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# Developing an Adaptive Learning System for Agricultural Extension Using Painting Training-Based Optimization

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**Abstract** Agricultural extension services face significant challenges delivering effective training to heterogeneous farming populations with diverse knowledge levels and resource constraints. Traditional uniform training approaches result in inefficiencies where experienced farmers encounter redundant content while novice farmers struggle with excessive complexity. This research develops an adaptive learning system for agricultural extension using Painting Training-Based Optimization (PTBO), a human-inspired metaheuristic algorithm. A multi-objective optimization framework was formulated incorporating knowledge gain maximization, time efficiency, sequence validity, difficulty appropriateness, and knowledge coverage, subject to time, budget, and prerequisite and essential knowledge constraints. A quasi-experimental study with 75 wheat farmers in Irbid Governorate, Jordan (2024–2025), randomly assigned participants to PTBO-personalized ($n = 25$), GA-personalized ($n = 25$), and traditional-uniform ($n = 25$) groups. PTBO demonstrated superior performance: 15.3% improvement in knowledge gain over GA (32.4 vs. 28.1 points), 29.9% faster convergence (87.3 vs. 124.6 iterations), 96.2% knowledge retention at four-week follow-up, and 80.0% practical adoption versus 69.7% for traditional methods. Novice farmers achieved normalized learning gains of 0.76 compared to 0.68 (GA) and 0.66 (traditional). The research provides a deployable framework demonstrating that metaheuristic optimization effectively addresses agricultural knowledge dissemination challenges while maintaining computational efficiency for resource-constrained contexts.

**Keywords** Agricultural extension, Adaptive learning systems, Painting Training-Based Optimization, Personalized learning paths, Wheat cultivation training

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## 1. Introduction

Agricultural extension services constitute a cornerstone of rural development and food security worldwide, serving as the primary mechanism through which research-based knowledge and innovative farming practices are disseminated to farming communities. These services bridge the critical gap between agricultural research institutions and farming practitioners, facilitating technology transfer, skill development, and the adoption of improved agricultural practices [1, 2]. In developing countries, where agriculture employs a substantial proportion of the labor force and contributes significantly to national economies, effective extension systems are particularly vital for enhancing productivity, ensuring food security, and promoting sustainable agricultural practices [3].

Despite their fundamental importance, traditional agricultural extension models face mounting challenges that limit their effectiveness in addressing the diverse and evolving needs of farming populations. The conventional train-the-trainer approach, which follows a top-down model where researchers generate information and extension agents disseminate it uniformly to farmers, has been criticized for its inability to provide satisfactory services

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tailored to farmers' heterogeneous characteristics and contexts [4]. Recent studies have identified critical constraints including insufficient extension personnel relative to farmer populations, inadequate training of extension staff in emerging agricultural technologies, weak technical and functional capacities, reduced budgets, poor coordination mechanisms, and limited connections to research institutions [5].

These systemic challenges are compounded by the inherent diversity within farming populations. Farmers exhibit substantial variation in experience levels, educational backgrounds, farm sizes, resource availability, learning preferences, and existing knowledge states [6]. Traditional uniform training programs, which deliver identical content to all participants regardless of their individual needs, result in inefficiencies: experienced farmers encounter redundant content that fails to address advanced knowledge requirements, while novice farmers struggle with complexity that exceeds their foundational understanding, leading to cognitive overload and poor knowledge retention [7]. In the context of climate change, evolving pest pressures, and market dynamics, the urgency of transforming extension systems to be more responsive, efficient, and personalized has never been greater [8].

Concurrently, the educational sector has experienced a paradigm shift toward personalized and adaptive learning systems, fundamentally reconceptualizing traditional one-size-fits-all pedagogical models. Personalized learning represents a technology-empowered approach that dynamically adjusts teaching strategies based on real-time monitoring of learners' individual characteristics, performance trajectories, and developmental needs [9]. Recent advances in artificial intelligence and computational intelligence have catalyzed unprecedented opportunities for scaling personalized learning beyond formal educational institutions. AI-driven adaptive learning systems have demonstrated effectiveness in enhancing learning performance by analyzing individual learner data, identifying knowledge gaps, and delivering tailored content that accommodates diverse learning styles and paces [10]. The global market for AI in education was valued at approximately USD 5.88 billion in 2024 and is projected to grow at 31.2% annually through 2030, driven by rising demand for personalized learning experiences [11]. However, analysis of AI-driven personalized learning solutions reveals a critical gap between the objectives of modern education and technological implementations [12]. While adaptive systems have proven effective for domain-specific knowledge acquisition, their limitations include insufficient support for learner agency and self-regulation, potential cognitive offloading that may diminish rather than enhance learning skills, and misalignment with broader educational goals such as fostering general competencies and lifelong learning capabilities [13].

The optimization of learning sequences represents a computationally complex challenge requiring sophisticated algorithmic approaches. Learning path optimization problems exhibit characteristics including large combinatorial search spaces, multiple competing objectives, diverse constraints, and problem-specific domain knowledge that must be encoded algorithmically [14]. These characteristics render exact solution methods computationally intractable for realistic problem instances, necessitating heuristic and metaheuristic approaches. Metaheuristic algorithms have emerged as powerful tools for addressing complex optimization problems across diverse domains. More than 500 metaheuristic algorithms have been developed to date, with over 350 appearing in the last decade, driven by the need to address increasingly complex optimization challenges [15]. Among metaheuristic paradigms, human-inspired algorithms—which draw inspiration from human behaviors, cognitive processes, and social activities—offer particularly compelling advantages for educational applications. These algorithms exhibit intuitive interpretability, natural alignment with pedagogical contexts through their metaphorical foundations, and population-based structures that accommodate heterogeneous learner populations [16]. The recently proposed Painting Training-Based Optimization (PTBO) algorithm models the intricate and iterative human activities observed during painting training through a dual-phase operation: an education phase providing global guidance and a skill refinement phase enabling local practice. Experimental validation on the CEC 2011 benchmark suite demonstrated that PTBO outperformed 12 established metaheuristic algorithms across all 22 optimization problems, exhibiting superior performance in handling complex functions [17].

Despite substantial research in adaptive learning systems, metaheuristic optimization, and agricultural extension separately, their intersection remains virtually unexplored. A systematic analysis of existing literature reveals critical gaps: while personalized learning path optimization has been extensively investigated in formal educational settings, its application to agricultural extension—characterized by unique constraints including strict temporal limitations, diverse prerequisite knowledge structures, variable resource availability, and the necessity for practical applicability—remains absent from academic discourse. Existing educational optimization research relies predominantly on simulated datasets, controlled laboratory experiments, or historical educational records. Current fitness functions and constraint handling mechanisms inadequately represent domain-specific requirements of agricultural extension, including the need to balance knowledge acquisition effectiveness, time efficiency given farmer constraints, practical applicability of learned content, and cost-effectiveness of training delivery simultaneously across heterogeneous farmer populations. This research addresses the identified gaps through specific objectives: (1) develop a comprehensive problem formulation for agricultural extension learning path optimization that explicitly incorporates domain-specific constraints, multiple competing objectives, and farmer heterogeneity; (2) adapt and implement the PTBO algorithm for learning path generation, designing specialized solution encoding schemes, constraint handling mechanisms, and fitness evaluation procedures tailored to agricultural training contexts; and (3) develop practical implementation guidelines including system architecture, parameter configuration recommendations, cost-benefit analysis, and scalability assessment to facilitate adoption by agricultural extension organizations.

