were organized according to the Political, Economic, Social, Technological, Environmental, and Legal (PESTEL) framework.

The Delphi technique was subsequently employed to refine and validate this set of drivers.

In the first Delphi round, semi-structured interviews were conducted with a group of experts, specialists, and professional practitioners who were directly or indirectly involved in AI-driven transformation processes within the media industry or possessed specialized knowledge and practical experience in this field. The objective of this round was to generate, clarify, and consolidate potential drivers across the study dimensions rather than to determine their relative importance.

The qualitative data obtained from these interviews were analyzed and integrated with insights derived from the literature review and policy document analysis to develop a consolidated list of 18 candidate drivers.

In the second round, a structured questionnaire was administered to the same expert panel. Participants were asked to evaluate the importance of each of the 18 drivers using a five-point Likert scale. Consensus was operationalized as the percentage of experts assigning each item to a predefined category of "high importance." All drivers achieved at least 70% consensus in this round, indicating that none of the 18 variables needed to be excluded on the basis of perceived relevance.

In the third Delphi round, controlled feedback was provided to the experts. For each driver, group-level statistical summaries from the previous rounds, particularly consensus percentages, were

presented to the panel. This enabled participants to reconsider their judgments in light of the emerging collective assessment.

Experts were invited to review their previous ratings and revise them if necessary, thereby promoting convergence while maintaining anonymity and independence of opinion. This iterative process resulted in high and generally increasing levels of agreement among all 15 experts, confirming the perceived importance of the identified factors as key drivers of artificial intelligence and media transformation.

The final list of drivers, together with their dimensional classifications and consensus levels from the second and third Delphi rounds, constituted the validated input for the subsequent structural analysis.

Following the validation of the 18 drivers, an 18×18 cross-impact matrix was constructed to capture the perceived causal relationships among them. The expert panel assessed the pairwise influence of each driver on every other driver using the MICMAC influence scale. This scale consisted of five response options: 0 for no influence, 1 for weak influence, 2 for moderate influence, 3 for strong influence, and P for potential influence, indicating a relationship that might become significant in the future.

For each ordered pair of drivers, experts evaluated the extent to which changes in the row variable directly influenced the column variable. These judgments were subsequently aggregated at the matrix level to obtain a single value for each cell, thereby estimating the influence and dependence of each driver. Influence represented the extent to which a variable shaped other variables, whereas dependence indicated the extent to which it was affected by them.

The completed cross-impact matrix was analyzed using MICMAC software to extract the system's direct and indirect influence structures.

In the first stage, the software generated the direct influence matrix and calculated the sum of the row values and column values for each driver. The row total represented the overall direct influence exerted by a driver on the rest of the system, whereas the column total indicated its overall direct dependence on all other drivers. These indicators provided an initial quantitative representation of the distribution of influence and dependence among the 18 variables and served as the basis for positioning them within the direct influence–dependence space.

In the second stage, the analysis was extended to potential and indirect effects. MICMAC repeatedly propagated influences through multiple-step pathways, generating matrices of potential direct and indirect influences. Accordingly, potential influence and dependence indices were calculated for each driver, capturing not only immediate effects but also longer causal chains operating within the system.

To refine the structural interpretation, the MICMAC proportions module was employed. This procedure converts raw potential influence and dependence indices into comparable scores on a scale ranging from 0 to 1,000 and ranks drivers according to their relative weight within the system.

Separate proportions were obtained for potential direct influence, potential direct dependence, potential indirect influence, and potential indirect dependence. This made it possible to identify drivers accounting for a substantial proportion of systemic influence, as opposed to those primarily characterized by potential dependence.

Finally, MICMAC software was used to generate graphical representations of the system, including a direct influence–dependence map, an indirect influence–dependence map, and direct and indirect influence graphs.

In these maps, each driver was positioned according to its influence and dependence scores, enabling its classification as a determinant, relay, dependent, or relatively independent variable. In the graphs, drivers were represented as nodes connected by directed arrows, indicating the strength and direction of direct or indirect influences.

Results

Table 1 presents the demographic characteristics of the Delphi expert panel (N = 15), including gender, educational attainment, years of professional experience in sports management, and age.

