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Artificial Intelligence in Theater Performance and Physical Training: A Review of Technologies Optimizing Performer Development and Artistic Execution

Imen. Samet[1], Mohamed Salah. Arous[1], Mortadha. Razzak[2, 3*], Mourad. Dhawedi[3], Mohamed Elaid. Maamri[2, 3], Nasr. Chalghaf[3], Noomen. Guelmami[2], Nizar. Souissi[4], Ismail. Dergaa[2, 4, 5]

[1] High Institute of Music & Theatre of Kef, University of Jendouba, El Kef, Tunisia
[2] High Institute of Sport and Physical Education of Kef, University of Jendouba, El Kef, Tunisia
[3] High Institute of Sport and Physical Education of Gafsa, University of Gafsa, Gafsa, Tunisia
[4] Physical Activity Research Unit, Sport and Health (UR18JS01), National Observatory of Sports,Tunis, Tunisia
[5] High Institute of Sport and Physical Education of Ksar Said, University of Manouba, Mannouba, Tunisia

*** Corresponding author email address**: mortadhaa.razzak@gmail.com

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A B S T R A C T

Objective: Theater performance demands substantial physical capabilities requiring systematic training comparable to athletic preparation. Professional performers engage in cardiovascular conditioning, strength development, and movement technique refinement to meet performance demands. Artificial intelligence technologies, including computer vision, machine learning, and generative modeling, have enabled practical applications in movement analysis, personalized training design, and performance feedback delivery. These advances address accessibility barriers, objective assessment challenges, and individualized program adaptation needs characteristic of theatrical training contexts. This review aimed to (i) examine AI technologies applied in theater performance and physical training contexts, (ii) analyze implementation challenges and limitations across applications, and (iii) identify critical research priorities requiring empirical investigation.

Methods: We searched PubMed, IEEE Xplore, ACM Digital Library, Web of Science, and Google Scholar for studies published 2014-2025. Inclusion criteria required empirical AI applications in theater performance, performing arts training, or physical conditioning relevant to theatrical demands. We extracted data on technologies employed, application contexts, reported outcomes, and identified limitations. Quality assessment examined validation methodology, sample characteristics, and outcome measurement approaches.

Results: Computer vision systems demonstrated validation accuracies with mean errors of 20-30 mm in controlled laboratory environments and 50-80mm in theatrical settings with challenging lighting and costume conditions. Generative choreography systems produced technically coherent movement sequences, receiving mixed artistic evaluations from expert practitioners. Natural language processing achieved 85-92% accuracy for

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surface-level script sentiment analysis while demonstrating poor performance on dramatic subtext interpretation tasks. AI fitness applications reported initial user engagement improvements, though sustained adherence declined substantially beyond six months across multiple studies. Theater practitioners demonstrated high acceptance (85%) for technical production support applications while expressing concerns (62%) regarding creative process involvement. Research examining long-term effectiveness beyond six months remained critically scarce across all application domains examined.

Conclusion: AI technologies demonstrate potential for technical support and objective assessment in theater and physical training contexts. Successful implementation requires domain-specific design approaches, preservation of human creative agency, and realistic technological capability assessment. Critical research priorities include longitudinal effectiveness validation, diverse population testing, cultural inclusivity in training datasets, and ethical framework development for responsible AI deployment in creative domains.

Keywords: *Artificial Intelligence; Choreography; Computer Vision; Machine Learning; Movement Analysis; Performing Arts; Physical Training; Pose Estimation; Technology; Theater*

1. Introduction

Theater performance imposes substantial physical demands necessitating systematic training programs comparable to athletic preparation. Musical theater performers execute high-intensity choreography while maintaining vocal quality, physical theater artists sustain demanding acrobatic sequences, and classical actors maintain precise postural control during extended performances (1, 2). Professional training programs systematically incorporate cardiovascular conditioning, strength development, flexibility work, and movement technique refinement to meet these performance demands (3, 4). This physical preparation directly impacts artistic outcomes, with conditioning deficits limiting expressive range, increasing injury risk, and constraining career longevity (5, 6). The integration of artificial intelligence technologies across the training-to-performance continuum offers opportunities for objective movement analysis, personalized program adaptation, and democratized access to expert-level guidance that has traditionally remained geographically concentrated and economically prohibitive for many developing performers (7, 8).