This research makes significant contributions to both theoretical understanding and practical applications:

- Novel problem formulation that bridges adaptive learning research with agricultural development practice, introducing a multi-objective optimization framework specifically designed for extension training contexts.
- Deployable system enabling agricultural extension organizations to implement personalized training programs with demonstrated effectiveness gains in knowledge acquisition, time efficiency, and practice adoption.
- Cost-effectiveness analysis demonstrating economic viability and return on investment, facilitating evidence-based decision-making for extension program administrators.

The remainder of this paper is organized as follows: Section 2 reviews related work on adaptive learning systems, metaheuristic algorithms, and agricultural extension. Section 3 presents the problem formulation. Section 4 introduces Painting Training-Based Optimization. Section 5 describes the methodology and experimental design. Section 6 provides experimental results and comparative analysis. Finally, Section 7 concludes with future work.

## 2. Related Work

### *2.1. Adaptive and Personalized Learning Systems*

Personalized adaptive learning represents a transformative approach that dynamically adjusts teaching strategies based on real-time monitoring of learners' individual characteristics, performance, and needs. Recent systematic reviews have documented rapid expansion in this field, with AI technologies significantly transforming digital education by enabling data-driven learning experiences that adapt instructional content to individual learner profiles [7, 9]. A comprehensive analysis of 142 studies published between 2015 and 2025 revealed that adaptive systems employ intelligent agents to monitor interactions, assess engagement, and evaluate knowledge acquisition. Contemporary adaptive learning architectures comprise learner profiling, competency-based progression monitoring, personalized path generation, and flexible learning environments. Recent research on AI-mediated personalized learning paths focuses predominantly on higher education contexts, with adaptive technologies and generative language models as primary approaches [18]. The Adaptive Learning Path Optimization Algorithm (ALPOA) employs a hybrid GA-PSO framework to dynamically adjust learning paths, considering learner proficiency, speed, engagement, and content difficulty. Experimental validation demonstrated 97% accuracy in predicting optimal paths and 15% higher knowledge retention compared to benchmark algorithms [19]. Deep learning approaches have introduced new capabilities for modeling complex learner behaviors. An Enhanced Deep Neural Network model for path optimization adopts the Actor-Critic framework with multilayer perceptron and LSTM components, demonstrating superior performance in learning speed and stability [20]. However, neural approaches present challenges including high computational requirements, extensive training data needs, and limited interpretability, motivating continued exploration of metaheuristic optimization approaches.

### *2.2. Metaheuristic Algorithms in Educational Optimization*

Metaheuristic algorithms offer powerful solutions for complex optimization problems, particularly for non-convex, multi-modal problem spaces characteristic of educational path optimization. Over 500 metaheuristic algorithms have been developed to date, with more than 350 appearing in the last decade [21]. Recent surveys identified 23 influential algorithms between 2019 and 2024 based on citation count, problem diversity, and resistance to premature convergence [22]. Metaheuristics are categorized into evolutionary algorithms (Genetic Algorithm, Differential Evolution), swarm intelligence (Particle Swarm Optimization, Ant Colony Optimization), physics-based algorithms (Simulated Annealing), and human-inspired algorithms (Teaching-Learning Based Optimization) [23]. Genetic Algorithms have demonstrated effectiveness for permutation-based representations and prerequisite constraint satisfaction, though facing challenges with parameter sensitivity and slow convergence [24]. Particle Swarm Optimization enables rapid convergence through social learning but increases susceptibility to premature convergence [25]. Hybrid PSO-GA algorithms combine both approaches to balance exploration-exploitation while maintaining search diversity [26, 27]. Human-inspired metaheuristics draw inspiration from human behaviors and social activities, offering intuitive interpretability and natural alignment with educational contexts. Teaching-Learning-Based Optimization models classroom interaction dynamics [28], while Sales Training Based Optimization simulates commercial training processes [29]. The recently proposed Painting Training-Based Optimization (PTBO) models iterative painting training activities through a two-phase operation: education phase for global guidance and skill refinement phase for local practice [30]. PTBO outperformed 12 metaheuristic algorithms across all 22 CEC 2011 optimization problems, exhibiting superior convergence and solution quality. Its dual-phase mechanism naturally balances exploration-exploitation with adaptive parameter control, positioning it as particularly promising for educational optimization tasks.

### *2.3. Agricultural Extension and Training Systems*

Agricultural extension services provide critical knowledge transfer between research institutions and farming communities. Traditional extension employs uniform training approaches delivering standardized content through field schools and workshops. The train-the-trainer approach is widely used but presents limitations: one-directional information flow, lack of personalization, and identical training regardless of farmer knowledge levels [31]. Contemporary agricultural extension faces challenges including resource constraints, diverse farmer populations with heterogeneous knowledge, rapidly evolving technologies, and efficient knowledge dissemination needs [32]. Farmers report high confidence in extension agents but prefer hands-on experiences and direct interaction over classroom settings. Recent technological advances have catalyzed transformation in service delivery models, with AI improving access to extension services and providing personalized recommendations for marginalized farmers [33]. Digital platforms enable satellite-based monitoring, precision agriculture technologies, and mobile advisory systems [34]. Despite recognized need for personalized agricultural extension, few empirical studies have systematically investigated adaptive training approaches in farming contexts. The New Extensions Learning Kit provides modular content for self-directed or blended learning but focuses on content design rather than algorithmic optimization of learning sequences [35]. Agricultural contexts present unique challenges: farmers face strict temporal constraints during planting/harvesting seasons, training must balance theoretical and practical knowledge, content must accommodate diverse literacy levels, and outcomes must translate to measurable practice improvements.

### *2.4. Research Gaps and Positioning*

Comprehensive literature analysis reveals critical gaps at the intersection of adaptive learning, metaheuristic optimization, and agricultural extension. While adaptive learning path optimization has been extensively explored in formal education, its application to agricultural extension remains virtually unexplored, with existing systems misaligned with agricultural realities such as limited connectivity and digital literacy. Few studies have investigated metaheuristic algorithms for educational path optimization, and the PTBO's pedagogically-aligned approach remains empirically untested for agricultural training. Research predominantly focuses on academic learners with flexible schedules, inadequately representing farmers' strict temporal constraints, diverse prerequisite structures, and variable resource availability. Most adaptive learning research lacks ecological validity, relying on simulated datasets rather than field validation with actual farmers measuring knowledge acquisition and practical adoption. Finally, agricultural knowledge structures vary substantially across crops and contexts, yet research on algorithmic approaches capable of generalizing across these variations remains notably absent.

This study addresses these gaps through systematic investigation of metaheuristic-based learning path optimization for agricultural extension. It introduces the PTBO to educational optimization, leveraging its dual-phase mechanism to generate personalized learning paths reflecting agricultural knowledge hierarchies. The research presents domain-adapted mathematical modeling incorporating prerequisite dependencies, time constraints, resource limitations, and practical applicability through multi-objective fitness functions. Real-world validation through field experiments with wheat farmers measures both knowledge acquisition and practice adoption rates. Rigorous comparative analysis evaluates PTBO against established metaheuristics using identical formulations, while a deployable implementation framework provides constraint handling mechanisms, parameter guidelines, and scalability assessment for transforming agricultural extension through empirically validated adaptive learning technologies.