Table 1. Frequency distribution and demographic characteristics of the Delphi expert panel

Characteristics	Category	Frequency / Range
Gender	Male	12
	Female	3
Educational attainment	Master's degree	3
	Doctoral degree	12
Professional experience (years)	Minimum	9
	Maximum	30
Age (years)	Minimum	33
	Maximum	57

Following a comprehensive review of the relevant literature and policy documents, the Delphi technique was employed to finalize the list of driving forces shaping artificial intelligence and media transformation.

In the first round, semi-structured interviews were conducted with the selected participants to generate and refine the preliminary list of drivers across the study dimensions.

In the second round, a structured questionnaire was distributed to the same participants to assess the importance of the identified factors using a five-point Likert scale. All items achieved at least 70% consensus within the predefined "high importance" category.

During subsequent iterations, experts were given the opportunity to revise their judgments in light of group-level statistical feedback. Consolidated results, including consensus percentages from the second and third rounds, were presented to participants during the third Delphi round.

The final outputs of the literature review and the three-round Delphi process are presented in Table 2.

Table 2. AI and media foresight: Delphi-validated PESTEL drivers and consensus levels

No.	Dimension	Driver	Delphi Round 2 (%)	Delphi Round 3 (%)
1	Political	P1. Institutional power balance among governments, platforms, and media organizations in AI governance	93.5	94.3
2	Political	P2. Public policy orientation toward the development or restriction of AI in the media industry	81.6	85.7
3	Political	P3. Government policies regarding transnational media platforms	83.9	87.2
4	Economic	E1. Reduction in content production and distribution costs through intelligent automation	79.6	82.9
5	Economic	E2. Transformation of media business models from content-oriented to data-driven models	82.1	84.4
6	Economic	E3. Concentration of capital, data, and market power within AI-based media ecosystems	77.7	81.3
7	Social	S1. Changes in media consumption patterns toward algorithm-driven and personalized content	90.5	91.8
8	Social	S2. Redefinition of public trust in media in the age of fake news and deepfakes	78.4	80.6
9	Social	S3. Erosion of cultural diversity and the emergence of dominant algorithmic narratives	89.2	90.9
10	Technological	T1. Maturity of automated multimedia content generation technologies	85.7	88.3
11	Technological	T2. Development of predictive algorithms and extreme content personalization	80.8	82.5
12	Technological	T3. Convergence of artificial intelligence with autonomous communication environments	74.9	78.2
13	Environmental	EN1. Conflict between the development of AI-based media infrastructures and environmental sustainability requirements	83.1	86.6
14	Environmental	EN2. Institutional and social pressure for the development of green and sustainable AI	84.4	88.1
15	Environmental	EN3. Integration of media social responsibility with the environmental considerations of technology	81.6	85.9
16	Legal	L1. Ambiguity regarding legal liability for AI-generated content	93.3	94.1
17	Legal	L2. Intellectual property challenges and the professional identity of media practitioners	81.4	85.7
18	Legal	L3. Requirements for algorithmic transparency, explainability, and bias control	83.7	87.2

Following the validation of the 18 key drivers influencing the development of artificial intelligence and media, an 18×18 cross-impact matrix was constructed. The expert panel evaluated the pairwise influence of each driver on every other driver using the five-point MICMAC influence scale (0 = no influence; 1 = weak influence; 2 = moderate influence; 3 = strong influence; P = potential influence). These ratings were aggregated to estimate the driving power of each variable. The completed matrix was subsequently analyzed using MICMAC software to extract the direct

and indirect influence structures of the system and to position and classify the drivers within the influence–dependence space.

After identifying the key drivers shaping the development trajectory of artificial intelligence and media, the expert panel completed the cross-impact matrix using the MICMAC influence scale. Based on these assessments, the software generated the direct influence matrix and calculated the row and column totals for each driver.

The row total represents the overall direct influence exerted by a driver on the other drivers, whereas the column total indicates its overall direct dependence on the rest of the system. Together, these indicators provide an initial quantitative overview of how influence and dependence are distributed among the drivers shaping the future of artificial intelligence and media. The results are presented in Table 3.

