REVIEW ARTICLE

Exploring the roles of artificial intelligence and wearable feedback technologies in figure skating performance analysis: A scoping review

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ABSTRACT

The application of artificial intelligence (AI) unlocks an exciting perspective for performance analysis in figure skating. A better understanding of AI and wearable feedback technologies of figure skating is warranted. The purpose of this study is to overview the roles of AI and wearable feedback technologies in figure skating performance analysis. Systematic searches through PubMed, Web of Science, and Scopus online databases were conducted for articles reporting AI and wearable feedback technologies applied to figure skating. Twelve studies were included in the review; three themes of AI and wearable feedback technologies emerged as being applied in figure skating. Emerging themes were wearable inertial and force sensors, marker less computer vision systems, and pose (marker) based deep learning. Body-worn IMU systems primarily support jump detection and counting, achieving very high accuracy for discrete event identification in controlled or semi-controlled settings. Body-worn IMU systems primarily support jump detection and counting, achieving very high accuracy. The current state of technology used for performance analysis in the area proposes a promising future with regard to figure skating. Further evaluation research based on real figure skaters is warranted to establish the predictive performance of specific AI and wearable technologies.

Keywords: Machine learning, Inertia measurement unit, Gyroscope.

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INTRODUCTION

The implementation of innovative systems on information and communication technologies in combination with sophisticated processing methods is becoming increasingly essential for the analysis of data in sports (Baca et al., 2009). The pursuit of athletic excellence in figure skating calls for an exceptional synthesis of artistic expression, technical accuracy, and physical competence (Gzenda et al., 2019; Stienstra et al., 2011). Traditionally, the analysis of jumps, spins, footwork, and overall performance has relied on the subjective eye of the coach, supplemented by video replay (Lockwood et al., 2006). This approach is fundamentally limited by human perceptual constraints and subjective assessment, making the analysis complex in biomechanical components such as angular momentum, force distribution, and aerial positioning. The arrival of artificial intelligence (AI) and wearable feedback technologies plays a role in overcoming these challenges, offering the promising solution for objective and data-based feedback in a sport (Kim et al., 2024; Novikova et al., 2024).

Artificial intelligence, over machine learning and computer vision systems, can transform sports performance from video in extraordinary detail to automatically classifying technical elements. Wearable feedback technologies like inertial measurement units (IMUs), pressure-sensitive insoles, and electromyography (EMG) sensors provide a continuous stream of physiological and biomechanical data directly from the athletes. These devices provide real data on jump height, rotational velocity, edge quality, muscle activation, and balance in real time, metrics that are classically inaccessible during training (Kim et al., 2024; Shi et al., 2020).

The transformation of this change lies in the use of biomechanical tools in the form of wearable inertial measurement units and 3D motion capture that breaks down complex skills into measurable units (Adesida et al., 2019). Studies indicate that IMUs offer objective information about the jump kinematics and accurate determination of the rotation speed, height, and landing forces (Vitali et al., 2017). At the same time, motion capture analysis can be used to identify potentially harmful biomechanical behaviours and prevent injuries. This technological basis shifts coaching towards a reactive error-correcting model rather than a proactive performance engineering and injury prevention model (Bandodkar et al., 2014; Tate et al., 2010; Zhang et al., 2019).

Although artificial intelligence and wearable feedback technologies are increasingly used to support performance analysis and injury prevention across a range of sports (Bandodkar et al., 2014; Souaifi et al., 2025; Valero et al., 2025), existing reviews focus on general sports biomechanics and do not address the demands of figure skating. Evidence for figure skating remains scattered across isolated studies. To date, no review has systematically mapped how artificial intelligence and wearable feedback technologies are being applied to figure skating performance analysis or what gaps remain to guide future research and practice in this domain.

Therefore, this paper presents the overview of the current literature on the application of AI and wearable feedback technologies in figure skating. Our objectives are first, to evaluate the types of AI and wearable devices being deployed, and second, to suggest accurate AI and wearable technologies for predicting performance in figure skating. Thirdly, we aim to identify potential areas for future research in the field of figure skating. Specifically, our review aimed to answer the following questions: (1) What types of AI and wearable technologies have been applied to analyse performance in figure skating? (2) Which AI and wearable technologies are accurate for predicting performance in figure skating? # (3) What is the research gap on figure skating in relation to technology use?