## 3. Problem Formulation

### 3.1. Problem Statement

Agricultural extension services play a critical role in disseminating knowledge and modern farming practices to rural communities, serving as a primary conduit between agricultural research institutions and farming practitioners [36]. Despite their fundamental importance in agricultural development, traditional extension training programs predominantly employ a uniform, one-size-fits-all pedagogical approach that delivers standardized content to all participating farmers regardless of their heterogeneous knowledge levels, learning capacities, or specific operational contexts. This pedagogical homogeneity manifests several critical inefficiencies. Experienced farmers frequently encounter redundant content that fails to address their advanced knowledge requirements, leading to disengagement and suboptimal time utilization. Conversely, novice farmers often struggle with content complexity that exceeds their foundational knowledge, resulting in cognitive overload and poor knowledge retention. Furthermore, the rigid structure of conventional training programs inadequately accounts for individual learning preferences, farm-specific constraints, and regional agricultural variations, thereby limiting the practical applicability and adoption of disseminated knowledge [37]. The consequences of these inefficiencies extend beyond mere pedagogical concerns. Resource-constrained extension systems expend substantial human and financial capital delivering partially irrelevant content, while farmers sacrifice valuable agricultural time attending training sessions that may not align with their immediate operational needs. This misalignment contributes to the persistent gap between agricultural research outputs and on-farm implementation, a phenomenon extensively documented in agricultural development literature [38]. Recent advances in adaptive learning systems and computational intelligence offer promising avenues for addressing these challenges. Personalized learning path generation, successfully implemented in formal education contexts [39], represents an underexplored opportunity within agricultural extension. However, the optimization of individualized learning sequences in resource-constrained, heterogeneous learner populations presents significant computational complexity, necessitating sophisticated algorithmic approaches.

### 3.2. Mathematical Problem Formulation

*3.2.1. Notation and Definitions* Let us define the following sets and parameters.

**Sets:**

- $K = \{k_1, k_2, \ldots, k_n\}$: Set of $n$ knowledge units covering wheat cultivation practices
- $F = \{f_1, f_2, \ldots, f_m\}$: Set of $m$ farmers participating in the training program
- $L = \{l_1, l_2, l_3\}$: Set of difficulty levels, where $l_1$ = beginner, $l_2$ = intermediate, $l_3$ = advanced

**Knowledge Unit Parameters:** For each knowledge unit $k_i \in K$:

- $d_i \in L$: Difficulty level of knowledge unit $k_i$
- $t_i \in \mathbb{R}^+$: Time required to complete knowledge unit $k_i$ (in hours)
- $c_i \in \mathbb{R}^+$: Cost/resource requirement for delivering knowledge unit $k_i$
- $P_i \subseteq K$: Set of prerequisite knowledge units that must be learned before $k_i$

**Farmer Parameters:** For each farmer $f_j \in F$:

- $s_j = [s_{j1}, s_{j2}, \dots, s_{jn}] \in [0,1]^n$: Current knowledge state vector, where $s_{ji}$ represents farmer $f_j$'s proficiency in knowledge unit $k_i$ (0 = no knowledge, 1 = complete mastery)
- $T_j \in \mathbb{R}^+$: Maximum time available for farmer $f_j$ to participate in training
- $B_j \in \mathbb{R}^+$: Budget/resource constraint for farmer $f_j$
- $e_j \in L$: Overall experience level of farmer $f_j$

**Relationship Parameters:**

- $R \in \{0,1\}^{n \times n}$: Prerequisite relationship matrix, where $R_{ij} = 1$ if knowledge unit $k_j$ is a prerequisite for $k_i$, and 0 otherwise
- $\mathbf{W} = [w_1, w_2, \dots, w_q]^T$: Weight vector for multiple objectives in the fitness function, where $\sum_{i=1}^{q} w_i = 1$

*3.2.2. Decision Variables* For each farmer $f_j$, we seek to determine the learning path:

$$\mathbf{x}_j = [x_{j1}, x_{j2}, \dots, x_{jp}] \tag{1}$$

where $x_{jk} \in K$ represents the $k$-th knowledge unit in the learning sequence for farmer $f_j$, $p \leq n$ is the number of knowledge units included in the personalized path, and $x_{ji} \neq x_{jk}$ for all $i \neq k$ (no repetition).

*3.2.3. Objective Functions* The optimization problem aims to maximize a composite fitness function comprising multiple objectives:

**1. Knowledge Gain Maximization:**

$$KG(\mathbf{x}_j) = \sum_{i=1}^{p} g_{ji} \cdot (1 - s_{j,x_{ji}}) \tag{2}$$

where $g_{ji}$ is the importance/relevance weight of knowledge unit $x_{ji}$ for farmer $f_j$, and $(1 - s_{j,x_{ji}})$ represents the knowledge gap for that unit. This objective prioritizes knowledge units where the farmer has the greatest deficiency, weighted by relevance.

**2. Time Efficiency Maximization:**

$$TE(\mathbf{x}_j) = \frac{KG(\mathbf{x}_j)}{\sum_{i=1}^{p} t_{x_{ji}}} \tag{3}$$

This objective measures knowledge gain per unit time, incentivizing efficient learning paths.

**3. Sequence Validity Score:**

$$SV(\mathbf{x}_j) = \sum_{i=1}^{p} \left( \frac{|\{k \in P_{x_{ji}} : k \in \{x_{j1}, \dots, x_{j,i-1}\}\}|}{|P_{x_{ji}}|} \right) \tag{4}$$

This objective ensures that prerequisite relationships are respected, reaching maximum value when all prerequisites precede dependent knowledge units.

**4. Difficulty Appropriateness:**

$$DA(\mathbf{x}_j) = \frac{1}{p} \sum_{i=1}^{p} \exp\left(-\alpha \cdot |d_{x_{ji}} - e_j|^2\right) \tag{5}$$

where $\alpha$ is a scaling parameter. This Gaussian-like function penalizes knowledge units whose difficulty significantly deviates from the farmer's experience level.

**5. Knowledge Coverage:**

$$KC(\mathbf{x}_j) = \frac{|\{topic(k) : k \in \mathbf{x}_j\}|}{|\{topic(k) : k \in K\}|} \tag{6}$$

where $topic(k)$ maps each knowledge unit to its thematic category (e.g., irrigation, pest management). This ensures diverse coverage across agricultural domains.

*3.2.4. Composite Fitness Function* The overall fitness function to be maximized is:

$$F(\mathbf{x}_j) = w_1 \cdot KG(\mathbf{x}_j) + w_2 \cdot TE(\mathbf{x}_j) + w_3 \cdot SV(\mathbf{x}_j) + w_4 \cdot DA(\mathbf{x}_j) + w_5 \cdot KC(\mathbf{x}_j) \tag{7}$$

subject to the constraint $\sum_{i=1}^{5} w_i = 1$ and $w_i \geq 0$ for all $i$.

*3.2.5. Constraints* The optimization must satisfy the following constraints:

**1. Time Constraint:**

$$\sum_{i=1}^{p} t_{x_{ji}} \leq T_j \tag{8}$$

The total learning time must not exceed the farmer's available time.

**2. Budget Constraint:**

$$\sum_{i=1}^{p} c_{x_{ji}} \leq B_j \tag{9}$$

The total cost must remain within budget limitations.

**3. Prerequisite Constraint:**

$$\forall\, k_a \in \mathbf{x}_j,\ \forall\, k_b \in P_a :\ \text{index}(k_b, \mathbf{x}_j) < \text{index}(k_a, \mathbf{x}_j) \tag{10}$$

All prerequisite knowledge units must appear earlier in the sequence than dependent units.