Table 3. Row totals (influence) and column totals (dependence) of each driver

No.	Driver	Row total (Influence)	Column total (Dependence)
1	P1	38	35
2	P2	44	44
3	P3	42	40
4	E1	27	28
5	E2	40	40
6	E3	45	39
7	S1	34	42
8	S2	35	44
9	S3	37	38
10	T1	42	36
11	T2	42	40
12	T3	44	31
13	EN1	34	25
14	EN2	33	32
15	EN3	28	35
16	L1	34	44
17	L2	39	39
18	L3	41	47
	Total	679	679

According to the results presented in Table 3, driver E3 (concentration of capital, data, and market power within AI-based media ecosystems) ranked first in terms of influence, with the highest row total (45). Furthermore, driver L3 (requirements for algorithmic transparency, explainability, and bias control) ranked first in terms of dependence, recording the highest column total (47).

To refine the structural analysis of the system, the MICMAC proportions module was employed. This method expresses potential influence and dependence indicators on a common scale ranging from 0 to 1,000 and ranks drivers according to their relative weight within the system. Consequently, it becomes possible to identify which drivers account for the largest shares of potential direct and indirect influence and which are primarily characterized by potential dependence.

Table 4 reports these normalized scores, including the rank, driver code, potential direct influence, potential direct dependence, potential indirect influence, and potential indirect dependence of each driver.

Table 4. Ranking of drivers based on direct and indirect influence and dependence

Rank	Driver (Direct influence)	Score	Driver (Direct dependence)	Score	Driver (Indirect influence)	Score	Driver (Indirect dependence)	Score
1	E3	662	L3	692	E3	659	L3	689
2	P2	648	P2	648	T3	649	S2	648
3	T3	648	S2	648	P2	638	L1	645
4	P3	618	L1	648	P3	618	P2	642
5	T1	618	S1	618	T1	611	S1	621
6	T2	618	P3	589	T2	621	P3	592
7	L3	603	E2	589	L3	604	T2	590
8	E2	589	T2	589	E2	590	E2	585
9	L2	574	E3	574	L2	571	L2	578
10	P1	559	L2	574	P1	564	S3	574
11	S3	544	S3	559	S3	556	E3	571
12	S2	515	T1	530	S2	522	P1	523
13	S1	500	P1	515	S1	509	T1	521
14	EN1	500	EN3	515	EN1	495	EN3	514
15	L1	500	EN2	471	L1	495	EN2	466

16	EN2	486	T3	456	EN2	481	T3	463
17	EN3	412	E1	412	E1	405	E1	411
18	E1	397	EN1	368	EN3	405	EN1	358

The results presented in Table 4 indicate that certain drivers play a dominant role in shaping AI-driven transformation in the media industry at both direct and indirect influence levels.

The high levels of direct and indirect influence associated with drivers such as concentration of capital and market power (E3), public policy orientation toward artificial intelligence (P2), and AI-based autonomous communication environments (T3) highlight their structural and strategic roles in system dynamics.

Conversely, the highest direct and indirect dependence scores are predominantly associated with drivers such as requirements for algorithmic transparency and explainability (L3), as well as certain social and legal variables. This indicates that these factors are more exposed than other drivers to the consequences of technological, economic, and policy-related changes.

Overall, the consistency between the direct and indirect influence results demonstrates the stability of the positions occupied by key drivers and supports the validity of the analyzed structural framework. These findings provide a reliable foundation for deriving strategic implications.

Conclusion

The present study aimed to identify the key drivers of media transformation and artificial intelligence (AI), examine the different forms of media, and explore their applications in sports media. The findings, derived from a three-stage Delphi process and an analysis of the interrelationships among the identified drivers, indicate that media transformation is not a linear process. Rather, it is shaped by complex interactions among technological, economic, institutional, social, and cultural factors. Accordingly, the future of sports media depends not only on technological developments but also on strategic choices, policy decisions, and the establishment of ethical governance frameworks [16,17].

The analysis revealed a dense network of interactions among the drivers of media transformation. Within such a network, even a relatively small change in AI models or emerging technologies may influence content-related decisions, broadcasting processes, and market structures. In this context, capital concentration, market power, and AI governance can function as strategic levers in shaping the future of the media industry [18,16,19].