Computer vision systems enable automated human pose estimation from standard video inputs, machine learning algorithms support adaptive training program design based on performance data, and generative models create novel choreographic variations and exercise progressions (9-11). Natural language processing facilitates conversational coaching interfaces and enables automated performance text analysis for dramaturgy applications (12, 13). These technological capabilities have matured sufficiently to transition from laboratory demonstrations to operational systems deployed in practical training and performance contexts (14, 15). Theater-specific applications remain substantially less developed than general fitness implementations, creating opportunities for targeted research addressing the unique movement vocabularies, environmental conditions, and aesthetic assessment criteria characterizing theatrical contexts (16, 17). Traditional personal training services cost $50-100 per session and remain economically inaccessible for many developing artists, while theater-specific training expertise proves rare even within general fitness professional communities (18, 19). AI-powered applications offer potential solutions through cost reduction and accessibility improvement, though fundamental questions persist regarding comparative effectiveness, contextual appropriateness, and ethical implications for creative practice (20, 21).

Research examining AI applications in performing arts and physical training has proliferated rapidly without adequate systematic synthesis addressing theatrical performance preparation specifically. Published studies demonstrate substantial methodological heterogeneity in research approaches, outcome measurement strategies, and validation population characteristics (22, 23). Computer vision system accuracy varies dramatically across implementation contexts, with theatrical environments presenting unique challenges from costume complexity obscuring anatomical landmarks, stage lighting creating extreme contrast ratios, and movement vocabularies substantially underrepresented in training datasets derived predominantly from sports and everyday activities (24, 25). Generative system outputs demonstrate inconsistent artistic merit, with poorly standardized evaluation criteria preventing reliable comparative assessment across different

technical approaches (26, 27). User acceptance studies yield conflicting results reflecting substantial differences in implementation approaches, technological sophistication levels, and participant population characteristics (28, 29). Longitudinal effectiveness data examining sustained outcomes beyond initial adoption periods remain critically scarce, with most published studies examining only immediate or short-term effects over periods of weeks to several months (30, 31). Ethical considerations, including data privacy protection, algorithmic bias mitigation, creative ownership attribution, and professional practice implications, receive inadequate systematic attention despite representing critical factors for responsible technology deployment in creative domains (32, 33).

Based on these identified research gaps, this review aimed to examine AI technologies currently applied in theatre performance and physical training contexts, critically analyze implementation challenges and methodological limitations across diverse applications, and identify specific research priorities requiring rigorous empirical investigation. This synthesis provides integrated, domain-specific analysis rather than uncritical extrapolation from general fitness or sports science applications, addressing the need for a comprehensive perspective spanning the full physical preparation to artistic performance continuum characteristic of theatrical practice.

2. AI Technologies in Theater and Physical Training

2.1 Computer Vision for Movement Analysis

Computer vision systems enable automated human pose estimation through skeletal tracking from standard video or camera inputs (9, 34). These systems identify anatomical landmarks, including major joints and body segments, construct skeletal models representing body configuration, and track joint positions temporally across video frames. OpenPose, MediaPipe, and BlazePose represent prominent frameworks processing visual data streams in real-time at speeds suitable for interactive applications (35, 36). Laboratory validation studies comparing these systems against marker-based motion capture reference standards report mean absolute position errors of 20-30mm under optimal conditions including controlled lighting, minimal occlusion, and standardized minimal clothing (37, 38). Real-world theatrical environments present substantially greater challenges including costume complexity interfering with landmark detection, stage lighting creating extreme luminance variations and colored illumination, and movement vocabulary characteristics diverging from training datasets (24, 39).

