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The Whale Optimization Algorithm and Markov Chain Monte Carlo-Based Approach for Optimizing Teacher Professional Development in Creative Learning Design with Technology

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Abstract

In this article, we present a hybrid optimization methodology using the whale optimization algorithm and Markov Chain Monte Carlo sampling technique in a teachers' training development program regarding creativity in technology-enhanced learning design. Finding the best possible training for creativity in learning design with technology is a complex task, as many dynamic and multi-model variables need to be taken into consideration. When designing the best possible training, the whale optimization algorithm helped us in determining the right methods, resources, content, and assessment. A further Markov Chain Monte Carlo-based approach helped us in deciding with accuracy that these were the correct parameters of our training. In this article, we show that metaheuristic algorithms like the whale optimization algorithm, validated by a Markov chain technique like Markov Chain Monte Carlo, can help not only in areas like machine learning but also in fields without structured data, like creativity in technology-enhanced learning design. The best possible training for a teacher's professional development in creative learning design is collaborative, hands-on, and utilizes creativity definitions for the product along with technology integration learning design models.

Keywords: learning design; creativity; technology; teaching professional development; whale optimization algorithm; Markov Chain Monte Carlo

Academic Editors: Antonio Sarasa Cabezuelo and María Estefanía Avilés Mariño

Received: 1 May 2025
Revised: 29 June 2025
Accepted: 30 June 2025
Published: 2 July 2025

Citation: Rigopouli, K.; Kotsifakos, D.; Psaromiligkos, Y. The Whale Optimization Algorithm and Markov Chain Monte Carlo-Based Approach for Optimizing Teacher Professional Development in Creative Learning Design with Technology. *Algorithms* **2025**, *18*, 407. https://doi.org/10.3390/a18070407

1. Introduction

Creativity development is an important endeavour for modern education. For the last fifty years, researchers have consistently shown interest in creativity within the field of education, as it is linked to individual well-being and successful academic achievements. Teachers utilize various tools and technology to stimulate creativity by igniting curiosity, aiding in idea development, creating digital products, organizing creative workflows, promoting collaborative creativity, and assessing with evaluation methods. Thus, creativity development is associated with advanced learning outcomes and with technology-enhanced learning [1]. Integrating emerging technologies into classroom learning strategies enhances education at every stage. However, possessing technology alone is not sufficient; effective pedagogical methods that promote learning are essential [2]. As defined in the technological, pedagogical, content, knowledge (TPACK) framework, teachers need three types of knowledge when implementing technology: content knowledge (CK), pedagogy knowledge (PK), and technology knowledge (TK). The interplay between technology, pedagogy, and content occurs in a dynamic environment, in which educators need to be able to creatively align these three components when designing their educational scenarios [3]. Teachers' Professional Development (TPD) programs are very important in helping educators cultivate their creativity when implementing technology in learning design. Educating teachers in technology-enhanced LD is very important because it helps them develop their TPACK, meaning their knowledge and design skills [4]. After the pandemic, there is a heightened need for educators to utilize creativity to effectively support learning in hybrid and online environments. However, the majority of studies related to the connection between creativity and technology do not take into account evidence-based research and educators' experiences and practices, so we can have a grounded knowledge of what creativity and technology mean in classroom settings [5]. Moreover, initiatives in creativity in TPD pose challenges because of educators' limited resources, resistance to change, lack of a clear conception of creativity, and lack of a unified framework [6]. Additionally, developing technology-enhanced learning design capability can be a complex task as it refers to theories of human cognition, the possibilities technology offers, and the fundamentals of instructional design [7].

In this article, we tried to address the issue of creativity in learning design with technology in teacher professional development. To find the best possible training, we relied on the Whale Optimization Algorithm (WOA) when designing our training approach and validated it through the Markov Chain Monte Carlo (MCMC) technique. We concluded with a well-structured design of training. WOA is a swarm intelligence optimization technique [8]. In summary, WOA imitates the hunting techniques of humpback whales. It was created to address optimization problems. The phases of WOA are encircling the prey, exploitation, and exploration. In a few words, the process involves conducting a literature review on the optimization target, identifying key components, and exploring alternatives to avoid local optima. This is crucial, as maintaining a balance between exploration and exploitation is essential in WOA problems. Implementing WOA in the design process helped us conceptualize and eventually conclude on a TPD focusing on creative learning design with technology. MCMC helped us evaluate that the WOA will give an optimal solution. A critique of WOA applications is that they fail to address multi-dimensional problems and might lead to a very good but not the 'best' solution. This is one of the reasons that there are modifications and hybridizations of the algorithm [9]. Our focus on MCMC helps WOA address these challenges, especially at the end of the process, when we have a solution, to validate indeed that it is optimal. MCMC allows for the representation of training as a probabilistic process. MCMC refers to algorithms that implement Monte Carlo sampling using a designed Markov chain, meaning that the following selection relies on the prior one in the sampling procedure [10]. Both WOA and MCMC have been implemented in educational research, especially in student performance and machine learning. In the realm of educational studies, we commonly utilize statistical techniques such as structural equation modeling (SEM) or qualitative approaches like conceptual modeling. However, there remains a gap in studies concerning optimizing training programs using computational methods and techniques.

When designing our methodology using WOA, we relied on a narrative review with an emphasis on recent and highly cited empirical evidence studies. The bibliography points out that an effective TPD must be collaborative and hands-on, providing opportunities for reflection with peer and expert evaluation. Additionally, it must be subject-focused, with coaching and sustained duration [10]. We combined each of the components of an effective TPD with research regarding creativity and technology-enhanced learning design. This was the first phase, which is called encircling the prey. In the second phase, which is called exploitation, we specify the components by illuminating those that do not fit and enhancing those that best fit and are closely connected to them, or trying new ones to prevent local optima.

