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ARTICLE

Efficacy of AI-Based Pilates on Motor Performance and Fear of Falling in Older Adults

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ABSTRACT: Over the past decade, research on artificial intelligence (AI) has expanded significantly, exploring its potential to enhance the quality of life for older adults. Therefore, the study aims to investigate the effect of a 4-week AI-generated Pilates training program on motor performance and fear of falling in older adults. This quasi-experimental study selected 30 female older adults aged 65 years and older, dividing them into two groups: one for experimental (N = 15) and another for control (N = 15). The experimental groups had four weeks of AI-based intervention with three sessions per week. During this period, the control group engaged in the routine activities. The Timed Up and Go and the Falls Efficacy Scale-International (FES-I) questionnaire were done as pre-posttest, respectively. The independent t-test was used for inferential statistics. Data analysis was conducted at a significance level of 95% with an alpha level less than or equal to 0.05. The findings showed that there was a significant difference between the two groups in the scores of the TUG test ($p<0.03$) and the FES-I questionnaire ($p<0.001$). By utilizing AI to develop personalized exercise programs, healthcare practitioners can improve motor performance and reduce the fear of falling in older adults. These findings highlight the potential of AI-driven rehabilitation strategies in geriatric care, emphasizing the need for further research to refine program parameters and extend their benefits to a broader aging population.

KEYWORDS: Artificial Intelligence, Elderly, Performance, Fall.

1 Introduction

In the 21st century, significant changes in global demographics have occurred, mainly due to an aging population attributed to longer life expectancies and lower birth rates [1]. By 2050, an estimated 16% of the population will be individuals aged 65 and older, with around 28–35% of this group experiencing falls each year [2]. The growing elderly population will lead to an increased risk of falls that significantly impact health, resulting in disability and higher mortality rates, while the economic burdens associated with falls

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are considerable and continue to rise globally [3]. The World Health Organization defines a fall as an unexpected collapse to the ground that can lead to serious injuries, including fractures and brain injuries, with the risk increasing with age [4]. Fear of falling (FOF) is a persistent anxiety among older adults that diminishes confidence in balance [5], adversely affecting their mental health and quality of life [6]. This fear can lead to a reduction in social activities for 13% to 50% of those affected, resulting in impaired balance, greater isolation, and increased feelings of loneliness, anxiety, and sadness [4, 7]. FOF affects between 20.8% and 85% of older adults, significantly impairing motor performance by increasing functional dependency and decreasing walking speed [8]. A study by Sapmaz et al. (2021) found that dual-task performance was impaired in elderly individuals with FOF [8]. Moreover, FOF leads to activity avoidance, which reduces muscle and grip strength [9], limits mobility, heightens attentional demands for balance and ultimately compromises gait and overall motor performance [10].

Physical fitness is crucial in maintaining functional independence among older adults [11]. Engaging in physical activity is recognized as a key health determinant, offering significant benefits across all age groups, with a particularly strong impact on the well-being of the elderly [12]. The Pilates method, created by Joseph Hubertus Pilates in the early 20th century, is a structured exercise program to enhance overall flexibility, core strength, posture, and general well-being [13]. Additionally, it emphasizes efficient motion through proper alignment of the limbs, coordination of the shoulder joint and cervicothoracic spine, and balanced movement patterns throughout the body [14]. Research indicates that Pilates effectively reduces FOF and enhances motor performance in older adults by strengthening muscles, improving balance, and boosting coordination [15]. Another study demonstrated that Pilates minimizes the FOF and the risk of falls in older adults by improving functional mobility, gait, and postural stability [16].

Artificial intelligence (AI) transforms healthcare by utilizing big data to provide insights that enhance evidence-based clinical decision-making and promote value-based care [17]. Implementing AI in healthcare significantly enhances elderly care by improving disease prediction, risk assessment, diagnosis, and treatment [18]. This advancement has led to increased research and the adoption of technologies specifically designed for older adults, including robots, exoskeletons, smart homes, wearables, and mobile applications [19]. These technologies collectively perform essential functions like rehabilitation, social interaction, companionship, and monitoring, addressing the unmet healthcare needs of older adults and relieving pressure on the healthcare system [20].