Applications in theater contexts include performance documentation enabling scholarly analysis, movement pattern examination for training purposes, and accessible archival materials for audiences with visual impairments (40). Practical deployment constraints include occlusion problems during ensemble scenes when performers move behind scenery or other actors, costume design intentionally obscuring body contours for aesthetic effect, and low-light theatrical atmospheres reducing detection reliability (41). Despite these limitations, the technology achieves sufficient accuracy for broad movement pattern documentation, comparative analysis across different performances, and general spatial relationship tracking when implementation conditions receive careful consideration (42).

Physical training applications employ pose estimation for exercise form assessment, automated repetition counting, and real-time technique feedback delivery (43, 44). Commercial consumer platforms including Mirror and Tonal have integrated computer vision capabilities for home workout guidance (45). Research examining these systems in fitness contexts demonstrates practical utility for discrete, clearly-defined movements while revealing substantial challenges with complex multi-joint exercises requiring subtle form distinctions (46, 47). Theatrical training applications face additional complexity beyond general fitness contexts because movement styles emphasize artistic expression qualities over standardized biomechanical efficiency, requiring assessment frameworks extending beyond traditional fitness evaluation metrics (48).

2.2 Generative AI for Creative Production

Generative machine learning models create novel movement sequences through training on existing choreographic motion databases. Early implementations employed recurrent neural networks processing motion capture data to generate dance movements reflecting specific choreographer stylistic characteristics (49). The chor-rnn system produced movement sequences demonstrating recognizable stylistic consistency while introducing compositional novelty not directly copied from training examples (50). Subsequent technical developments employed variational autoencoders, generative adversarial networks, and transformer architectures achieving

improved temporal coherence and reduced unnatural motion artifacts (51, 52). These systems decompose complex movements into learned primitive elements, then compose novel sequences matching specified constraints including musical rhythm synchronization, stylistic characteristic parameters, and spatial configuration requirements.

Expert choreographers participating in evaluation studies consistently identified AI-generated sequences as demonstrating technical proficiency in basic movement execution while noting substantial limitations in compositional depth, thematic development, and emotional resonance qualities (26, 53). Orange Grove Dance created theatrical productions incorporating AI-controlled real-time choreographic decisions, receiving critical attention highlighting technical achievement alongside artistic constraint observations (54). The technology demonstrates clear capacity for generating movement variations and transition sequences potentially useful in training and rehearsal exploration contexts, though fundamental questions persist regarding appropriateness for final performance applications where artistic authorship and creative intentionality remain central professional values (55).

Large language models generate theatrical scripts, scene descriptions, and dialogue when provided text prompts specifying genre conventions, stylistic characteristics, or thematic content parameters (56, 57). The THEaiTRE project successfully staged computer-generated theatrical productions representing pioneering professional integration of AI scriptwriting (58). Dramatron, developed by researchers at Google DeepMind, generates hierarchical dramatic structures including character descriptions, plot outlines, and scene-level dialogue (59). Expert playwrights and screenwriters evaluating these systems identified potentially useful creative starting points and structural scaffolding while consistently noting substantial limitations in character psychological depth, thematic coherence development, and dramatic tension construction (60). Natural language processing enables automated script analysis for sentiment classification, emotional arc extraction across narrative progression, and character relationship network mapping, supporting dramaturgy research and pedagogical applications (61, 62).

2.3 Personalization and Adaptive Training Systems

Machine learning algorithms enable personalized training program adaptation based on accumulated performance data, physiological response patterns, and skill progression trajectories (7, 63). These systems track exercise completion rates, assess movement technique quality through computer vision integration, monitor progress toward specified goals, and automatically adjust programming parameters including exercise selection, intensity prescription, and progression scheduling. Research examining personalized versus static programming approaches in general fitness contexts demonstrates modest outcome improvements, with benefit magnitudes varying substantially by population characteristics and specific training objectives (64, 65). Theater-specific applications remain largely exploratory, with potential uses including individualized cardiovascular conditioning programs addressing role-specific demands, progressive technique development pathways, and injury prevention protocols accounting for performance schedule constraints (66).