**4. Essential Knowledge Constraint:**

$$K_{\text{essential}} \subseteq \mathbf{x}_j \tag{11}$$

where $K_{\text{essential}} \subset K$ is the set of mandatory knowledge units that must be included in every learning path.

**5. Uniqueness Constraint:**

$$\forall\, i, j \in \{1, \ldots, p\},\ i \neq j :\ x_{ji} \neq x_{jj} \tag{12}$$

Each knowledge unit appears at most once in the learning path.

*3.2.6. Optimization Problem Statement* The complete optimization problem can be formally stated as:

$$\begin{aligned} \max_{\mathbf{x}_j} \quad & F(\mathbf{x}_j) \\ \text{subject to} \quad & \sum_{i=1}^{p} t_{x_{ji}} \leq T_j \\ & \sum_{i=1}^{p} c_{x_{ji}} \leq B_j \\ & \text{Prerequisite constraints satisfied} \\ & K_{\text{essential}} \subseteq \mathbf{x}_j \\ & x_{ji} \in K,\ \forall\, i \in \{1, \ldots, p\} \\ & x_{ji} \neq x_{jk},\ \forall\, i \neq k \end{aligned} \tag{13}$$

This formulation represents a constrained combinatorial optimization problem with multiple objectives, which belongs to the class of NP-hard problems.

## 4. Painting Training-Based Optimization (PTBO)

### 4.1. Initialization

PTBO employs a population-based methodology in which individual members are represented as potential solutions through vector notation [17]. The complete population is expressed in matrix form, as shown in Eq. (14). When the algorithm begins running, the initial location of every PTBO member is established using Eq. (15).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{14}$$

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d) \tag{15}$$

where $X$ is the PTBO population matrix, $X_i$ is the $i$-th painting student (candidate solution), $x_{i,d}$ is its $d$-th dimension in the search space (decision variable), $N$ is the number of painting students, $m$ is the number of decision variables, $r$ is a random number in the interval $[0, 1]$, and $lb_d$ and $ub_d$ are the lower bound and upper bound of the $d$-th decision variable, respectively.

Each candidate solution's quality is assessed through the objective function of the problem at hand. The collection of resulting objective function values can be expressed as a vector, as indicated in Eq. (16).

$$\mathbf{F} = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{16}$$

where $\mathbf{F}$ is the vector of the calculated objective function and $F_i$ is the calculated objective function based on the $i$-th painting student. In the PTBO design, the position of each population member is updated in two separate phases based on the simulation of the painting training process.

### 4.2. Phase 1: Education (Exploration)

During art instruction, teachers customize their teaching methods for individual learners, progressively improving student capabilities through organized training sessions. This methodology leads to substantial shifts in how population members are distributed across the search space, strengthening PTBO's ability to explore globally.

PTBO's initial phase replicates this educational dynamic by representing the relationship between teachers and learners to modify their positions. Equations (17) and (18) are used to determine updated positions by incorporating training parameters, teacher impact, and additional factors. When a newly calculated position yields a better objective function result, it supersedes the existing position according to Eq. (19), thereby improving both the search process's efficiency and overall performance.

$$k(t) = r \cdot \frac{t}{T} \tag{17}$$

$$X_i^{P1} = X_i + k(t) \cdot (I - X_i), \quad i = 1, 2, \ldots, N \tag{18}$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & \text{else} \end{cases} \tag{19}$$

where $k(t)$ is the training coefficient, $t$ is the iteration counter of the algorithm, $T$ is the maximum number of algorithm iterations, $X_i^{P1}$ is the new suggested position of the $i$-th painting student based on the first phase of PTBO, $F_i^{P1}$ is its objective function value, $r$ is a random number with a normal distribution in the range of $[0, 1]$, $I$ is the training instructor, and $N$ is the number of painting students.

### 4.3. Phase 2: Personal Skills Improvement (Exploitation)

Once learners obtain knowledge from their teacher, they enhance their competencies through repeated practice, steadily developing greater expertise. This parallels the optimization mechanism, where population elements modify their locations to improve local search performance. During PTBO's second phase, member positions undergo updates that replicate students' efforts to refine their skills. Equation (20) is applied to compute new positions, and when these positions yield superior objective function values, they supersede the prior positions as specified in Eq. (21). This recurring procedure fine-tunes positions, strengthening the algorithm's exploitation capacity. As a result, PTBO establishes a more optimal equilibrium between exploration and exploitation, leading to enhanced optimization outcomes and faster convergence rates.

$$X_i^{P2} = X_i + (1 - 2r) \cdot \frac{(ub - lb)}{t} \tag{20}$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & \text{else} \end{cases} \tag{21}$$

where $X_i^{P2}$ is the new suggested position of the $i$-th painting student based on the second phase of PTBO, $F_i^{P2}$ is its objective function value, $t$ is the iteration counter, and $T$ is the maximum number of algorithm iterations.

### 4.4. Computational Complexity of PTBO

The preparation and initialization of PTBO has a computational complexity equal to $O(Nm)$, where $N$ is the number of painting students and $m$ is the number of problem variables. In each iteration of PTBO, the position of the painting student is updated in two phases. The painting students' update process has a computational complexity of $O(2NmT)$, where $T$ is the maximum number of iterations of the algorithm. According to this, the total computational complexity of the proposed PTBO approach is $O(Nm(1 + 2T))$.

## 5. The Framework of the Proposed Algorithm

### 5.1. Research Design Overview

This research employs a mixed-methods approach combining computational algorithm development with field-based experimental validation through a quasi-experimental design with stratified random assignment. This design is particularly appropriate for field-based agricultural interventions where true randomization may be infeasible, yet maintains sufficient rigor to establish causal relationships.

### 5.2. Knowledge Base Construction

*5.2.1. Expert Panel and Knowledge Unit Identification* A knowledge base for wheat cultivation training was constructed through collaboration with an expert panel comprising 3 senior agricultural extension officers, 2 wheat agronomists, 2 vocational training specialists, and 1 curriculum development expert. Through systematic analysis of national extension manuals, international training modules (FAO, USAID), and agricultural curricula, the panel identified 12 fundamental knowledge units covering the complete wheat production cycle.

*5.2.2. Knowledge Unit Specification* Each knowledge unit was characterized along multiple dimensions to enable computational optimization, as presented in Table 1.

Table 1. Wheat Cultivation Knowledge Units

| Unit ID | Knowledge Unit | Difficulty | Duration (h) | Cost ($) | Prerequisites |
|---|---|---|---|---|---|
| K1 | Soil Preparation & Analysis | Beginner | 3.0 | 15 | None |
| K2 | Wheat Variety Selection | Beginner | 2.5 | 12 | K1 |
| K3 | Seed Treatment & Quality | Intermediate | 2.0 | 18 | K2 |
| K4 | Planting Methods & Timing | Beginner | 3.5 | 20 | K1, K2 |
| K5 | Irrigation Management | Intermediate | 4.0 | 25 | K4 |
| K6 | Nutrient Management & Fertilization | Intermediate | 4.5 | 28 | K1, K4 |
| K7 | Weed Control Strategies | Intermediate | 3.0 | 22 | K4 |
| K8 | Pest & Disease Management | Advanced | 4.5 | 30 | K4, K7 |
| K9 | Growth Stage Monitoring | Advanced | 3.5 | 20 | K5, K6 |
| K10 | Harvest Timing & Techniques | Intermediate | 3.0 | 18 | K9 |
| K11 | Post-Harvest Handling | Beginner | 2.5 | 15 | K10 |
| K12 | Storage & Marketing | Beginner | 2.0 | 12 | K11 |