For our procedure, we utilized creativity theories that would help us with the content and the evaluation of the creative product, which in our case are the technology-enhanced learning designs. According to the literature, most definitions of creative products agree with these two aspects: novelty and effectiveness. A creative solution provides something distinctive and original, while also providing value to certain groups. Mishra and Henriksen have enhanced the definition, which builds on Besemer's work, with the aspect of the 'whole'. According to them: 'an innovative mathematical proof or a unique beautiful painting are incredibly different things, yet they are both creative'. Thus, they have added the aesthetic sensibility in context, which they called "wholeness", and it is the third component of creativity [11]. With this, they offered a comprehensive definition when we address creativity, specialized in education contexts, and in measuring creative artifacts. This is the Novel, Effective, and Whole (NEW) definition.

In parallel, we utilized technology integration models for our training, as the main purpose is to creatively implement technology and enhance creative skills among educators. The Triple E framework by Kolb speaks of engagement, enhancement, and extension of learning goals when we integrate technology into lesson planning. It is a model that emphasizes effectiveness in lesson planning with technology [12]. Furthermore, the SAMR model by Puentedura helped us innovate when designing with technology, as it speaks about moving from simple technology use (Substitution) towards transformative use (Redefinition) [13]. In other words, we could have the criteria of effectiveness and novelty with these two models. For the wholeness aspect, meaning the context, we relied on the basic theories and principles when creating an LD (define objectives and roles, align activities with goals and resources, etc.). In this way, we created the content/assessment of the process. The methodology was collaborative and hands-on as suggested, so we used the Think-Pair-Share (TPS) methodology. TPS motivates learners to think for themselves and generate their concepts (Think), communicate and debate their concepts with a peer (Pair), and subsequently share them with the class. For resources, we used learning management systems and LD graphical tools for a sustained duration. It is important to mention that we considered design factors in TPDs for technology integration and teachers' creativity. These variables, like the 'effective TPD' parameters, interact horizontally in our training. In the last phase of the WOA, which is called exploration, we enhanced our design with a different cooperative strategy to examine further effectiveness in our training. The bibliography revealed that the Team-Based Learning (TBL) strategy would be suitable for our purpose. This active learning strategy boosts subject knowledge, comprehension, engagement, critical thinking, and participation among group members. TBL offered coaching and support, which are components of the effectiveness of TPDs.

The training was designed with these components, as the WOA methodology and the literature review have indicated to us during the design process. To test our variables, we conducted an MCMC sampling technique. Combining these methods to find optimal training solutions in educational research remains a novel approach.

The research questions derived from the above are the following:

RQ1: Is there a combination of methods, resources, content, assessment, and duration that is optimal when designing a TPD for creativity in technology-enhanced learning design?

RQ2: Can WOA be used as a method to obtain optimal solutions when designing training in creative learning design?

RQ3: Can MCMC help us validate this training in creative learning design in a TPD, giving the expected accuracy to our proposed results?

The article is as follows: In the second section, we present the related literature for the WOA and MCMC optimization algorithm and their applications in educational research. In the third section, we present our methodology. In the fourth chapter, we analyze the conceptualization of WOA in our training. In the fifth section, we present the mathematical formulation and the algorithmic precision as combined with the MCMC application. In the sixth section, we present the results. Lastly, in the final section, we show the conclusions and future remarks of this article.

2. Whale Optimization Algorithm, Markov Chain Monte Carlo, and Their Applications in Educational Research

The WOA is a metaheuristic algorithm that draws inspiration from the bubble-net feeding technique of humpback whales, in which they generate spirals of bubbles to ensnare prey before striking. In 2016, Mirjalili and Lewis introduced whale swarm optimization methods. The key concepts of WOA [14] are:

- Encircling Prey: The optimal solution is viewed as the prey. Other whales modify their locations concerning this optimal solution through mathematical equations.
- Bubble-net Attaching (Exploitation): Two mathematical models have been suggested to simulate the whale's behavior while hunting their prey: the shrinking encircling method and spiral position updating. In this phase, which is called the exploitation phase, whales enhance their search for the optimal solution by either reducing their movement range or adhering to a spiral pattern. A probability factor (50%) governs which approach is utilized.
    1. Shrinking Encircling: The whales gradually converge towards the best solution.
    2. Spiral Updating: Whales move in a spiral formation toward the optimal solution.
- Search for Prey (Exploration Phase): Whales randomly choose a target and adjust their movements toward or away from it. This method guarantees a global search for the most effective combination.

WOA has been implemented in education, especially in machine learning, but also in other educational research, involving student performance. For example, the article named "An Enhanced Evolutionary Student Performance Prediction Model Using Whale Optimization Algorithm Boosted with Sine-Cosine Mechanism" presents a refined approach to forecasting student success by augmenting the Whale Optimization Algorithm (WOA). This improvement combines the Sine Cosine Algorithm (SCA) and Logistic Chaotic Map (LCM) to tackle WOA's shortcomings in both the exploration and exploitation stages [15]. Another example is a hybrid application of WOA in Teacher Professional Development (TPD). The article 'Teaching learning-based whale optimization algorithm for multi-layer perceptron neural network training' presents a valid way to optimize the multi-layer perceptron neural network [16]. WOA could serve to improve training programs by identifying the most effective training modules for educators. It potentially aids in TPD optimization, as methods, resources, assessment, time, context, and processes must be fluidly adjusted for teacher development. Computational modelling focuses on building progressively better models of phenomena rather than collecting individual results. In our case, it will be a suitable enhancement in educational research to utilize them for a dynamic output like the creation of a TPD in technology and creativity [17]. Algorithms help us graph this iterative process in an 'easy-to-use' way, providing at the same time more accurate starting points because of their flexibility to evolve during the process.

The WOA has its mathematical models and applications. In this article, we will present a novel application of WOA combined with the MCMC. Monte Carlo methods comprise a set of computational techniques that depend on the outcomes of numerous random experiments to determine an unknown value. MCMC is a collection of sampling methods. MCMC was initially developed in 1953 and experienced significant growth in the 1990s. The origins of MCMC can be traced back to chemical physics, while its advancement was supported by applied mathematics (statistics), leading to its application in various fields, including social sciences. By the 20th century, MCMC sampling techniques had become widely recognized in academia. MCMC refers to algorithms that implement Monte Carlo sampling using a Markov chain. Conventional Monte Carlo techniques sample independently. In comparison, MCMC possesses a Markovian property: the following selection relies on the prior one in the sampling procedure [18].