MATERIALS AND METHODS

Procedure
The review methodology adopted the PRISMA guidelines (15). The JBI data extraction tool was used to extract relevant data. The quality appraisal was completed by the two authors. The Population (P), Intervention (I), Comparison (C), Outcomes (O), and Study Design (S) (PICOS) search formula was used to retrieve articles (Table1).

Table 1. PICOS framework.

Component	Description
The Population (P)	Figure skaters who are amateur and professional levels and Videos of figure skating
Intervention (I)	Application of artificial intelligence, such as machine learning, deep learning, computer vision, and reinforcement learning, to analyse and wearable technologies in performance analysis of figure skating
Comparison (C)	Traditional performance analysis methods such as manual assessments, conventional statistical techniques or comparisons among different AI-based methodologies.
Outcomes (O)	Quantitative metrics such as accuracy, precision, recall, F1-score, mean absolute error and qualitative outcomes such as tactical decision support, improved training strategies, enhanced performance monitoring
Study Design (S)	Empirical studies including experimental, observational, and quasi-experimental designs, as well as systematic reviews and meta-analyses that report on AI and Wearable Feedback Technologies applications in figure skating performance analysis.

Data sources and search strategy
A comprehensive literature search was conducted across multiple high-impact databases, including PubMed, Web of Science, and Scopus. Search terms were developed based on adapted PICOS questions to identify relevant literature. Keywords such as “*Figure skating*,” “*Performance analysis*,” “*Wearable technology*,” and “*Artificial intelligence*” were used to develop a search strategy to identify articles. We employed “*AND*” and “*OR*” Boolean operators. A PRISMA critical appraisal follow-up chart was used to determine the number of studies.

Eligibility criteria and selection process
The studies were included based on the following inclusion criteria, with two authors double-checking. If doubt arose, the third author was involved in the final decision. The inclusion criteria were:

1. The study was written in English.
2. The study was published in a peer-reviewed journal as a full-text and original research paper.
3. Data was just for the figure skating report's empirical findings on qualitative and quantitative performance metrics such as accuracy, precision, recall, or F1-score.
4. The participants were amateur and professional figure skaters as well as video databases.
5. The AI and wearable feedback technologies must be described and tested.

Quality Assessment and data collection
The quality of all studies was evaluated using evaluation criteria (Table 2) described by Saw et al (Saw et al., 2016) .Scores were allocated based on how well each criterion was met, assuming a maximum possible score of 7 (low risk of bias). Studies with a risk of bias score of 4 or less were considered poor and excluded. Once the studies to be included were selected, we performed a review by checking reference lists (*Checking reference lists to find additional studies for systematic reviews - Horsley, T - 2011* | *Cochrane Library*, n.d.) to identify additional peer-reviewed studies.

Table 2. Risk of bias assessment criteria.

Criteria		Definition	Scoring		
			0	**1**	**2**
A	Peer-reviewed	Study published in peer-reviewed journal	No	Yes	-
B	Real-world approach	The approach was performed with real results/data of the athletes	No	Yes	-
C	Population defined	Age, gender, sport, and level was described	No	Partly	Yes
D	Experimental design	Experimental design of the study period was described and replicable	No	Partly	Yes
E	Artificial intelligence	The artificial intelligence or wearable device were described	No		-

RESULTS

Identification of studies

The initial search returned 435 articles (for details, see Figure 1). After the removal of duplicated articles (n = 143), a total of 292 studies were retained for further screening and eligibility assessment. Following eligibility assessment, 14 were retained for final risk of bias assessment. 2 studies with a risk of bias score of 4 or less were considered poor and were excluded. The remaining studies were evaluated between 6 and 7 points in terms of quality (supporting document Table 3). During the revision of the reference lists, we haven't found anything that meets all the criteria for inclusion in the analysis. This scope review included a total of 12 studies (Bruening, 2018; Chen et al., 2025; Hara et al., 2024; Seiji Hirosawa et al., 2023; Li et al., 2021; Y. Liu et al., 2023; Panfili et al., 2022; Tanaka et al., 2023a, 2024; Tian et al., 2023; Zhao, 2025).