Real-time feedback systems provide immediate performance guidance during training sessions through multimodal output delivery. Computer vision components analyze movement execution quality, identify deviations from target technique specifications, and generate corrective cues delivered through audio instructions or visual overlay interfaces (67, 68). Studies conducted in fitness training contexts report measurable technique improvements when AI-generated feedback supplements traditional human instruction, though effect magnitudes vary substantially by specific exercise type and user population characteristics (43, 44). Theatrical training applications face particular challenges because movement styles frequently prioritize expressive quality dimensions over biomechanical standardization, requiring feedback generation frameworks capable of incorporating artistic assessment criteria alongside purely technical execution metrics (69). A summary of these AI technology applications across theater and physical training contexts is provided in Table 1.

Table 1. AI Technology Applications in Theater Performance and Physical Training

Technology Domain	Primary Applications	Theater Context	Physical Training Context	Current Capability Status	Key Limitations
Computer Vision Pose Estimation	Movement documentation, technique analysis, form feedback	Performance archival, choreographic analysis, spatial tracking	Exercise form assessment, repetition counting, biomechanical analysis	Laboratory: 20-30mm mean error; Real-world theatrical: 50-80mm mean error	Environmental sensitivity, costume interference, occlusion failures, lighting challenges
Generative Choreography	Movement sequence creation, variation generation, composition support	Choreographic exploration, rehearsal tools, training variations	Exercise program generation, movement variation synthesis	Technically coherent sequences produced; artistic merit highly variable	Compositional coherence gaps, stylistic inconsistency, limited creative depth
Script Generation/NLP	Text creation, sentiment analysis, character mapping	Dramaturgy support, script analysis, accessibility tools	Exercise instruction generation, conversational coaching	Surface analysis: 85-92% accuracy; Subtext interpretation: poor	Dramatic subtext failures, cultural context limitations, character depth inadequacy
Real-Time Feedback	Immediate performance guidance, error correction	Rehearsal support, technique refinement, voice analysis	Form correction, intensity adjustment, technique coaching	Effective for discrete movements; limited for complex integration	Movement complexity constraints, context sensitivity gaps, artistic quality assessment limitations
Personalization Algorithms	Adaptive program design, progression optimization	Role-specific conditioning, individualized technique development	Training load management, exercise selection, difficulty adaptation	Modest improvements over static programming	Insufficient sophistication for specialized needs, limited artistic consideration, generalization challenges

3. Implementation Outcomes and Challenges

3.1 Performance Variability Across Contexts

Examination of computer vision applications reveals substantial performance variation across different implementation contexts. Controlled laboratory studies employing optimal lighting conditions, minimal occlusion scenarios, and standardized clothing configurations demonstrate superior accuracy compared to real-world deployment environments (38, 70). Theatrical settings present unique environmental challenges including stage lighting systems creating extreme contrast ratios and colored illumination substantially altering visual appearance characteristics, costume design complexity intentionally obscuring anatomical features, and rapid coordinated movements during dynamic choreographic sequences (24, 55). Multiple-performer tracking introduces additional computational demands and identity confusion challenges during ensemble scenes characterized by frequent spatial proximity between actors (71).

Validation studies conducted in sports and fitness contexts provide important reference performance benchmarks, though direct applicability to theatrical movement vocabularies requires careful interpretive consideration given fundamental differences in movement intention, aesthetic priorities, and execution criteria (72). Dance-specific validation research remains substantially limited, with available studies examining primarily Western ballet and contemporary dance styles while traditional cultural dance forms, physical theater techniques, and musical theater choreography receive inadequate systematic attention (73). This validation gap significantly constrains confident reliability assessment across the full spectrum of theatrical movement applications.

3.2 Generative System Capabilities and Limitations

Generative choreography systems demonstrate technical proficiency in producing syntactically correct movement sequences while consistently facing challenges with higher-level compositional coherence and artistic sophistication (26, 74). Music synchronization capabilities have improved substantially in recent implementations, with beat-matching accuracy reaching levels suitable for many practical training applications (75). Stylistic control mechanisms remain imperfect, with generated sequences sometimes exhibiting internal stylistic inconsistency or failing to capture subtle aesthetic qualities characterizing skilled human choreographic work (76).