This situation can be compared with the development of sports talent identification and championship facilities. Although facilities and resources have been distributed across different regions of the country, management systems and coaching capabilities have not developed at the same pace. Consequently, these investments have not necessarily produced effective outcomes.

This comparison highlights the limitations of development strategies that lack a comprehensive strategic plan and an integrated talent identification system. Similarly, improving a single driver of media transformation, in isolation, cannot guarantee the sustainable development of sports media.

The quality, volume, and diversity of data, together with issues of ownership and equal access, constitute another important dimension of media transformation. The dominance of major digital platforms may intensify competitive inequalities and marginalize certain forms of news and content. Therefore, appropriate legal and governance frameworks are required to protect diversity of voices and promote transparency [16,19]. In the sports sector, the large volume of data generated through sporting events, festivals, and educational activities can represent both a challenge and an opportunity. Sports-related regulation should therefore address the fair use of behavioral data and ensure that access to such data does not become a source of structural inequality.

Automation is also transforming content production, editing, translation, and distribution. These processes can increase productivity and reduce costs; however, they may also create algorithmic dependency and undermine professional independence. Excessive reliance on algorithms may widen the gap between media content and factual accuracy, while changing the role of human professionals from content producers to supervisors of automated systems. This shift requires a reconsideration of professional identity, ethical responsibilities, and educational approaches [20,21].

The emergence of autonomous AI-based communication environments also raises questions about legitimacy and the role of algorithms in content production, selection, and distribution. As sports media organizations increasingly rely on automated systems, their role may shift toward supervising algorithmic processes. This transformation creates challenges for their authority and professional standing. Although algorithmic integration may threaten the integrity and independence of media processes, targeted human intervention can still provide opportunities for strategic change. Understanding these developments therefore requires institutional and cultural analysis, rather than a purely technological perspective [17,18].

Delegating content-related tasks to AI systems may improve efficiency, but it can also generate significant risks. This observation should not be interpreted as opposition to technological development. Rather, it highlights the need for fair regulations and coherent strategic policies to ensure that the benefits of AI are realized without compromising professional standards and public interests.

Public trust in AI-supported media increasingly depends on algorithmic transparency, explainability, and clear legal accountability. Without these safeguards, AI-generated and algorithmically distributed content may contribute to misinformation, the spread of fake news, and a decline in institutional legitimacy. AI governance should therefore be understood as a social, cultural, and institutional issue, rather than merely a technical one. Furthermore, personalization algorithms may marginalize minority perspectives and reduce content diversity. Transparency,

explainability, and legal accountability are consequently essential conditions for responsible AI adoption in media organizations [19,16].

Despite these challenges, AI offers substantial opportunities for sports media. It can facilitate the production of timely and rapidly accessible content, improve operational efficiency, enhance broadcasting services, and support multilingual and multichannel communication. These capabilities may reduce production and distribution costs while increasing the value of media services. They can also improve the experience of audiences both inside stadiums and at home, while creating new opportunities for advertising and sponsorship [17,18].

AI can also support personalized fan experiences and strengthen audience loyalty. Through data-driven services, sports media organizations may develop new revenue models, including tiered subscription plans, interactive content, and non-fungible tokens (NFTs). In addition, dynamic pricing and targeted advertising based on data analytics can provide new opportunities for revenue generation and audience engagement [16,22].

To address the challenges and benefit from these opportunities, sports media organizations should prioritize transparency, explainability, and accountability. Cooperation with public authorities and alignment with international standards can reduce uncertainty and facilitate market development. Managers and policymakers should pay particular attention to influential drivers, including capital concentration and market power, AI governance, and autonomous communication environments. At the same time, strengthening human capabilities through continuous training and the development of digital skills is essential. These efforts should be supported by institutional cooperation, effective governance mechanisms, and partnerships with technology providers [19,16,21,23].

Overall, the future of sports media over the next five years will not be determined by technology alone. Instead, it will depend on the interaction among technological developments, economic conditions, policy-making institutions, and cultural priorities. AI can improve content production, accessibility, and personalization. However, in the absence of appropriate governance, ethical principles, and effective management, its adoption may reduce narrative diversity, weaken the role of journalists, and undermine public trust. The future direction of sports media will therefore depend on policy choices, data management practices, and the development of human capabilities.