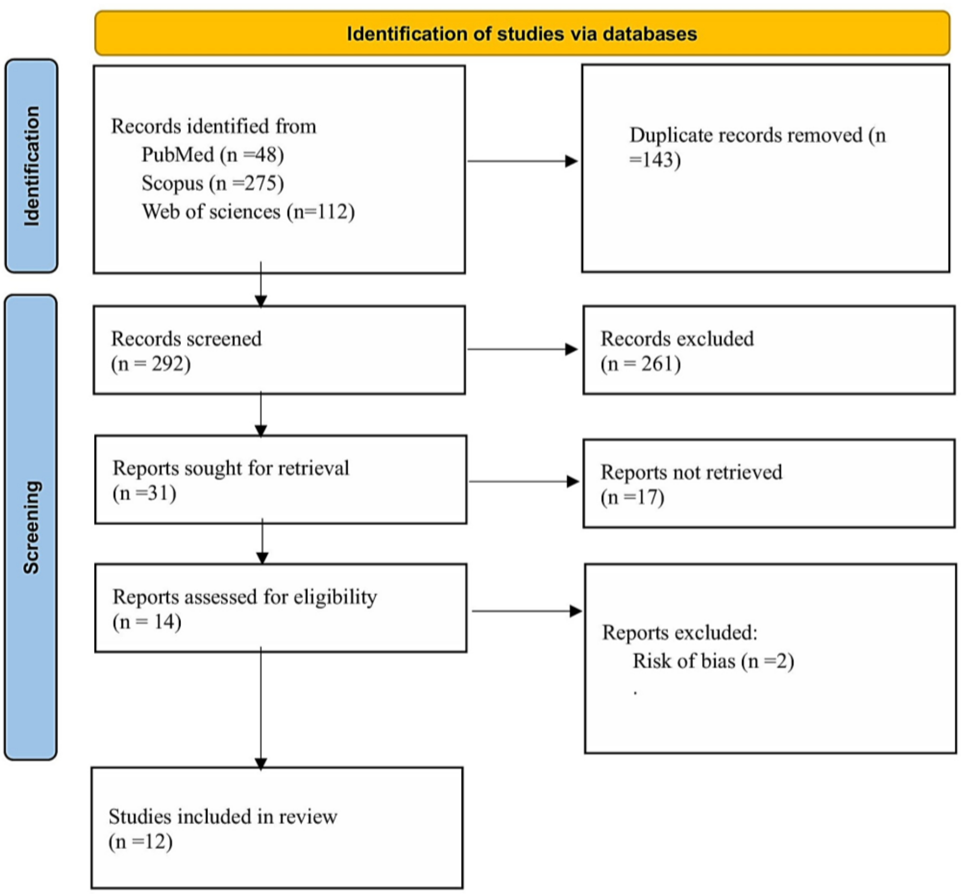

Figure 1. Identification of studies via databases.

Table 3. Risk bias evaluation result.

	List of studies	A (Peer-reviewed)	B (Real-world approach)	C (Population defined)	D (Experimental design)	E (AIor wearable device	Total
1	Antonio	1	1	2	2	1	7
2	Royota	1	1	1	2	1	6
3	Dustin	1	1	2	2	1	7
4	Congran	1	1	0	2	1	5
5	Ekelund	1	1	2	2	1	7
6	LI	1	1	0	2	1	5
7	Dan Chen	1	1	1	2	1	6
8	Limao	1	1	2	2	1	7
9	YU	1	1	1	2	1	6
10	Reyota	0	1	2	2	1	6
11	Sieji	1	1	1	2	1	6
12	Yuse	1	1	1	2	1	6

Characteristics of included studies

The majority of the included studies used video databases, and the human samples were tiny. About half of the 12 included research employed some kind of artificial intelligence (AI) or machine learning (ML) model; 33% used body-worn wearables alone, 33% used pure vision, and the remaining studies used wearables plus vision or other external sensors in combination. About half of the studies used deep learning, such as convolutional neural network (CNN), graph convolutional network (GCN), transformer, or recurrent neural network (RNN) based architectures for pose estimation, action segmentation, or scoring; one-third of the studies used rule-based or classical methods; and one-sixth used simple machine learning.