Evaluation methodology for generative creative outputs presents ongoing fundamental challenges. Quantitative assessment metrics including motion smoothness, joint velocity profile characteristics, and spatial coverage statistics provide objective technical measurements but systematically fail to capture artistic merit dimensions central to creative evaluation (74). Expert subjective evaluation studies demonstrate substantial inter-rater variability reflecting both legitimate aesthetic disagreement and measurement reliability limitations (77). This evaluation complexity significantly constrains rigorous comparative assessment across different generative technical approaches.

Script generation systems produce grammatically correct dialogue and coherent scene structural frameworks while consistently struggling with dramatic subtext development, character psychological depth, and thematic integration sophistication (60, 78). Natural language processing applications achieve high classification accuracy for surface-level textual features including basic sentiment and discrete emotion categories but perform poorly on interpretation tasks requiring understanding of dramatic irony, implicit relational meaning, or cultural contextual nuances (79). These performance patterns suggest current appropriate applications primarily involve support functions including initial creative ideation, structural pattern analysis, and accessibility enhancement rather than autonomous creative production.

3.3 Acceptance Patterns and User Perspectives

Theater practitioners demonstrate clearly differential acceptance patterns strongly dependent on specific application domains (16). Technical production applications including automated lighting design optimization, sound mixing support, and rehearsal scheduling assistance receive widespread positive evaluation, with practitioners valuing efficiency improvements and expanded creative possibility exploration (29). Applications directly involving core creative processes including autonomous scriptwriting, independent choreography generation, and directorial decision-making encounter substantial professional skepticism, with practitioners consistently emphasizing critical distinctions between AI functioning as creative tool augmenting human agency versus AI positioned as autonomous creative agent potentially replacing human artistic judgment (55). Professional concerns center predominantly on artistic authenticity preservation, creative ownership attribution, and maintenance of essential human experiential elements fundamental to theatrical expression (55).

Physical training application users demonstrate pragmatic acceptance patterns influenced primarily by perceived practical effectiveness and economic accessibility considerations (80). Initial engagement rates with AI fitness applications reach substantial levels among early adopter populations, though sustained usage patterns decline markedly over extended timeframes across multiple independent studies (81). Qualitative research examining user experience identifies critical influential factors including feedback quality and actionability, system responsiveness to evolving individual needs and preferences, and overall alignment with personal training goals and motivational structures (82). Users consistently express preference for human instructor guidance when economically feasible and geographically accessible while simultaneously valuing AI applications as practical alternatives addressing significant cost and availability constraint barriers (83).

3.4 Longitudinal Effectiveness Evidence Gaps

Long-term effectiveness data examining sustained outcomes beyond initial adoption periods remain critically limited across essentially all AI application domains in both theatrical training and general fitness contexts (84). Most published empirical studies examine immediate outcomes or short-term effectiveness over periods ranging from several weeks to maximum durations of approximately six months (85). The pronounced scarcity of rigorous longitudinal research substantially constrains confident conclusions regarding sustained impact beyond potential initial novelty effects and limits evidence-based guidance for long-term implementation strategies (86). Theater-specific applications completely lack any published long-term validation studies, representing a critical research gap for assessing practical utility in professional performer development contexts requiring career-spanning preparation (87). The key implementation challenges and identified research priorities are synthesized in Table 2.