As discussed, MCMC entered social studies in 1990 as a quantitative analysis method in research. In education, we have various practical applications of MCMC. For example, an application in education is about student performance prediction. In the paper, 'Mathematical Model for Early Prediction of Learning Success' [19], there is an attempt to address the challenges of overseeing educational success in real-time, regardless of the discipline, and with great accuracy. The model utilizes information from Learning Management Systems (LMSs), which monitor students' engagement, advancement, and performance instantly. MCMC helped define these valuable elements from the data and then used them. Another important application of MCMC in education is when designing assessments. For example, in the recent study, 'Markov Chain Monte Carlo Methods for Dynamic Student Assessment' [20], we have the utilization of the MCMC in creating the best possible assessment in real-time. Thanks to MCMC techniques, the model can estimate complex probability distributions, allowing for adaptive assessment and monitoring of each student's progress. At the same time, it provides quantification of uncertainty in estimates, making the assessment more accurate and personalized. Lastly, we have recent examples of research in teacher decision-making and practices that utilize the MCMC methodology. The paper 'The Application of Markov Chain in Middle School Mathematics Teaching Evaluation' presents how the MCMC can analyze teaching effects and guide teachers to improve their teaching methods in mathematics. By creating an initial state vector and a transition probability matrix, the research assesses variations in student performance among various classes. The results show that this method offers an objective way to evaluate teaching effectiveness and can assist educators in improving their instructional strategies. In particular, the research revealed that this is a good quantitative method to assess teacher quality [21].

To summarize, WOA and MCMC have their place in scientific research analysis in the educational field. Computational methods in general are an emerging field of knowledge in social sciences. They are inductive, especially in opposition to theoretical or statistical, which are deductive. These are characterized by hierarchy or hypothesis and are rigid. With stochastic models like algorithms, we start with the conceptualization of complex and dynamic concepts like creativity, which involves processes and interactions. In [22], we see, for example, the benefits of multi-level agent-based modeling to predict valuable outcomes from an initial state of design. This ability to predict improves the effectiveness of educational research by directing the creation of more focused interventions. Additionally, it aids in evidence-based educational practice, which is important in creativity studies. The combination of WOA and MCMC will be a novel application of great value in optimization and probabilistic modeling tasks, in the field of educational research, especially in optimizing TPDs for creative learning design with technology. WOA can set effective initial parameters for MCMC by examining the probability distribution surrounding these ideal points and helping in the decision process. Ultimately, MCMC outcomes are reintroduced into WOA for additional refinement. The outcome/optimal training was collaborative and hands-on, with content and assessment on creative product and technology integration models like Triple E and SAMR.

3. Methodology

In our methodology, we attempted to model the design of optimal training for creativity in technology-enhanced LD. We did this by employing the WOA and validating it through the MCMC. The parameters of WOA were evaluated through a narrative literature review. This approach is helpful when we need to acquire knowledge from a variety of studies, as we have in our case. For example, when investigating creativity, we need to know about educational and psychological studies. It is a more flexible approach that is well-suited for research in multi-dimensional concepts and for investigating emerging fields, like creativity and technology [23]. Following this approach, we decided to start searching and eventually find the components (optimal solutions) and the connections of the following dynamic relationships. These are:

(1) Effective TPDs
(2) Effective TPD in technology-enhanced LD
(3) Effective TPD in Teachers' Creativity

This is the initialization in WOA. These three relationships will generate different solutions and connections between them. We start by selecting the initial components of a TPD, which are:

(1) Methodology,
(2) Resources,
(3) Content,
(4) Evaluation,
(5) Framework,
(6) Design factors.

In the first phase, which is called 'encircling the prey', we identify all relevant literature of these three relationships that correspond to the components. We search for 'effective TPDs' and narrow our review to recent studies with a focus on empirical evidence. Our literature review started in Google Scholar search engines and Scopus databases. The type of literature is 'Theme-centric search'. The keywords we first initiated in our search were 'effective teacher professional development' between the years 2020 and 2025. We seek highly cited journals like 'The search for evidence-based features of effective teacher professional development: a critical analysis of the literature, 'Shifting the focus of research on effective professional development: Insights from a case study of implementation', and 'A new framework for teachers' professional development'. During this stage, we analyze and synthesize the papers and draw conclusions. The same procedure is done for the keywords: the teacher's professional development in technology-enhanced learning design. We identify recent and highly cited papers like 'Technology Use for Teacher Professional Development in Low- and Middle-Income Countries: A systematic review' and 'The role of technology-based education and teacher professional development in English as a foreign language class. We rely on the 'Designing effective professional development for technology integration in schools' due to its direct relevance in the design process of a TPD. Lastly, we searched for 'teachers' professional development AND teachers' creativity'. From this search, a highly cited journal was 'The role of teachers' creativity in higher education: A systematic literature review and guidance for future research' and 'How am I a creative teacher? Beliefs, values, and affect for integrating creativity in the classroom'.

After finding the fundamental theories and concepts of these highly cited journals, we began to synthesize the knowledge and connect the dots between the three pillars and the six components. The results are forming the first phase of WOA. We assume in this phase that all given variables and connections between them could be possibly correct. In the second phase, which is called exploitation, we apply either shrinking encircling or bubble-net feeding mechanisms. In our literature, we assume that the most relevant intersections between the three pillars will point out whether we use one strategy or the other. For example, in the case of the content, we know that efficient TPD is subject-focused, so we create content with a focus on creativity. Additionally, we know from TPACK that for teachers to connect creatively through technology, pedagogy, and content, they need to acquire the necessary knowledge. In other words, we derive elements both from creativity and LD with technology to develop the content. This simulates the bubble-net attacking because we use theories that are different from each other to connect them and create content regarding creativity. In another example, where we have the shrinking enriching, we move towards the solution in an instant way, simulating the hunting behaviour technique. For example, when we want to decide to focus on the creative product, meaning the LD, only two definitions will be of great value: the standard definition and the NEW. We conclude that the NEW is of value because it has been proven through empirical evidence research on lesson plans.