Types of AI or technology used

Wearable inertial and force sensors

Body-worn sensors are wearable inertial and force sensors, which are designed to sense and measure multidimensional aspects of human motion, including overall body movement, jump detection, jump counting, flight time, and rotational velocity. These tools are a cornerstone of modern sports performance analysis systems, which allow accurate biomechanical evaluation and real-time feedback. The inertial sensors are usually combined with accelerometers, gyroscopes, and magnetometers to detect dynamic movement, but the force sensors are used to measure the contact forces and pressure distributions during athletic movements. Wearable inertial and force-sensing systems are typically divided into two broad categories, namely, body-worn sensors (Bruening, 2018; Panfili et al., 2022), and force-plate-integrated wearables, depending on their configuration and integration (Hara et al., 2024).

The body-worn wearables without external cameras were able to reach great levels of accuracy for motion analysis investigations in figure skating. For example, during controlled pattern skating, Panfili et al. used a combination time-of-flight laser and IMU system to detect jumps with 97–99% accuracy (Panfili et al., 2022). Similarly, Bruening et al used a single waist-mounted IMU to identify jump counts, estimate flight times, and measure rotation speeds with a 95% accuracy rate (Bruening, 2018). In contrast, only 8% (1 out of 12) of studies used instrumented skate or force-plate wearables. Hara et al. constructed custom, wearable force plates integrated in the skating blades that reliably recorded 3D (three-dimensional forces (Hara et al., 2024).

Marker less computer vision systems

Marker less motion capture is a technology that captures human movement without the need for physical markers on the body. It uses depth-sensing cameras or computer vision algorithms to track and analyse the subject's movements in real time. In this review, marker less computer-vision systems, which constituted approximately 33% (4 out of 12) of studies, leverage 2D and 3D pose estimation based on video input rather than body-worn sensors. These approaches typically employ frameworks such as MediaPipe or OpenPose-like architectures, using multi-view or monocular RGB camera setups for 3D reconstruction and the extraction of skeletal and kinematic features. Chen et al. reported 79.09% overall accuracy in real-time blade-type discrimination with a MediaPipe-based pipeline, which suggested the automatic identification of edges was possible (Chen et al., 2025). Liu and Zhou reported a true positive rate of 98% on jumping-action recognition by combining skeleton-based pose features with deep reinforcement learning (Y. Liu et al., 2023). Additionally, Zhao et al. propose AutoSco, a broadcast video-driven automated figure skating scoring model that integrates the C3D feature and the Bi-LSTM networks with multi-layer attention mechanisms to enhance long-term temporal action sequence analysis (Zhao, 2025).

Pose (marker) based deep learning

Pose-based deep learning systems take up approximately half of the studies (six out of twelve). They combine high-end machine-learning models with pose-estimation algorithms to obtain spatiotemporal information in skeletal data from an athlete. These systems rely on spatio-temporal graph convolutional networks (ST-GCN), transformer-based 3-D pose estimators such as MotionAGFormer, and temporal-action segmentation networks such as FACT to identify jump phases and other technical details at the fine scale.

Tanaka (2024) coupled MotionAGFormer and FACT into an automated assessment system and obtained 83 percent accuracy on skater data based on 3-D joint positions reconstructed by monocular cameras (Tanaka et al., 2023b, 2023a). A CNN proposed by Hirosawa et al. uses gaze-guided and temporal attention to estimate the grade of execution (GOE) of each individual jump; using gaze data of expert judges, the hybrid model reduced the RMSE to 0.775, which was lower than human judges and baseline models (Seiji Hirosawa et al., 2023). Tian et al. constructed a multi-view 3-D reconstruction pipeline with the OpenPose to achieve accurate motion capture. Their method had a joint reconstruction success rate of 93.38, 92.57, and 91.55 within 70 mm, 50 mm, and 30 mm error margins, respectively (Tian et al., 2023).