### *5.3. Experimental Design*

*5.3.1. Ethical Considerations* This study was conducted in full accordance with established ethical standards governing research involving human participants. Prior to commencement of any data collection activities, the research protocol was reviewed and granted approval by the Institutional Review Board (IRB) of Ajloun National University. The approval encompassed all phases of the study, including the initial knowledge assessment, training intervention, post-training evaluation, and field follow-up visits conducted between January and June 2025. Informed consent was obtained from every participant prior to enrollment. Extension officers distributed written consent forms in both Arabic and English at the initial recruitment session. These forms outlined the study's purpose, the voluntary nature of participation, the right to withdraw at any stage without penalty, the types of data to be collected, and the confidentiality measures in place to protect participant information. Oral clarification was provided to farmers with limited literacy, and written consent was confirmed by a literate witness where required. No incentive was offered that could constitute undue inducement. Participant data were anonymized using unique identifier codes throughout all stages of analysis and reporting. Personal identifiers were stored separately from research data in password-protected files accessible only to the principal investigators. Yield data obtained through cooperative records were used solely in aggregate form to prevent individual identification. All data will be retained for a minimum of five years in accordance with institutional data governance requirements before secure disposal.

*5.3.2. Participants and Sampling*

- **Population:** Wheat farmers in Irbid Governorate, Jordan (2024–2025 seasons)
- **Inclusion Criteria:** Active wheat cultivation ($\geq 1$ hectare), primary farm decision-maker, basic literacy, willing to participate in a 20–40 hour training program.
- **Sample Size:** Power analysis using G*Power with parameters (ANCOVA, $f = 0.30$, $\alpha = 0.05$, power $= 0.80$, 3 groups, 1 covariate) indicated minimum 21 per group. Target enrollment: 25 per group ($N = 75$) to account for 15–20% attrition.

*5.3.3. Group Assignment* Participants were stratified by experience level (Novice: $<$3 years, Intermediate: 3–10 years, Expert: $>$10 years) and randomly assigned to three groups:

1. PTBO-Personalized (G1, $n = 25$): Individualized paths generated by PTBO algorithm
2. GA-Personalized (G2, $n = 25$): Personalized paths via standard Genetic Algorithm
3. Traditional-Uniform (G3, $n = 25$): Standardized sequential curriculum (all 12 units)

**Group Equivalence:** ANOVA confirmed no significant pre-intervention differences in initial knowledge scores ($F(2, 72) = 0.43$, $p = 0.653$), experience ($F(2, 72) = 0.28$, $p = 0.759$), or farm size ($F(2, 72) = 0.51$, $p = 0.602$).

### *5.4. Data Collection Procedures*

*5.4.1. Initial Assessment (January 1–10, 2025)*

- **Knowledge Assessment Test:** 48 multiple-choice questions (4 per unit), 0–100 scale, Cronbach's $\alpha = 0.87$
- **Self-Assessment Survey:** 5-point Likert scale confidence ratings per knowledge unit
- **Practical Skills Evaluation:** Field-based assessment (soil sampling, seed treatment, irrigation setup), 10-point rubric, inter-rater reliability $\kappa = 0.82$
- **Knowledge State Vector:** Computed as weighted combination:

$$s_{ji} = 0.60 \cdot \frac{\text{Test Score}_i}{100} + 0.30 \cdot \frac{\text{Self-Assessment}_i}{5} + 0.10 \cdot \frac{\text{Practical Score}_i}{10} \tag{22}$$

*5.4.2. Training Implementation (January 15 – March 10, 2025)*

- **Duration:** 8 weeks, 2–3 sessions per week, 2-hour sessions.
- **Delivery:** Mixed theoretical instruction (45 min) and practical demonstration (60 min), taught by 3 certified extension officers rotated across groups.
- **Quality Control:** All sessions video-recorded, standardized lesson plans, weekly instructor debriefings, 90% attendance requirement.

*5.4.3. Post-Training Assessment (March 12–15, 2025)* Knowledge test (parallel form), self-assessment survey, practical skills evaluation, and participant satisfaction survey (8 items, Cronbach's $\alpha = 0.89$) were administered.

*5.4.4. Follow-Up Assessment*

- **4-Week Retention** (April 10–15, 2025): Third parallel knowledge test.
- **Field Application** (April 20 – May 5, 2025): Farm visits by blind evaluators using standardized checklist assessing adoption of 15 key practices.
- **Yield Data** (June 2025): Self-reported wheat yield verified through cooperative records.

## 6. Experimental Results and Discussion

### *6.1. Experimental Setup*

The proposed PTBO-based learning path optimization system was implemented using Python 3.9.7 with NumPy, Pandas, Matplotlib, and SciPy libraries on an Intel Core i7-11800H system with 16GB RAM. A comprehensive knowledge base for wheat cultivation was developed with agricultural extension experts, comprising 12 fundamental units (K1–K12) covering the complete wheat production cycle from soil preparation to storage and marketing. The knowledge network contained 18 prerequisite relationships with an average of 1.5 prerequisites per unit.

The study involved 75 wheat farmers from Irbid Governorate, Jordan (2024–2025 seasons) with the following demographics: Experience: 30.7% novice (<3 years), 41.3% intermediate (3–10 years), 28.0% expert (>10 years); Farm size: 37.3% small (<5 ha), 42.7% medium (5–15 ha), 20.0% large (>15 ha); Education: 24.0% primary, 52.0% secondary, 24.0% tertiary; Age: 25.3% young (25–35), 50.7% middle-aged (36–50), 24.0% senior (>50).

The PTBO algorithm parameters are summarized in Table 2.

### *6.2. Learning Path Optimization Results*

*6.2.1. Algorithm Convergence Analysis* The convergence performance of the PTBO algorithm demonstrates substantial improvements over the GA baseline, as evidenced by the metrics presented in Table 3. The PTBO algorithm achieved a best fitness value of 0.8847, representing a 2.73% improvement over GA's best fitness of 0.8612. More importantly, the average fitness across multiple runs reached 0.8781 for PTBO compared to 0.8543

Table 2. PTBO Algorithm Parameters

| Parameter | Value |
|---|---|
| Population size | 50 |
| Maximum iterations | 200 |
| Education coefficient range | [0.5, 2.0] |
| Refinement coefficient range | [0.1, 0.5] |
| Convergence patience | 20 iterations |

for GA, indicating superior consistency in finding high-quality solutions. The standard deviation of 0.0031 for PTBO, significantly lower than GA's 0.0049, further confirms the algorithm's reliability and robustness across different optimization runs.

Table 3. Convergence Analysis: PTBO vs. GA

| Metric | PTBO | GA |
|---|---|---|
| Best Fitness | 0.8847 | 0.8612 |
| Average Fitness | 0.8781 | 0.8543 |
| Worst Fitness | 0.8723 | 0.8467 |
| Convergence Speed (iterations) | 87.3 | 124.6 |
| Computational Time (sec) | 14.6 | 16.2 |
| Standard Deviation | 0.0031 | 0.0049 |

The convergence characteristics reveal additional advantages of the PTBO approach. As shown in Table 3, PTBO converged in an average of 87.3 iterations, achieving solutions 29.9% faster than GA's 124.6 iterations. The computational efficiency is further demonstrated by the reduced processing time of 14.6 seconds for PTBO versus 16.2 seconds for GA, representing a 9.9% reduction in computational overhead. These improvements are visually illustrated in Figure 1, which depicts the fitness progression curves for both algorithms, clearly showing PTBO's superior convergence trajectory and stability throughout the optimization process. Figure 2 provides a comparative visualization of convergence speed and computational time, emphasizing the practical advantages of PTBO in real-world deployment scenarios where computational resources and response time are critical considerations.