In the last phase, which is the search for prey, we try new solutions that might be a better fit for our purpose. We decided in this phase to change the methodology from TPS to TBL. A further MCMC validated that indeed it was the correct approach. In the following chapter, we show in detail through concept maps the process of the conceptualization of WOA.

4. Whale Optimization Algorithm and Creativity in Learning Design with Technology in Teacher Professional Development

In this section, we present how we utilized the WOA during the design phase to optimize the best possible training for creative learning design with technology. To investigate the conclusions and outcomes of the WOA, we created a concept map divided into four sections, each encompassing the phases of WOA (Figures 1–4), conceptualizing the iterations between our variables. A concept map is a great tool for visualising processes and connections. It has been used in educational research for modelling and conceptualizing complex relationships. It has potential for growth in algorithmic representation. Studies found that as a designing tool, a concept map could help in the advancement of computational thinking, meaning, it can enhance our understanding of the algorithmic process [24].

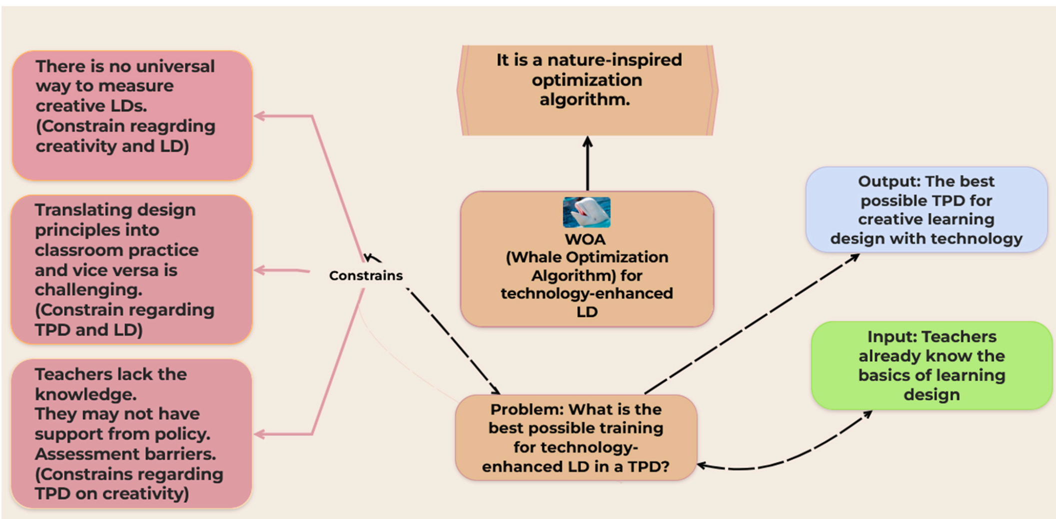

Figure 1. Analysing the problem: constraints, inputs, and outputs.