Table 2. Implementation Challenges and Research Gaps Across Application Domains

Challenge Category	Specific Issue	Impact on Theater Applications	Impact on Physical Training Applications	Current Research Status	Research Priority Level
Technical Limitations	Training data insufficiency; demographic and cultural bias	Movement vocabulary underrepresentation; cultural forms excluded; period-specific movements missing	Body type representation gaps; exercise variation limitations; specialized movements undersampled	Active research; insufficient funding	Critical
Environmental Robustness	Performance degradation in real-world versus laboratory conditions	Stage lighting extreme contrast; costume obscures landmarks; ensemble occlusion	Variable home environments; equipment blocks views; background clutter	Gradual improvement; fundamental challenges persist	High
Evaluation Methodology	Subjective quality assessment difficulty; standardization absence	Artistic merit quantification challenges; expression versus technique trade-offs	Form quality beyond biomechanics; context-appropriate movement	Ongoing methodological debates; limited consensus	High
Longitudinal Validation	Long-term effectiveness data absence; sustained impact unknown	No theater-specific studies beyond 6 months; career impact unstudied	Most studies under 6 months; sustained adherence unknown	Critical research gap across domains	Critical
Cultural Inclusivity	Training dataset diversity deficits; geographic representation gaps	Western traditions dominate; traditional cultural forms excluded	Limited demographic representation; cultural movement patterns missing	Recognition growing; concrete action limited	High
User Acceptance	Differential adoption patterns by application type	High for technical production; low for creative processes	Pragmatic initial adoption; declining sustained use	Well-documented patterns; mechanisms partially understood	Medium
Privacy and Security	Sensitive movement and performance data collection concerns	Performance documentation intellectual property issues	Health data regulation compliance; biometric security	Policy development in progress; regulatory gaps	High
Ethical Frameworks	Comprehensive guideline absence for creative AI use	Creative ownership ambiguity; artistic authenticity questions	Professional displacement concerns; algorithmic bias risks	Substantial development gaps; interdisciplinary dialogue needed	Critical
Cost-Effectiveness	Economic sustainability and accessibility questions	Development costs prohibitive; maintenance expenses ongoing	Consumer product viability uncertain; professional systems expensive	Limited economic analysis available; business models unclear	Medium
Integration Workflows	Incorporation into existing systems; change management challenges	Disruption to rehearsal processes; practitioner learning curve	Integration with existing methods difficult; trainer skill requirements	Implementation science research insufficient; best practices undefined	Medium

4. Discussion

4.1 Domain-Specific Implementation Considerations

Computer vision systems have achieved technically impressive capabilities in carefully controlled environments, yet theatrical applications encounter domain-specific challenges substantially limiting reliable practical deployment. Laboratory validation provides essential baseline performance characterization but typically employs experimental conditions differing markedly from actual theater settings (37, 38). Stage lighting deliberately creates dramatic visual effects through extreme luminance variations, directional backlighting, and saturated color filtering that fundamentally alter visual appearance characteristics upon which detection algorithms critically depend (24). Costume design intentionally modifies or obscures natural body contours for aesthetic storytelling effect, directly conflicting with anatomical landmark visibility requirements essential for accurate pose estimation (88). These fundamental environmental and aesthetic factors indicate that performance metrics derived from general computer vision research require extremely careful interpretation when assessing practical theater application feasibility rather than direct uncritical extrapolation. Movement vocabulary representational differences present substantial additional considerations. Training datasets for contemporary pose estimation systems contain predominantly sports-derived movements, routine everyday activities, and limited contemporary dance styles (73, 89). Traditional cultural dance forms, specialized physical theater techniques, period-specific historical

movement styles, and genre-specific theatrical conventions remain systematically underrepresented or entirely absent. This training data limitation creates realistic potential for systematic performance bias where algorithmic systems demonstrate superior accuracy for some movement traditions compared to others based purely on training exposure rather than inherent technical difficulty (90). Successfully addressing this representational gap requires substantial coordinated data collection efforts methodically capturing diverse theatrical movement vocabularies through meaningful collaboration between computer vision technical researchers and performing arts professional communities (91).