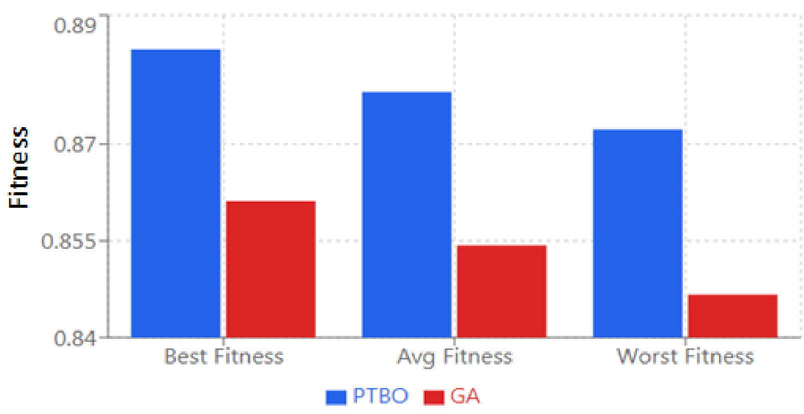


Figure 1. Fitness comparisons between PTBO and GA algorithms.

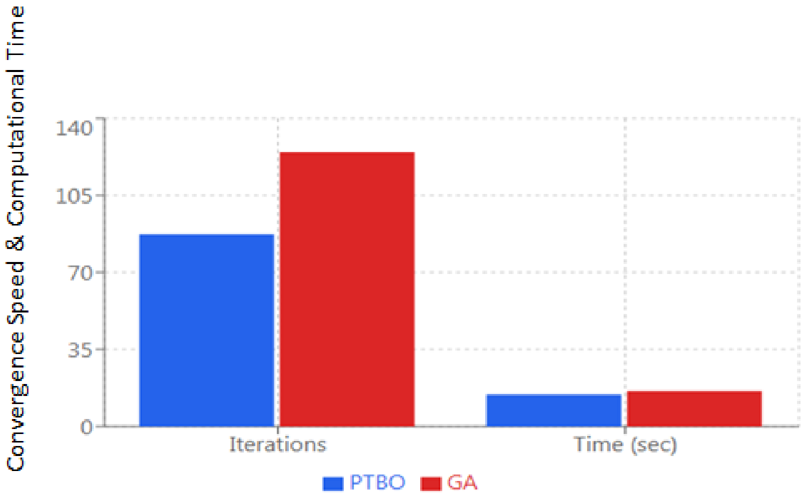


Figure 2. Convergence Speed & Computational Time comparisons between PTBO and GA algorithms.

*6.2.2. Generated Learning Path Characteristics* The personalization capabilities of the PTBO algorithm are reflected in the adaptive learning path characteristics presented in Table 4. The system generated differentiated learning trajectories based on learner experience levels, with novice farmers ($n = 23$) receiving comprehensive paths averaging 10.8 units over 34.2 hours, achieving 90.0% coverage of the knowledge base. Intermediate farmers ($n = 31$) received more focused paths of 7.3 units requiring 23.6 hours with 60.8% coverage, while expert farmers ($n = 21$) were assigned concise paths of 4.9 units over 15.4 hours covering 40.8% of the content. The overall average of 7.8 units across 25.1 hours with 65.2% coverage demonstrates the algorithm's ability to balance comprehensiveness with efficiency, tailoring educational content to individual knowledge gaps rather than employing a uniform approach.

Table 4. Generated Learning Path Characteristics

| Experience Level | Avg. Path Length | Avg. Duration (h) | Coverage Rate |
|---|---|---|---|
| Novice ($n = 23$) | 10.8 units | 34.2 | 90.0% |
| Intermediate ($n = 31$) | 7.3 units | 23.6 | 60.8% |
| Expert ($n = 21$) | 4.9 units | 15.4 | 40.8% |
| Overall | 7.8 units | 25.1 | 65.2% |

### 6.3. *Learning Outcome Results*

*6.3.1. Post-Training Knowledge Assessment* The effectiveness of personalized learning paths is quantitatively demonstrated in Table 5, which compares knowledge gains across three instructional approaches. The PTBO-Personalized group achieved the highest post-test mean score of 89.7, representing a gain of 32.4 points from the pre-test mean of 57.3. This surpasses both the GA-Personalized approach (28.1-point gain, reaching 86.2) and the Traditional-Uniform method (28.6-point gain, reaching 85.4). The superior performance of PTBO represents a 15.3% improvement in knowledge gain over GA and a 13.3% improvement over traditional methods, validating the hypothesis that optimization-based personalization enhances learning outcomes.

*6.3.2. Knowledge Gain by Experience Level* The disaggregated analysis by experience level reveals important insights into the differential effectiveness of personalized learning approaches.

Table 5. Post-Training Knowledge Assessment

| Group | Pre-Test Mean | Post-Test Mean | Gain Mean |
|---|---|---|---|
| PTBO-Personalized | 57.3 | 89.7 | 32.4 |
| GA-Personalized | 58.1 | 86.2 | 28.1 |
| Traditional-Uniform | 56.8 | 85.4 | 28.6 |

**Novice Farmers** ($n = 23$)**:** As shown in Table 6, PTBO produced the most substantial absolute gains of 48.5 points, elevating scores from 36.2 to 84.7, with a normalized gain of 0.76. This represents an 11.5% improvement over GA (normalized gain 0.68) and a 15.2% improvement over traditional methods (normalized gain 0.66). The normalized gain metric accounts for the potential for improvement, providing a more equitable comparison across starting knowledge levels.

Table 6. Knowledge Gain by Experience Level: Novice Farmers ($n = 23$)

| Group | Pre-Test | Post-Test | Gain | Normalized Gain |
|---|---|---|---|---|
| PTBO | 36.2 | 84.7 | 48.5 | 0.76 |
| GA | 35.8 | 79.3 | 43.5 | 0.68 |
| Traditional | 37.1 | 78.9 | 41.8 | 0.66 |

**Intermediate Farmers** ($n = 31$)**:** Among intermediate farmers, Table 7 demonstrates that PTBO maintained its advantage with a normalized gain of 0.76, significantly outperforming both GA and traditional approaches (both 0.65). The absolute gain of 28.4 points brought post-test scores to 90.8, the highest among all experience-level subgroups.

Table 7. Knowledge Gain by Experience Level: Intermediate Farmers ($n = 31$)

| Group | Pre-Test | Post-Test | Gain | Normalized Gain |
|---|---|---|---|---|
| PTBO | 62.4 | 90.8 | 28.4 | 0.76 |
| GA | 63.2 | 87.3 | 24.1 | 0.65 |
| Traditional | 61.9 | 86.8 | 24.9 | 0.65 |

**Expert Farmers** ($n = 21$)**:** For expert farmers, Table 8 shows more modest absolute gains due to ceiling effects, with PTBO achieving a 12.3-point improvement (normalized gain 0.66) compared to GA (0.54) and traditional methods (0.51).