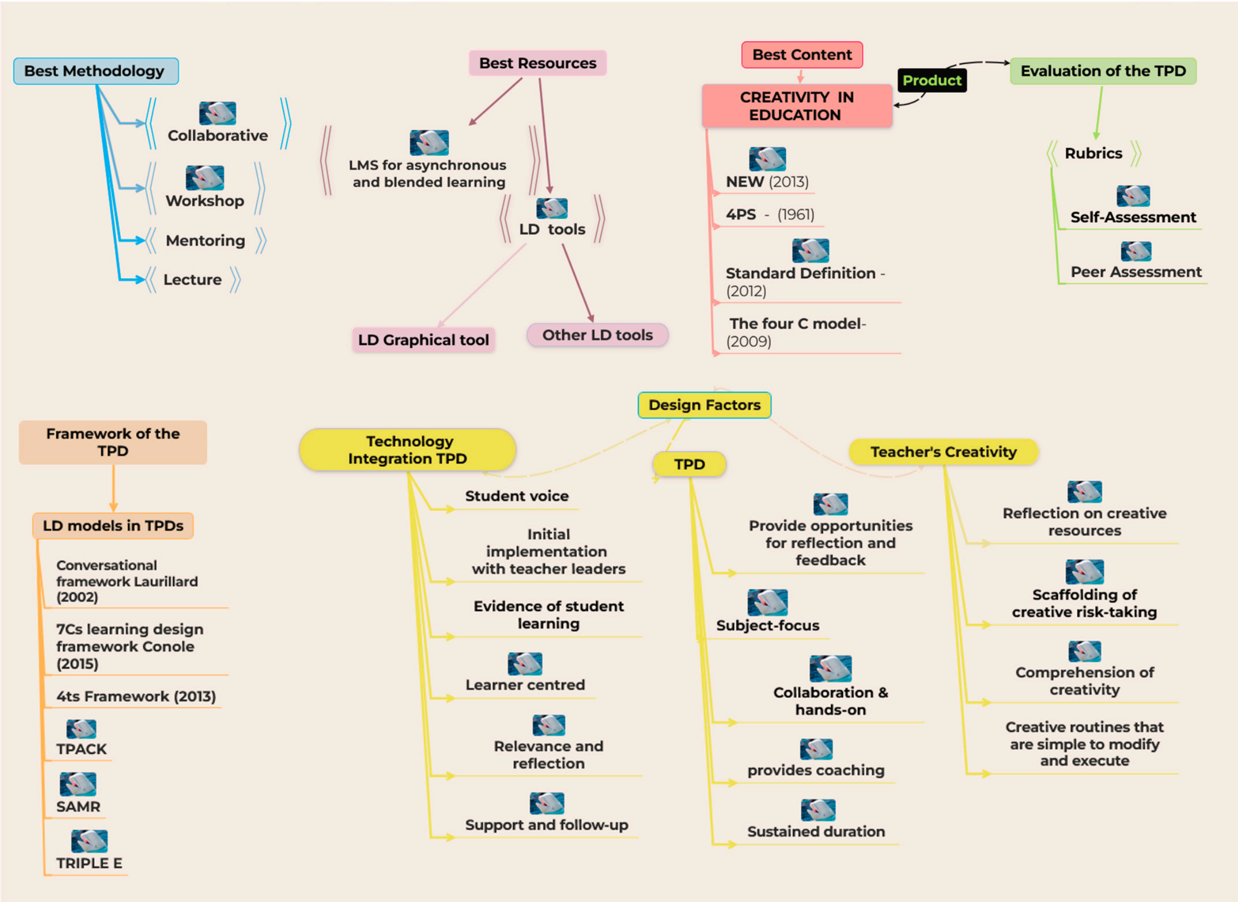

Figure 2. First phase of the WOA: encircling the prey.

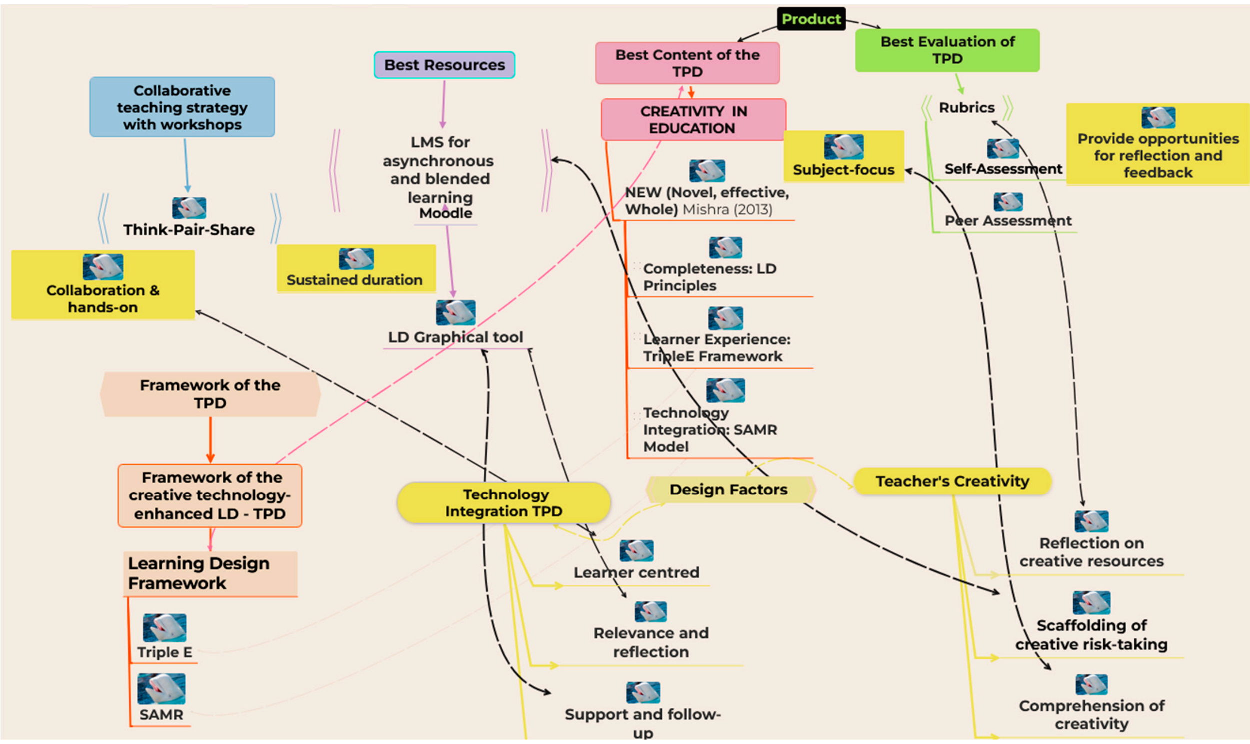

Figure 3. Second phase of the WOA: bubble-net attacking.