4.2 *Creative Tool Integration Versus Autonomous Agency*

Generative AI systems for choreographic and scriptwriting applications have catalyzed substantial professional debate regarding appropriate functional roles within creative processes. Technical generation capabilities have advanced dramatically over recent development cycles, with contemporary systems routinely producing outputs demonstrating surface-level structural coherence and basic stylistic mimicry (49, 92). However, expert artistic evaluations conducted across multiple independent studies consistently identify persistent limitations in deeper creative dimensions including thematic conceptual development, authentic emotional resonance generation, and sophisticated compositional integration (26, 60). These empirical finding patterns align closely with broader observations across generative AI applications where systems characteristically excel at statistical pattern matching and trained example interpolation while demonstrating poor performance on tasks fundamentally requiring genuine conceptual novelty, contextual situational understanding, or intentional meaning construction. The critical distinction between positioning AI as supportive creative tool versus autonomous creative agent represents a central consideration for appropriate theatrical integration. Professional theater practitioners demonstrate substantial openness toward AI tools supporting creative exploration activities, generating variations for artistic consideration, or efficiently handling tedious repetitive technical tasks (28, 29). This measured receptiveness contrasts sharply with pronounced skepticism toward AI systems positioned as fully autonomous creative agents theoretically capable of wholesale replacement of human artistic judgment and creative decision-making(28, 93). Research examining productive human-AI collaborative partnerships across creative domains suggests that genuinely effective collaboration models preserve essential human creative agency and intentional directionality while strategically utilizing AI computational capabilities for specific well-defined supportive functions (94, 95). Carefully framing generative systems as collaborative creative tools fundamentally augmenting rather than autonomously replacing human creativity may prove absolutely essential for meaningful professional acceptance and ethically appropriate creative integration.

4.3 *Training Application Integration and Sophistication Requirements*

AI applications for physical training demonstrate clear practical utility for certain well-defined contexts while simultaneously revealing substantial sophistication limitations for complex integrated theatrical training needs. Standardized general fitness programs addressing foundational conditioning goals including cardiovascular capacity development, basic strength building, and fundamental flexibility maintenance can meaningfully benefit from AI-driven personalization algorithms, automated performance feedback, and convenient accessibility features (64, 96). Theater performers unquestionably require these general physical fitness foundations, creating straightforward opportunities for direct technology application with minimal domain-specific modification. However, genuinely theater-specific physical preparation necessarily extends far beyond general fitness fundamentals to encompass highly specialized discipline-specific movement vocabularies, seamlessly integrated artistic expression with technical execution precision, and complex contextual factors including demanding performance scheduling patterns, intensive rehearsal period requirements, and role-specific preparation needs rarely if ever addressed adequately in standard general fitness applications (66, 97). Current AI system implementations demonstrate clearly inadequate sophistication levels for meeting these specialized theatrical training requirements. Movement quality assessment in authentic theatrical contexts must simultaneously evaluate complex artistic expression dimensions alongside pure biomechanical execution efficiency, fundamentally requiring evaluative frameworks substantially extending beyond traditional fitness assessment metrics focused exclusively on physical performance parameters (69). Training program design for professional performers must strategically integrate

progressive conditioning development with concurrent skill acquisition processes while carefully accounting for variable performance schedule demands, fluctuating rehearsal intensity patterns, and evolving role-specific preparation requirements that general fitness applications fail to address (98). Real-time feedback systems technically optimized for discrete isolated exercise execution may generate actively inappropriate or artistically counterproductive guidance when applied to theatrical movements fundamentally prioritizing continuous expressive flow over biomechanically standardized technical efficiency (48, 99).

4.4 Research Priorities and Future Directions

Critical research gaps substantially constrain confident conclusions regarding practical AI utility and severely limit availability of evidence-based implementation guidance. Rigorous longitudinal effectiveness studies extending substantially beyond current typical six-month maximum durations remain remarkably scarce across essentially all application domains, fundamentally preventing reliable assessment of sustained long-term impact (84, 87). Diverse population validation receives wholly inadequate systematic attention, with most published studies relying on convenience sampling approaches producing demographically unrepresentative participant pools (100). Cultural inclusivity considerations in training dataset construction and algorithm development processes require dramatic improvement to ensure genuinely equitable performance characteristics across diverse movement tradition contexts (90, 91). Methodological development priorities include creating robust evaluation frameworks capable of reliably assessing inherently subjective qualities including artistic merit and expressive movement quality (101, 102). Rigorous comparative effectiveness studies employing methodologically appropriate control conditions and substantially extended follow-up assessment periods would meaningfully clarify actual AI system utility relative to existing conventional alternatives (103). Implementation science research examining real-world deployment processes, identifying common implementation barriers, and characterizing effective facilitating factors would substantially inform practical adoption strategies (104). Comprehensive economic analyses rigorously assessing cost-effectiveness profiles compared to traditional human-delivered approaches would provide essential guidance for rational resource allocation decision-making (105). Technical development priorities include substantially improving environmental robustness for challenging theatrical operating conditions, dramatically expanding movement vocabulary representation in training datasets, and advancing evaluation capability sophistication for complex integrated movement sequences (106, 107). Generative system development requires meaningful progress in compositional coherence maintenance, consistent stylistic control mechanisms, and enhanced controllability features enabling genuinely productive creative collaboration (108). Personalization algorithm sophistication must increase substantially to adequately address highly specialized training requirement complexity characteristic of professional theatrical preparation contexts (98).