Managers in sports media organizations can make more effective use of AI by adopting an integrated approach that considers content-generation technologies, algorithmic transparency and governance, and personalized audience experiences simultaneously. A one-dimensional approach focused exclusively on technological adoption is unlikely to produce sustainable results. Similarly, neglecting audience personalization may weaken revenue-generating capacity and reduce opportunities for social participation and engagement.

In conclusion, the findings suggest that the transformation of sports media should be approached as a multidimensional process. Sustainable development requires more than investment in

emerging technologies; it also depends on appropriate governance, fair access to data, professional accountability, strategic management, and the continuous development of human skills. Integrating these dimensions can help sports media organizations respond more effectively to technological change while preserving public trust and the diversity of media content.

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Compliance with ethical guidelines

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«مقاله پژوهشی»

شناسایی پیشران‌های کلیدی تحول رسانه و هوش مصنوعی: فرصتهایی برای صنعت ورزش

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صادق‌زاده، ح.، صانیعی، م.، تربتی، س. شناسایی پیشران‌های کلیدی تحول رسانه و هوش مصنوعی: فرصتهایی برای صنعت ورزش. مجله فناوری پیشرفته ورزش. ۲۰۲۶؛ ۱۰ (۳)

چکیده

این مطالعه عوامل اصلی مؤثر بر تحول رسانه و هوش مصنوعی را بررسی می‌کند و بر شناسایی چالش‌ها و فرصت‌های مهم در ورزش تأکید دارد. تحول رسانه‌ها در عصر هوش مصنوعی صرفاً نتیجه پیشرفت‌های فناورانه نیست، بلکه حاصل تعامل پیچیده‌ای از نیروهای اقتصادی، اجتماعی، فرهنگی و حقوقی است که مسیر آینده این رسانه‌ها را به صورت غیرخطی و چندسناریویی شکل می‌دهند. لذا این تحقیق با استفاده از روش‌شناسی آینده‌نگری، با ادغام تحلیل تأثیر متقابل دلفی و میک مک، محرک‌های اساسی را در حوزه‌های سیاسی، اقتصادی، اجتماعی، فناوری، زیست‌محیطی و حقوقی شناسایی می‌کند. این پژوهش از نظر هدف، کاربردی-توسعه‌ای و از حیث روش، ترکیبی (کیفی-کمی) است. در گام نخست، با استفاده از پویش محیطی و مرور نظام‌مند ادبیات علمی، مجموعه‌ای از عوامل مؤثر بر تحول هوش مصنوعی در صنعت رسانه شناسایی شد. سپس این عوامل در سه دور دلفی و با مشارکت خبرگان حوزه رسانه، ارتباطات و فناوری اطلاعات پالایش گردید که در نهایت ۱۸ پیشران نهایی مورد اجماع قرار گرفت. در گام بعد، به منظور تحلیل روابط متقابل میان پیشران‌ها، از روش تحلیل ساختاری و نرم‌افزار میک مک استفاده شد. نتایج تحلیل تأثیرات مستقیم و غیرمستقیم نشان داد که پیشران‌هایی نظیر تمرکز سرمایه و قدرت بازار پلتفرم‌های رسانه‌ای مبتنی بر هوش مصنوعی، جهت‌گیری سیاست‌گذاری و تنظیم‌گری عمومی، زیرساخت‌های داده‌ای و الگوریتمی، و میزان استقلال فناوری، در زمره متغیرهای کلیدی و اثرگذار سیستم قرار دارند. در مقابل، متغیرهایی مانند الزامات حقوقی شفافیت الگوریتم‌ها، اعتماد اجتماعی به محتوای تولیدشده توسط هوش مصنوعی و مهارت‌های حرفه‌ای نیروی انسانی رسانه‌ای، عمدتاً در دسته متغیرهای وابسته و تأثیرپذیر شناسایی شدند. یافته‌های پژوهش با تأکید بر صنعت ورزش به عنوان یکی از مهمترین بخشهای رسانه‌ای فرصتهایی را برای توسعه رسانه ورزش برای بهره‌گیری مدیران این بخش پیشنهاد نموده است.

واژه‌های کلیدی: هوش مصنوعی، تحول رسانه، صنعت ورزش