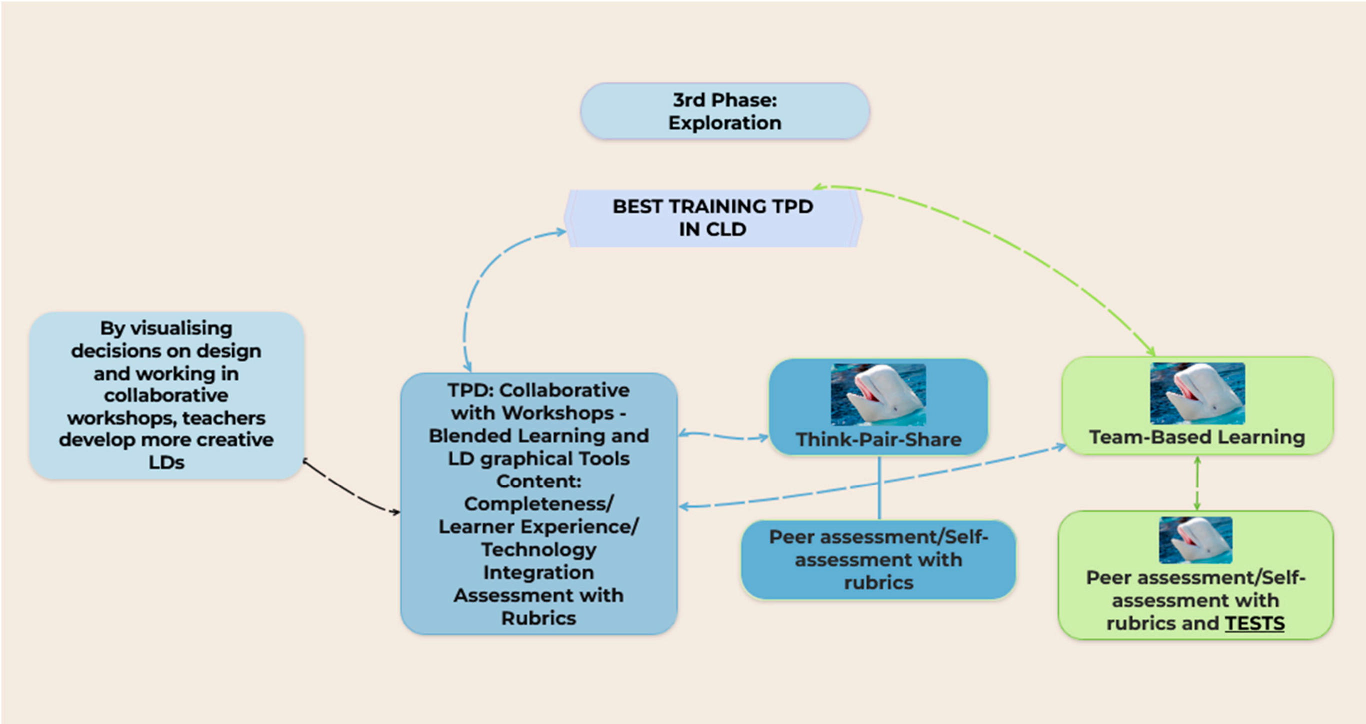

Figure 4. Third phase of the WOA: encircling the prey.

Our goal is to find the best possible training for creative LDs. The proposed terms of creativity, learning design with technology, and TPD have constraints when addressing them. As shown in the concept map (Figure 1), we have a constraint in the creativity term and subsequently, its assessment, as there is no explicit definition for creative LDs.

In the bibliography, we have definitions that refer to the product, the process, the person, or the press. In most cases, there might be a combination that includes all of these. Finding a reliable definition will guide us in determining the right assessment [25]. As a second constraint, the process of LD means translating design principles into classroom practice, something that is challenging. This is the second thing we need to consider in our research. The other constraint involved professional development in learning design with technology. Integrating technology in lesson planning does not come without challenges. Some of them are resources, expertise and abilities, organizational traits, perceptions and attitudes, evaluation, and disciplinary culture [26]. The input of the process is that this training is for a teacher's professional development program, where teachers are novices in learning design. The output of the proposed process is to find the best possible training based on the WOA and the MCMC.

In Figure 2, we are in phase 1, which is called encircling prey. We conducted a literature review on the key themes: 'effective TPDs, 'effective TPD in technology-enhanced LD', and 'effective TPD in Teachers' Creativity'. Additionally, we define important components to guide the design of the process of the TPD. These are: methodology, resources, content, evaluation, framework, and design factors. For the first theme, we found that an effective TPD is collaborative, hands-on, with sustained duration, provides opportunities for reflection, draws on effective practice models, provides coaching, and is subject-focused [27]. Collaboration is the most significant element in every efficient training program. Various studies have shown the benefits when working in groups, especially in teacher professional development programs and TPDs focusing on LDs. While in the first phase (enriching the prey), we choose collaboration and workshops (hands-on) from the pool of methodologies. Additionally, for resources, we choose to implement the Moodle Learning Management

System. Hybrid and online approaches to learning are essential in contemporary education. Thus, they provide opportunities for flexibility that are very important in professional development and adult education. Having asynchronous learning material in the LMS will give us the sustained duration that is needed. Another important element is the tool we choose, which can guide us and assist us in the reflection of the design process. This aspect is very important to consider, as these tools scaffold the design process. Research on learning design tools indicates that graphical representations of lesson planning are preferred among teachers because of their visual representation, guidance, and flexibility [28].

For the content, we seek definitions concerning the product, because we want our teachers to develop a creative LD with technology. According to Rhodes' 4Ps framework, person embodies creative characteristics, press includes environmental factors, process involves mental techniques, and product signifies tangible outcomes of creative endeavours. According to Kaufman and Beghetto, creative products can be categorized into four types: mini-c, which involves learning about new things in the environment, and little-c, which involves personal creative insights. Professional creativity involves work outputs. Big-C creativity refers to products or inventions that have a global impact [29]. Two definitions are directly associated with the product. One is the standard definition by Runco and Jaeger [30]. According to them, originality or innovation, along with utility or efficiency, are key concepts. Originality refers to a creative output that introduces something new or is at least somewhat distinctive within its context. Utility implies that the product is beneficial, reasonable, comprehensible, or offers value to others. Additionally, Mishra and Henriksen discussed the Novel, Effective, and Whole (NEW) definition, which includes the extra element of 'whole'. According to them, 'A creative product/process has an element of novelty or uniqueness. It also must be effective (appropriate, valuable) in its given context'. Finally, a creative artifact is whole, which speaks to the style, make, or crafting of the process/product, and its "fit" within a specific context. We decided to utilize this definition because of its application in lesson planning and educational contexts [31]. As mentioned earlier in our scheme, the content will point to the assessment. Assessments of creativity in education are divided between psychological and educational research, emphasizing cognitive aspects. They are generally broad, focusing on divergent thinking, self-report questionnaires, and subjective product-based techniques [30]. We are focusing on assessing the product because we want to rely on practical applications from classroom settings that are important in education research. The evaluation of the product, meaning the LD through the rubrics, could give us this advantage. It also gives opportunities for reflection through self and peer evaluation.

Afterward, we pointed out the frameworks of LD with technology and the frameworks that are associated with creativity. These will guide us by giving the teachers a practical and conceptual method for designing their LDs. We have found four key frameworks for learning design with technology. The first one is the conversational framework by Laurillard [32]. Her framework speaks of six types of activities designed to assist students in their learning journey. The educators utilize them to create learning experiences that effectively incorporate technology. The elements include acquisition, inquiry, discussion, practice, collaboration, and production. Another important framework is the 7Cs by Conole. According to this, there are seven phases when designing: conceptualize, capture, create, communicate, collaborate, consider, and consolidate. Then we have the four Ts framework introduced by Pozzi and Persico. The framework aids in decision-making and instructional planning concerning tasks, teams, technology, and time in computer-supported collaborative learning environments. We argue that these frameworks in learning design are important when creating a lesson plan or, in our case, training. Because we need technology integration as a necessary component in our approach, we decided to eliminate these frameworks and move to more technology-based approaches, like the TPACK learning design framework, Triple E, and SAMR [33].