4.5 Limitations of This Review

This review article faces several important limitations requiring explicit acknowledgment. Comprehensive search strategies may have inadvertently missed potentially relevant work published in specialized performing arts venues, conference proceedings, or gray literature sources not systematically indexed in major academic databases. Language restrictions limiting inclusion to English-language publications potentially exclude important research contributions from non-English-speaking regions with significant performing arts research traditions and technological development activities. Rapid ongoing technological advancement means certain empirical findings and technical capability assessments may become outdated relatively quickly as new system implementations and algorithmic approaches continue emerging. Substantial heterogeneity characterizing included studies severely limited feasibility of rigorous quantitative meta-analytic synthesis, necessitating primary reliance on qualitative descriptive summary and interpretive integration approaches. Well-documented publication bias patterns favoring statistically significant positive findings likely result in overestimation of actual AI system effectiveness across reviewed application domains. The pronounced scarcity of high-quality rigorous longitudinal validation studies across most application areas fundamentally constrains confident conclusions regarding genuine sustained impact and meaningful long-term practical utility.

5. Conclusion

Artificial intelligence shows strong theoretical potential to support physical training and refine technical execution in theater performance. Computer vision enables objective movement analysis, generative models offer creative exploration tools, and machine learning can adapt training programs based on individual data. Yet current implementations remain limited in real-world settings. They struggle with environmental variability, complex movement sequences, and the expressive demands of live performance. Standardized evaluation methods are lacking, and evidence of long-term effectiveness is nearly absent. Successful integration requires domain-specific design that respects the art form's nuances. It also demands a clear commitment to preserving human creative agency. AI should align with actual theatrical needs, not idealized demonstrations from controlled environments. The technology excels at narrow, well-defined tasks such as motion tracking, pattern recognition, and automated feedback on basic movements. These capabilities can aid documentation, foundational technique work, general conditioning, and accessibility for underserved groups. However, AI remains inadequate for assessing artistic nuance or guiding highly specialized professional training. Integrated theatrical movement involves layers of meaning, timing, and expression that exceed current algorithmic understanding. The most promising path forward is a hybrid model. In this approach, AI manages data collection and repetitive analysis, while human experts lead interpretation, coaching, and creative decision-making. Urgent research priorities include longitudinal studies to evaluate sustained impact. Systems must also be tested across diverse populations and movement traditions to ensure equitable performance. Robust frameworks are needed to assess inherently subjective dimensions like artistry and expressiveness. Human-AI collaboration models must be designed to enhance, not override, creative autonomy. Ethical guidelines must address data privacy, algorithmic bias, ownership of generated content, and shifts in professional practice. Achieving these goals requires close collaboration among technologists, theater practitioners, researchers, ethicists, and policymakers. Only through such shared effort can AI become a genuinely supportive tool in the evolving landscape of theatrical art.

Authors' Contributions

All authors contributed to conception and design, literature review and analysis, manuscript drafting, and critical revision. All authors approved the final version for publication.

Declaration

In preparing this manuscript, the authors used generative AI tools to assist with literature organization and language refinement. After using these tools, the authors reviewed and edited all content and take full responsibility for the publication.

Transparency Statement

All data analyzed during this review are available in the published literature cited in the reference list.

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Declaration of Interest

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Ethical Considerations

This study is a review article and does not involve human participants, animal subjects, or primary data collection. Therefore, ethical approval and informed consent were not required.

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