The recent development of deep learning in combination with other methods has been further expanded by the ST-GCN of Liu and Zhou, which uses deep reinforcement learning and has a true positive rate of 98 percent in jump recognition (Y. Liu et al., 2023), Similarly, the skeleton-based AQA model by Li et al. outperformed the traditional RGB-only approaches to the long-term performance scoring, like SENet and C3D (Li et al., 2021). On the same note, the AutoSco system developed by Zhao, which is based on Bi-LSTM and multi-layer attention networks, improved the ability to model long-term temporal dependencies in automated figure skating scoring. All these results highlight a paradigm shift to hybrid AI systems with skeleton-based motion features, human perceptual features, and temporal deep-learning models, and they achieve high, human-comparable scoring and performance-evaluation accuracy (Zhao, 2025) (Table 4).

Table 4. Types of AI or technology used description.

Type	Description
Wearable inertial and force sensors	MUs (accelerometers + gyroscopes) for jump detection and rotation, uniaxial accelerometers for energy expenditure, and instrumented skates with embedded force sensors, primarily analysed with threshold-based algorithms or linear/statistical models.
Marker less computer-vision systems	MediaPipe or OpenPose-like 2D pose estimators, multi-view RGB setups with custom 3D reconstruction, and broadcast-video pipelines for skeleton extraction without body-worn devices.
Pose-based deep learning	Spatio-temporal GCNs on skeleton sequences, transformer-based 3D pose estimators (e.g., MotionAGFormer) and temporal action segmentation networks (e.g., FACT) for fine-grained jump phase recognition.

DISCUSSION

The present scoping review mapped emerging technological and artificial intelligence (AI) approaches in figure skating performance analysis, revealing three main technological themes, each with distinct functions and accuracy profiles that together outline the current landscape of automated evaluation in figure skating. Body-worn IMU systems primarily support jump detection and counting, achieving very high accuracy for discrete event identification in controlled or semi-controlled settings (Panfili et al., 2022; Ridge et al., 2025), whereas instrumented skates provide rich three-dimensional force and moment data for detailed technique analysis but are less practical for routine deployment and do not report a single summary accuracy value (Hara et al., 2024).

Other validation and review papers on body-worn IMU systems used in various sports, including jump-dominant sports, demonstrate that jump event detection accuracy is typically around 99% when compared to gold-standard references, where IMU-based systems achieved high jump detection accuracy or sensitivity values from controlled match analysis protocols (Clemente et al., 2022; Pino-Ortega et al., 2018).

However, applications that are run on iced surfaces are still limited by the issues that are related to sensor mounting, motion interference, and contact with the ice substrate. Experiments with force-integrated systems, such as custom instrumented skating blades, have provided priceless information about three-dimensional ground reaction forces and blade dynamics and thus highlight the opportunities for improving models of kinetic skating technique. However, they are not very common, as less than 10 percent of the reviewed literature uses such systems, which is likely due to challenges in integrating equipment, the complexity of calibration, and the lack of generalizability across proficiency levels (Bruening, 2018; Panfili et al., 2022; Ridge et al., 2025).

Vision-only computer vision approaches, which operate on RGB video without sensors, span applications from blade edge discrimination (Chen et al., 2025) to jump recognition and automated scoring. Scoring models are typically reported in terms of relative improvements over RGB-only baselines rather than simple accuracy (Zhao, 2025). Another published review of vision-based human action quality assessment (AQA) reports that most AQA studies in sports start from RGB video features and then compare new architectures (pose-based, multi-stream, or multimodal) to RGB-only baselines using relative improvements in correlation or error, not simple accuracy, especially for scoring and quality assessment tasks (J. Liu et al., 2025).