Despite the well-documented benefits of Pilates in enhancing motor performance and reducing FOF, there is a significant gap in research regarding AI-generated Pilates training programs specifically for older adults. The urgency to incorporate artificial intelligence in this field arises from the potential for personalized, adaptive exercise prescriptions that can cater to the unique needs of this demographic. Current studies predominantly focus on traditional or therapist-guided interventions, leaving AI-driven solutions largely unexplored. Given the heightened concern among older adults about preventing falls, leveraging AI could revolutionize how Pilates is delivered, making it safer and more accessible. The effectiveness of AI-generated Pilates programs remains uncertain, and these interventions' safety, adaptability, and long-term impact have not been thoroughly investigated. This highlights the critical need for rigorous research to explore the feasibility and efficacy of AI-generated Pilates in improving motor performance and alleviating the FOF among older adults.

2 Methods

2.1 Participants

The present study was quasi-experimental and conducted in the field. Thirty female older adults aged 65 years and older were purposefully selected and assigned to either the experimental group (n = 15) or the control group (n = 15). Participants were included if they were 65 years or older, lived independently in the community, could walk without assistive devices, had no significant medical contraindications for physical activity, could communicate, had sufficient self-reported vision and hearing to follow the exercises, and provided written informed consent. Exclusion criteria were individuals unable to walk independently, those with a Mini-Mental State Examination (MMSE) score below 24 [21] or a Barthel Index (BI) score under 80 [22], severe visual or auditory impairments, unstable cardiovascular conditions, neurological disorders that could hinder participation, or a history of upper- or lower-limb fractures within the past year. Initially, demographic data of the participants were collected. Subsequently, the Timed Up and Go (TUG) test and the Falls Efficacy Scale-International (FES-I) were administered to assess motor performance and fear of falling, respectively. The results of these assessments were recorded as pre-test data for each participant. Then, the experimental group did the selected AI-based Pilates exercises for 4 weeks, but the control group continued their usual physical activities as part of their regular daily routine. After 4 weeks, all the tests were repeated, and the results were recorded as post-test data. Additionally, for ethical considerations based on the Declaration of Helsinki, all stages of the study were discussed with the subjects. Written informed consent was obtained from the participants themselves. Additionally, they were told that the examiner would take appropriate measures if there were any issues during the assessments. The subjects were instructed on how to perform each test. All steps were explained verbally to the participants. Before starting the tests, the procedure was presented to them verbally. The TUG test was performed three times, with the mean value of each variable recorded as study data, while the FES-I was administered only once.

2.2 Measurement and Tools

Assessment of Motor Performance

This study evaluated motor performance using the TUG test. Participants were instructed to stand up from an armless chair without hand support, walk 8 feet (2.44 meters), turn around, return to the chair, and sit down. They were encouraged to complete the task as quickly and efficiently as possible without running, and the total time taken was recorded as their score [23]. Good validity and reliability have been reported for this test [24].

Assessment of Fear of Falling

The Falls Efficacy Scale-International (FES-I) questionnaire assessed the fear of falling among older adults. This questionnaire comprises 16 items, each rated on a four-point Likert scale, where "1" indicates no fear, "2" represents mild fear, "3" corresponds to moderate fear, and "4" signifies severe fear. The total score ranges from 16 to 64, with higher scores reflecting greater fear of falling [25]. A study examined the validity and reliability of the Persian version of this questionnaire, yielding a satisfactory value of 0.70 [26]. Additionally, internal consistency was evaluated using Cronbach's alpha, which demonstrated an excellent reliability coefficient of 0.98, confirming the strong psychometric properties of this scale [26].