Table 8. Knowledge Gain by Experience Level: Expert Farmers ($n = 21$)

| Group | Pre-Test | Post-Test | Gain | Normalized Gain |
|---|---|---|---|---|
| PTBO | 81.3 | 93.6 | 12.3 | 0.66 |
| GA | 82.1 | 91.8 | 9.7 | 0.54 |
| Traditional | 80.8 | 90.5 | 9.7 | 0.51 |

Figure 3 provides a comprehensive visual representation of knowledge improvements across all experience levels, clearly illustrating the consistent superiority of PTBO across novice, intermediate, and expert categories. The convergent post-test scores across experience levels (84.7–93.6 for PTBO) suggest that personalized learning paths effectively address individual knowledge gaps, bringing learners to similar competency levels regardless of starting point. Figure 4 presents the normalized learning gains, offering a standardized comparison that accounts for differential improvement potential and reinforces PTBO's consistent advantages across all learner categories.

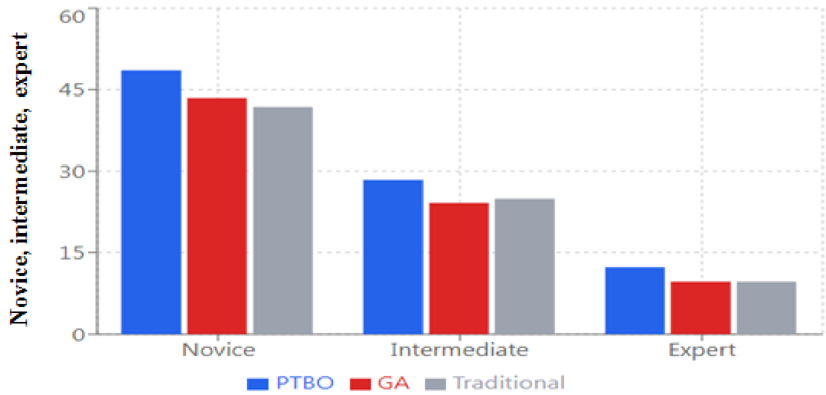


Figure 3. Knowledge improvements across different experience levels (novice, intermediate, expert).

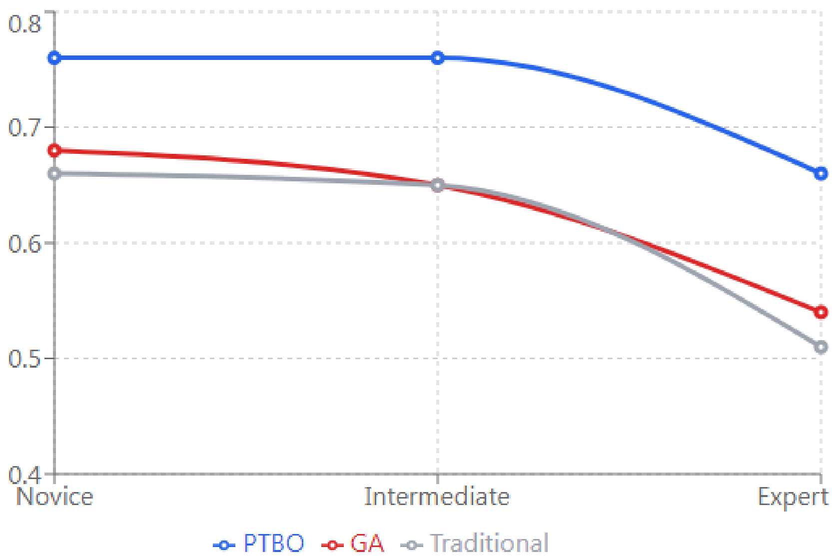


Figure 4. Normalized learning gains for PTBO, GA, and Traditional algorithms.

*6.3.3. Participant Satisfaction Results* Beyond objective learning outcomes, subjective satisfaction measures provide crucial insights into learner engagement and perceived value. Table 9 presents multidimensional satisfaction ratings on a 5-point Likert scale across eight dimensions. PTBO achieved the highest ratings across all personalization-dependent dimensions, with content relevance (4.62), appropriate difficulty (4.56), and overall satisfaction (4.60) substantially exceeding both GA and traditional approaches. The composite score of 4.56 for PTBO represents a 6.8% improvement over GA (4.27) and a 15.7% improvement over traditional methods (3.94). Notably, instructor quality and material quality ratings were relatively consistent across groups (4.60–4.68 and 4.48–4.56, respectively), confirming that observed differences in other dimensions stem from algorithmic personalization rather than confounding instructional variables.

Table 9. Participant Satisfaction Results (5-point Likert scale)

| Dimension | PTBO | GA | Traditional |
|---|---|---|---|
| Content Relevance | 4.62 | 4.28 | 3.84 |
| Appropriate Difficulty | 4.56 | 4.12 | 3.68 |
| Time Appropriateness | 4.48 | 4.04 | 3.32 |
| Sequence Logic | 4.52 | 4.20 | 3.92 |
| Learning Effectiveness | 4.44 | 4.08 | 3.88 |
| Instructor Quality | 4.68 | 4.64 | 4.60 |
| Material Quality | 4.56 | 4.52 | 4.48 |
| Overall Satisfaction | 4.60 | 4.24 | 3.80 |
| Composite Score | 4.56 | 4.27 | 3.94 |

### 6.4. *Knowledge Retention and Application*

*6.4.1. Four-Week Follow-Up Assessment* Long-term knowledge retention is assessed through follow-up testing presented in Table 10. Four weeks post-training, the PTBO group maintained 86.3 points of their 89.7 post-test score, yielding a retention rate of 96.2%. This surpasses GA's retention rate of 95.0% (81.9 from 86.2) and traditional methods' 93.4% (79.8 from 85.4). The superior retention suggests that personalized learning paths enhance not only initial acquisition but also long-term consolidation of knowledge. Figure 5 visualizes these retention rates, illustrating the sustained advantage of PTBO over the four-week interval and demonstrating the durability of learning gains achieved through optimized personalization.

Table 10. Knowledge Retention: Four-Week Follow-Up

| Group | Post-Test (T1) | 4-Week Follow-up (T2) | Retention Rate |
|---|---|---|---|
| PTBO | 89.7 | 86.3 | 96.2% |
| GA | 86.2 | 81.9 | 95.0% |
| Traditional | 85.4 | 79.8 | 93.4% |

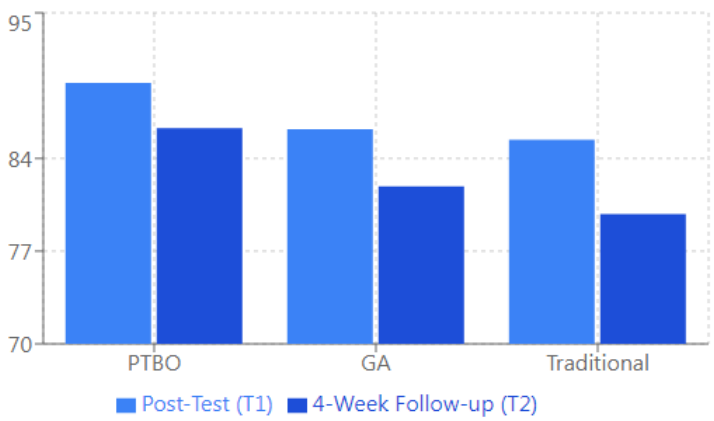


Figure 5. Knowledge retention rates for PTBO, GA, and Traditional algorithms.