Nevertheless, a general survey of action quality evaluation shows that, in dynamic sports like diving, gymnastics, and figure skating, pipelines that are trained on RGB imagery alone are always able to achieve better detection and segmentation results, but score prediction is often measured using correlation and ranking metrics; performance improvements are often reported relative to RGB-only baselines (J. Liu et al., 2025; Zhou et al., 2024). However, the ongoing differences in camera setup, lighting, occlusion management, and video quality still pose a major constraint, compromising the data integrity and reproducibility across different rinks and broadcasting systems. The recent introduction of hybrid systems, where inertial measurement unit signals are combined with vision-based features, provides promising opportunities to improve the generalization to untested athletes and heterogeneous environmental conditions (Chen et al., 2025; G. Liu, 2025; Y. Liu et al., 2023; Zhao, 2025).

Pose-based deep learning and other machine learning methods are central to this ecosystem. They combine skeleton-based representations with spatiotemporal architectures such as ST-GCN, transformers, and Bi-LSTM networks. Sometimes, they also use expert gaze information. These methods achieve around 80-83%

accuracy when evaluating figure skaters and up to 98% true positive rates for jump recognition. Some models even outperform human judges in predicting execution grades (Tanaka et al., 2023a; Tian et al., 2020, 2023). Other published reviews of sports reported that pose-based deep learning with skeleton inputs and ST-GCN, transformer, or Bi-LSTM architectures is now the most effective to evaluate complex skills. These reviews highlight typical evaluation accuracies above 80% and very high event detection rates. They also mention that pose- and gaze-augmented models can match or exceed human judges for scoring or grade of execution, often exceeding RGB-only baselines (J. Liu et al., 2025; Lu, 2024; Zhou et al., 2024).

Integration of human perceptual cues represents a new frontier. Hirosawa's gaze-guided attention model showed that combining expert gaze features with temporal convolutional networks improved model interpretability and lowered prediction errors below human-level baselines. This finding suggests a future of hybrid intelligence where algorithmic insights and human expertise come together to improve judging consistency and training feedback (S Hirosawa et al., 2024; Seiji Hirosawa et al., 2023; Tanaka et al., 2024; Tian et al., 2020, 2023).

Taken together, these findings indicate that IMU-based wearables and ST-GCN or deep reinforcement learning models provide the highest performance for jump detection and recognition, while transformer-based, skeleton-driven, and gaze-augmented models currently offer the strongest performance for action quality assessment and automated scoring, suggesting that a hybrid pipeline combining robust event detection with advanced pose-based scoring is likely to yield the most reliable and comprehensive evaluation framework (S Hirosawa et al., 2024; Tanaka et al., 2023a, 2024; Tian et al., 2023).

Although tremendous progress has been achieved, some methodological deficiencies have emerged in current studies. Data sets are still of limited size and variability, and models have been trained on data sets of limited numbers of figure skaters only or in simulated settings. Additionally, some degree of standardization is still lacking in benchmark settings and evaluation metrics. Furthermore, few studies focus on ethical and privacy related questions on athlete data, especially on broadcast settings. Future studies should focus on the implementation of open data sets, multimodal data fusion incorporating physiological data, and the combination of AI techniques that can be used for an increased trustworthy automated evaluation. Longitudinal validation studies on professional and amateur groups could also help identify how AI related kinematic knowledge can be used as an aid for coaching and injury prevention.

Overall, the technological trajectory that emerges from this review is indicative of the maturing of the integration of the fields of biomechanics, computer vision, and AI research. Because a certain level of technical proficiency as well as an artistic judgment of figure skating components is necessary for proficient skating skills, it can be said that the trend towards vision-based deep learning models and hybrid models is poised to bring a revolution to the art of evaluating skating skills, from technical evaluation of jumps and turns to artistic interpretations of their executions.

CONCLUSIONS

In conclusion, this scope review mapped the existing literature on technology used in figure skating performance analysis, those used in figure skating were wearable inertial and force sensors, Marker less computer vision systems, pose based deep learning. The current state of technology used to performance analysis in the area proposes a promising future with regard to figure skating. Further evaluation research based on real figure skaters is warranted to establish the predictive performance of specific AI and wearable technologies.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author.

DECLARATION OF GENERATIVE AI USE

In preparing this manuscript, AI-assisted technologies were employed to improve the clarity, flow, and readability of the text. The AI tools were used strictly as language enhancement assistants, helping refine grammar, sentence structure, and overall coherence. The author reviewed and took full responsibility for the content of the publication.

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