Implementation of the training programs

A day after the pre-testing, the implementation of the respective training programs for the experimental group commenced. The experimental group was administered the 4-week AI-generated Pilates training program, which was created using Scopus AI. The prompt includes the specifics of the training program using the principles of frequency, intensity, time, and type. Below is the exact prompt inputted in the Scopus AI. It should be noted that the training sessions were 30–40 minutes, including a warm-up (10 minutes), Pilates exercise (20 minutes), and a cool-down (10 minutes). Moreover, we provided clear, concise verbal instructions for each movement and used tactile cues to guide body positioning.

Prompt : Write a 4-week Pilates exercise program for a 65-year-old older adult based on the FITT principle (Frequency, Intensity, Time, and Type) for optimal results. Please ensure the program includes specific exercises targeting the identified aging issues and adheres to the FITT principles. Additionally, it provides explanations for a better understanding of each exercise, emphasizing proper form and technique.

Table 1. Ai-generated Pilates training program

Week	Exercise	Description	Repetitions/Sets	FITT Principle
Week 1	Diaphragmatic Breathing	Deep inhalation through the nose, ribcage expansion, and slow exhalation through the mouth while engaging the core	5 minutes	F: 3x/week, I: Low, T: 20 min, T: Mat-based Pilates
	Pelvic Tilt (Supine)	Lying down, tilt the pelvis backward to flatten the lower back	10 reps	F: 3x/week, I: Low, T: 20 min, T: Mat-based Pilates
	Heel Raises	Standing on toes and lowering back down	10 Reps	F: 3x/week, I: Low, T: 20 min, T: Mat-based Pilates
Week 2	Bridging	Lifting hips off the ground while lying down	10 Reps	F: 3x/week, I: Low, T: 20 min, T: Mat-based Pilates
	Standing Side Leg Raises	Lifting one leg sideways while standing	10 reps per leg	F: 3x/week, I: Low, T: 20 min, T: Mat-based Pilates
	Seated Leg Extensions	Extending one leg at a time while seated	10 reps per leg	F: 3x/week, I: Low, T: 20 min, T: Mat-based Pilates
Week 3	Wall Roll-Downs	Rolling down the spine against a wall and back up	10 Reps	F: 3x/week, I: Moderate, T: 20 min, T: Balance & flexibility exercises
	Chair-Assisted Squats	Performing controlled squats using a chair	10 Reps	F: 3x/week, I: Moderate, T: 20 min, T: Balance & flexibility exercises
	Seated Hamstring Stretch	Stretching hamstrings while seated	Hold for 20 sec per leg	F: 3x/week, I: Moderate, T: 20 min, T: Balance & flexibility exercises
Week 4	Side-Lying Leg Lifts	Lifting the top leg while lying on the side	10 reps per leg	F: 3x/week, I: Moderate, T: 20 min, T: Strength & mobility exercises

	Step-Ups (Using Low Step)	Stepping up onto a stable platform and stepping down	10 reps per leg	F: 3x/week, I: Moderate, T: 20 min, T: Strength & mobility exercises
	Standing Arm Circles	Moving extended arms in small circular motions	10 reps forward & backward	F: 3x/week, I: Moderate, T: 20 min, T: Strength & mobility exercises

F frequency, I intensity, T time, T type

2.3 Data analysis

This study used descriptive statistics to summarize the variables, while inferential statistics were applied for data analysis. The Shapiro-Wilk test was conducted to assess the normality of data distribution. An independent t-test was employed for between-group comparisons of variables. Data analysis was conducted at a significance level of 95% with an alpha level less than or equal to 0.05 using SPSS software version 27.

3 Results

The Shapiro-Wilk test results indicated that the data followed a normal distribution. Table 1 displays the demographic characteristics of participants in both groups.