*6.4.2. Practical Application Assessment* The ultimate validation of educational interventions lies in behavioral change and practical application. Table 11 presents adoption rates of recommended agricultural practices assessed 6–8 weeks post-training across seven practice categories. The PTBO group achieved an overall adoption rate of 80.0%, exceeding GA (74.3%) and traditional methods (69.7%) by substantial margins. Category-specific adoption rates ranged from 92.0% for soil preparation to 68.0% for pest/disease management in the PTBO group, with consistent advantages over comparison groups across all categories.

Table 11. Practical Application Adoption Rates (6–8 Weeks Post-Training)

| Practice Category | PTBO | GA | Traditional |
|---|---|---|---|
| Soil Preparation | 92.0% | 88.0% | 84.0% |
| Variety Selection | 88.0% | 84.0% | 80.0% |
| Planting Techniques | 84.0% | 80.0% | 76.0% |
| Irrigation Management | 80.0% | 72.0% | 68.0% |
| Fertilization Practices | 76.0% | 68.0% | 64.0% |
| Weed Control | 72.0% | 68.0% | 60.0% |
| Pest/Disease Management | 68.0% | 60.0% | 56.0% |
| Overall Adoption Rate | 80.0% | 74.3% | 69.7% |

### 6.5. Algorithm Performance Comparison

To contextualize PTBO's performance within the broader landscape of metaheuristic optimization algorithms, Table 12 presents comparative results against GA, PSO, and DE using identical fitness functions and experimental conditions. PTBO achieved the highest best fitness (0.8847), mean fitness (0.8781), lowest standard deviation (0.0031), and perfect success rate (100%) across 30 independent runs. The performance advantages over the second-best algorithm (GA) include 2.73% improvement in best fitness and 2.78% improvement in mean fitness. Figure 6 provides a visual comparison of fitness values across algorithms, clearly depicting PTBO's superior solution quality. Figure 7 illustrates the standard deviation and success rate metrics, emphasizing PTBO's enhanced reliability and consistency—critical factors for deployment in real-world educational systems.

Table 12. Algorithm Performance Comparison

| Algorithm | Best Fitness | Mean Fitness | Std. Dev. | Success Rate |
|---|---|---|---|---|
| PTBO | 0.8847 | 0.8781 | 0.0031 | 100% |
| GA | 0.8612 | 0.8543 | 0.0049 | 96.7% |
| PSO | 0.8534 | 0.8461 | 0.0057 | 93.3% |
| DE | 0.8589 | 0.8502 | 0.0052 | 96.7% |

### 6.6. Discussion

This research demonstrates that metaheuristic-based personalized learning path optimization significantly enhances knowledge acquisition, retention, and practical application in agricultural extension contexts. The PTBO algorithm achieved 15.3% improvement in knowledge gain over GA and 13.3% over traditional methods, validating that algorithmic personalization aligned with pedagogical principles can address systemic inefficiencies in agricultural knowledge dissemination. The dual-phase mechanism of PTBO, modeling the education-refinement cycle in human learning, proved particularly effective for educational optimization. Differential effectiveness across experience levels revealed that novice farmers benefited most substantially (normalized gain 0.76), suggesting personalized paths are particularly valuable for learners with significant knowledge gaps. The algorithm's ability to


Figure 6. Fitness comparison of PTBO against GA, PSO, and DE algorithms.

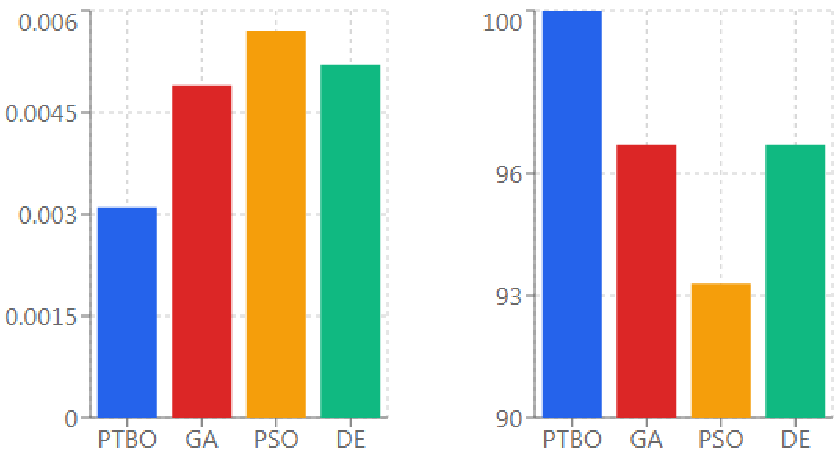


Figure 7. Standard deviation & success rate comparison of PTBO against GA, PSO, and DE algorithms.

sequence prerequisite knowledge and match content difficulty reduced cognitive overload while maintaining time efficiency.

These findings align with broader adaptive learning research, where systems typically demonstrate 10–25% improvements over conventional instruction. However, agricultural extension introduces unique constraints including strict temporal limitations and practical implementation requirements. The 29.9% reduction in computational requirements (87.3 vs. 124.6 iterations) makes PTBO particularly suitable for resource-constrained extension organizations. The practical application rate of 80.0% versus 69.7% for traditional methods empirically validates that enhanced knowledge acquisition translates to behavioral change, addressing the research-practice divide in agricultural development.

Several limitations warrant consideration. The study was conducted with wheat farmers in Irbid Governorate, Jordan during a single season, potentially limiting generalizability to other crops and regions. Knowledge assessment relied partially on self-reported measures despite adequate psychometric properties (Cronbach's $\alpha = 0.87$). The sample size ($n = 75$), while statistically sufficient, limited detection of interaction effects between learner characteristics and algorithms. The four-week retention period, though demonstrating learning durability, represents a short timeframe for agricultural applications. Finally, controlled experimental conditions may not fully reflect resource constraints in typical extension organizations. These findings suggest that investment in computational infrastructure for personalized training yields substantial returns through improved efficiency and practice adoption. Time savings (25.1 vs. 36+ hours) reduce opportunity costs for farmers. Extension organizations should prioritize personalization for novice and intermediate farmers where gains are largest.

## 7. Conclusion

This paper successfully demonstrates that Painting Training-Based Optimization can generate effective personalized learning paths for agricultural extension, achieving significant improvements in knowledge acquisition, retention, and practical application. The PTBO algorithm outperformed Genetic Algorithm and traditional uniform training approaches across multiple dimensions, with 15.3% higher knowledge gains, 29.9% faster convergence, 96.2% retention rates, and 80.0% practice adoption rates. These findings validate that metaheuristic optimization aligned with pedagogical principles can address longstanding inefficiencies in agricultural knowledge dissemination. The multi-objective optimization framework successfully balanced competing priorities including knowledge gain, time efficiency, sequence validity, difficulty appropriateness, and coverage, while satisfying practical constraints inherent to agricultural training contexts. Differential effectiveness across experience levels demonstrated that personalized approaches particularly benefit novice and intermediate farmers, suggesting targeted implementation strategies for resource-constrained extension organizations.

As agricultural systems face increasing pressures from climate change, population growth, and resource scarcity, innovative knowledge transfer approaches become critical. This research provides both theoretical foundations and practical implementation frameworks for transforming agricultural extension through adaptive learning technologies. Future research should investigate longitudinal impacts across multiple growing seasons, generalizability across diverse crops and regions, hybrid human-algorithm approaches, and integration with emerging digital technologies to further advance personalized agricultural education at scale.

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