Table 2. Demographic characteristics of participants

Variable	Groups	Mean±SD	P-value
Age (years)	**Experimental**	69.2±4	**0.88**
	Control	69.0±3.2	
Height (cm)	**Experimental**	156.9±7.7	**0.25**
	Control	159.7±9	
Weight (kg)	**Experimental**	71.2±11.9	**0.08**
	Control	78.7±16.2	
BMI (kg/m²)	**Experimental**	29.0±4.5	**0.20**
	Control	30.8±5.5	

BMI Body Mass Index

Table 3. Independent t-test results

Variable	Group	Pre-test	Post-test	t	P-value
Motor Performance +	Experimental	9.2±1.8	7.6±2	-1.58	0.03*
	Control	9±1.8	8.7±1.8		
Fear of Falling	Experimental	37.76±3.08	28.59±3.16	-7.72	0.001*
	Control	35.76±2.90	37.30±1.88		

* Indicating a significant change from pre-test to post-test

+ Mean and standard deviations scores of the TUG test in seconds

The findings (Table 3) showed that there was a significant difference between the two groups in the scores of the TUG test ($p<0.03$) and the FES-I questionnaire ($p<0.001$).

5. Discussion and Conclusion

This study demonstrated the effectiveness of an AI-generated training program in enhancing motor performance and reducing fear of falling among older adults. The rapid advancement of AI technology offers a promising avenue for improving the quality of life in aging populations. While AI has traditionally been developed to assist older adults, its applications extend to alleviating various functional impairments. Research on AI-driven rehabilitation programs for older adults suggests that AI has potential benefits for the elderly [27]. A study showed that a hybrid exercise program consisting of eight-form Tai Chi and strength and endurance exercises can more effectively improve physical fitness and reduce frailty among the elderly [28]. Another study indicated that artificial intelligence-based serious games can help older adults prevent dementia [29]. Ensuring the transparency and interpretability of AI models is crucial in healthcare, as medical professionals must utilize AI-driven insights and comprehend the rationale behind them. When transparently designed, AI systems can seamlessly integrate into digital healthcare platforms, including telemedicine services and mobile health applications [30]. These integrations improve the accessibility of AI-powered medical solutions, benefiting healthcare providers, caregivers, and patients [31]. Additionally, AI-powered robotic systems have shown great potential in therapeutic contexts for the elderly, enhancing social engagement and communication through adaptive interventions [32]. Concerning this matter, it was found that the humanoid robot is designed for close interaction with older adults, monitoring vital signs, emotions, and cognitive states while assisting with daily tasks and alerting caregivers to anomalies [27]. Communication was also enabled via a Telegram bot, and a machine learning model based on the Modified Early Warning Score (MEWS) was developed to predict health status. In a systematic review, it was revealed that chatbots may improve physical activity [33]. Constrained AI chatbots are rule-based, well-structured, and easy to build, control, and implement, thus ensuring quality and consistency in content structure and delivery [34]. The findings of this study highlight the potential of AI-based Pilates as an effective intervention for improving motor performance and reducing fear of falling in older adults. Given the high prevalence of balance impairments and fall-related injuries in aging populations, integrating AI-driven exercise programs into rehabilitation and preventive care can enhance accessibility, personalization, and adherence. AI-based systems can provide real-time feedback, adapt difficulty levels based on individual progress, and ensure consistent training, making them scalable solutions for clinical and home-based settings. These results emphasize the need for further research on AI-assisted rehabilitation strategies to optimize mobility, independence, and overall quality of life in older adults.

Limitations and Future Directions

Despite the promising outcomes of this study, several limitations must be acknowledged. First, the sample size was relatively small, which may limit the generalizability of the findings to a broader population of female older adults. Additionally, the study focused on a short intervention period of four weeks, and the long-term effects of the AI-generated Pilates training on motor performance and fear of falling remain uncertain. Another limitation is the potential variability in individual responses to the training, as factors such as baseline physical fitness, muscle strength, and adherence to the program could influence the results.

Furthermore, while AI-generated programs offer personalization, they may not fully account for nuanced biomechanical adaptations unique to older adults. Future studies should further incorporate larger sample sizes, extended follow-up periods, and comparisons with traditional rehabilitation methods to validate the efficacy and sustainability of AI-driven interventions.

Conflict of interest

The authors declared no conflicts of interest.

Authors' contributions

All authors contributed to the original idea and study design.

Ethical considerations

The participants have considered ethical issues, including informed consent, plagiarism, data fabrication, misconduct and/or falsification, double publication and/or redundancy, submission, etc.

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