Lastly, we consider design factors for technology integration, TPDs, and teachers' creativity. For the first group, we have found recent literature that points to these criteria [34]:

a. Evidence of student learning;
b. Relevance and reflection;
c. Support and follow-up;
d. Student's voice;
e. Learner-centered;
f. Initial implementation with teacher leaders.

These components were aligned with those of effective TPD.

For the second group, which is TPDs in teachers' creativity, we have found recent literature that points to the following criteria: reflection on creative resources, comprehension of creativity, provision of creative routines that are simple to modify and execute, and the scaffolding of creative risk-taking. These two design concepts, along with our main concept, which is the effective TPD, will be horizontally aligned with our other variables [35]. Encircling the prey phase has ended. In this phase, we have gathered the most important and relevant literature on what effective training for creative learning design with technology means.

The second phase of the WOA, as it is presented in Figure 3, is called the bubble-net attack. In this stage, we move to the closest optimal solution by illuminating those that do not fit and at the same time search for new ones, near the chosen ones that will enhance them. We illuminate design factors that are relevant to school policies, like the initial implementation of school leaders. We also illuminate design parameters like 'evidence of student outcomes. This design of TPD is implemented on an initial state, before implementation in the classroom. For the enhancement of parameters, we use the first grouping, which is the 'effective TPD. Thus, the first important parameter that needs to be considered is the collaborative methodology of the TPD. We decided on the TPS because research connects this strategy with the enhancement of creativity skills. Furthermore, it provides opportunities for peer assessment and reflection through its stages of pair and share. In that way, we are also serving the assessment criteria of an effective TPD. The second component of the training is the resources. In the previous stage, we decided to use LD graphical tools and the LMS for reflection and sustained duration.

Thirdly, we move to the content of the TPD that is directly associated with the definition and, as a result, with the assessment. We need to know what to evaluate to evaluate it. We decided to rely on the NEW definition by Mishra and Henriksen. The evaluation will be guided by this definition. Furthermore, we decided on LD frameworks like the Triple E and SAMR. In this way, which is called 'spiral update', we try new solutions for the content. Instead of relying only on creative content, we seek technology integration possibilities and models that will help us work creatively when implementing technology. Especially, the Triple E has its rubric that can guide us through the effective technology integration of the LDs. Additionally, the SAMR has its practical hierarchical model, which can guide us in the process of achieving novel use of technology integration. The technology integration models will be employed to form the evaluation of the training.

Lastly, we should mention the design factors for TPD in technology integration and teachers' creativity that were employed. By this, we mean the support follow-up and learner-centered training like in our methodology with TPS, and in addition, the reflection and relevance to the rubrics we have in the evaluation methods. These all adhere to the 'effective TPD'. Secondly, with regards to teachers' creativity and effectiveness interactions, we have a reflection on creative resources (through evaluation methods and LD tools), comprehension of creativity (through definition), and the scaffolding of creative risk-taking (through online tools). Our training in this phase of the WOA has been formatted:

a. There is a collaborative strategy, as indicated by the effectiveness of the TPD criteria. This is TPS. We can have workshops with real-life applications, like the creation of LDs in the pair phase. It is a learner-centered methodology with support from peers.
b. There are resources stored in an LMS, so we have a hybrid and asynchronous experience. Having the content in this format is helpful for us to have a sustained duration. This aids in creative risk-taking. Online opportunities scaffold the process by diminishing the creativity anxiety that is more present in classroom settings. Additionally, LD graphical tools [36] scaffold the process and offer opportunities for reflection.
c. There is specific content that involves the creative product, and it is based on the NEW definition by Mishra and Henriksen. This definition helped us in the creation of the evaluation method, meaning rubrics with the criteria of novel, effective, and whole. We built on technology integration models to form the criteria of effectiveness and novelty. We assumed that effectiveness could be referred to as the 'learner experience', so it can relate to the Triple E and its effectiveness criteria: engagement, enhancement, and extension. We assume that novelty is related to higher levels of technology integration and link this criterion with the SAMR model, which speaks of novel tasks when reaching higher levels of technology integration. We assume that wholeness speaks of the context of a scenario, meaning the design principles and elements that are needed to form the basic structure of an LD. For example, this means alignment of activities with objectives, resources, and roles.
d. We consider the evaluation methods to be rubrics with self and peer assessment that can help us in reflection and feedback.

The TPD has been formatted, and we are in the process of exploring a new solution to see if it serves better.

In the third stage of the WOA (Figure 4), we are in the exploration phase, where we seek other solutions that will be optimal to compare with the already best known.

TPACK, one of the most influential models in technology integration, speaks of knowledge in technology, pedagogy, and content. We are advancing our research and broadening it to other methodologies for better retention of learning and bigger gains in knowledge. Additionally, we need to have coaching, as it is mentioned in the components of effective TPDs. For this reason, we change the methodology and move from the TPS to the Team-based Learning strategy (TBL). TBL is a methodology known for its application in higher education, but also for its positive results in the retention of learning material. TBL has five stages: pre-class preparation, individual readiness assurance test (iRAT), team readiness assurance test (tRAT), clarification session, and application activities. In the pre-class preparation phase, students examine assigned resources such as articles, videos, or textbook sections to establish a foundational understanding. During the iRAT, students complete a quiz to assess their comprehension of the material independently. Following that, in the tRAT, students collaborate in small groups to discuss the same quiz questions and agree on the most accurate answers, enhancing their learning through peer dialogue. In the clarification phase, the instructor addresses any unclear subjects. Subsequently, in the team application activities, groups utilize their knowledge to address real-world challenges regarding their learning material. This method gives us an extra advantage with the tests, as we have one more evaluation method in our training. Additionally, it aids in the mentoring and scaffolding through the classification task. The final phase of the WOA has ended, leading to the exploration of an optimal training solution. The training has the following characteristics:

- It is collaborative and hands-on (effective TPD). Indeed, we use the collaborative strategy TBL, which has application tasks, meaning co-creation of LDs.
- It has a sustained duration (effective TPD), as it is designed for a hybrid or online environment. We use the Moodle LMS, where we can store the educational material to be used by the learner for a considerable amount of time.
- It is subject-focused (effective TPD). We focus on content regarding creativity and technology integration, which is the initial purpose of this training, to design an effective TPD on creative technology-enhanced LD. We built on the NEW definition of creative product and translated it into LD principles (completeness), Triple E (learner experience), and SAMR (technology integration).
- It provides opportunities for feedback and reflection with the evaluation methods that use peer and self-assessment. (Design factors for teachers' creativity TPDs).
- There is support and follow-up (design factors for technology integration, TPDs) through the LD tool.

This is our training. In the next section, we will show how we validate our decisions based on a concrete and reliable mathematical model, the MCMC.

5. The Markov Chain Monte Carlo in Creative Learning Design with Technology

In this section, we incorporate a more rigorous definition of the optimization objective and explicitly present the mathematical and algorithmic backbone of our hybrid WOA and MCMC approach. Our goal is to optimize a TPD program for creativity in technology-enhanced learning design. We have used a linear regression model using one response variable and five main independent variables. The model is formulated in (1):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \varepsilon, \quad (1)$$

where:

Y: Response variable—the effectiveness of the TPD in creative learning design with technology (measured through implementation success, creativity in lesson plans, etc.);
X_1: Methodology (e.g., TPS, TBL);
X_2: Resources (e.g., LMS, learning design tools);
X_3: Content and Evaluation (e.g., use of NEW definition: Novel, Effective, Whole);
X_4: Frameworks/Models (e.g., Triple E, SAMR, TPACK);
X_5: Design Factors (e.g., collaboration, reflection, student voice);
ε: Standard error with normal distribution [0, 1].

The MCMC method is used to iteratively evaluate and refine the model's parameters to maximize its predictive accuracy. MCMC sampling represents a strong class of algorithms used for extracting samples from probability distributions when direct sampling is difficult. In our paper, we integrated WOA with MCMC. This approach offers a sampling method that is more dynamic and exploratory while maintaining a probabilistic framework, ensuring it remains focused yet searches efficiently. WOA identified new areas, while MCMC determined where to proceed based on probability. In other words, we utilized WOA to find initial solutions in 'enriching the prey' and 'searching for prey' and then used the MCMC to decide, with accurate mathematical modeling, which decisions are best suited during the exploitation phase. In the exploration phase, we gathered data based on these three classifications that encompass different interactions in and between them:

(1) Effective TPDs.
(2) Effective TPD in technology-enhanced LD.
(3) Effective TPD in teachers' creativity.

In the multiple linear regression equation, the coefficients, β_1, β_2, β_3, β_4, and β_5, are the regression coefficients. Each coefficient quantifies the relationship between its corresponding independent variable and the dependent variable y, holding other variables constant. The term β_0 is the constant term. It signifies the expected value of y when all independent variables X_1, X_2, X_3, X_4, and X_5 are zero. Before starting the Markov Chain, we need to initialize the parameters (Figure 5). Thanks to WOA, we have a very good starting point, as elaborated in the concept maps in the previous section. During this stage, we found that the methodology, resources, content/evaluation, framework/models design factors of the TPD, and design elements are important when designing this training. These are the variables of the MCMC equation, which are aligned conceptually with the aspects of effective TPD (collaborative, hands-on, sustained duration, providing opportunities for reflection and feedback, etc.), and follow our theme, which is creativity in technology-enhanced learning design (Figure 6). Thus, the next step is to use the MCMC and find the best solutions. The initialization has already been done through the WOA. The next step is to generate samples from the distribution, and then we move to the iteration process, where we repeat the sampling process until convergence to the desired distribution. We assume that all the variables can have a normal distribution:

$\beta_0 \sim N(\mu_0, {\sigma_0}^2)$
$\beta_1 \sim N(\mu_1, {\sigma_1}^2)$
$\beta_2 \sim N(\mu_2, {\sigma_2}^2)$
$\beta_3 \sim N(\mu_3, {\sigma_3}^2)$
$\beta_4 \sim N(\mu_4, {\sigma_4}^2)$
$\beta_5 \sim N(\mu_5, {\sigma_5}^2)$

Pseudocode: Hybrid WOA-MCMC for TPD Optimization

```
Input:
    Data matrix X (n x 5), response vector Y (n x 1)
    Number of iterations N
    Initial beta vector β = [β₀, β₁, β₂, β₃, β₄, β₅]
    Proposal variance σ²_proposal
    Prior variance σ²_prior
    Likelihood variance σ²_likelihood (or estimate it)
Initialize:
    β_current = initial β (e.g., [0, 0, 0, 0, 0, 0])
    Store β_samples = []
For i in 1 to N:
    Propose β_new from a proposal distribution:
        β_new ~ Normal (β_current, σ²_proposal * I)
    Compute log-likelihoods:
        logL current = log Gaussian (Y | X * β_current, σ²_likelihood)
        logL new     = log Gaussian (Y | X * β_new, σ²_likelihood)
    Compute log priors:
        logP_current = log Gaussian (β_current | 0, σ²_prior)
        logP_new     = log Gaussian (β_new | 0, σ²_prior)
    Compute the log acceptance ratio:
        log_accept_ratio = (logL_new + logP_new) − (logL_current + logP_current)
    Draw u ~ Uniform (0, 1)
    If log(u) < log_accept_ratio:
        Accept β_new, β_current = β_new
    Append β_current to β_samples Output:
    β_samples (matrix of posterior samples)
```

Figure 5. Pseudocode.

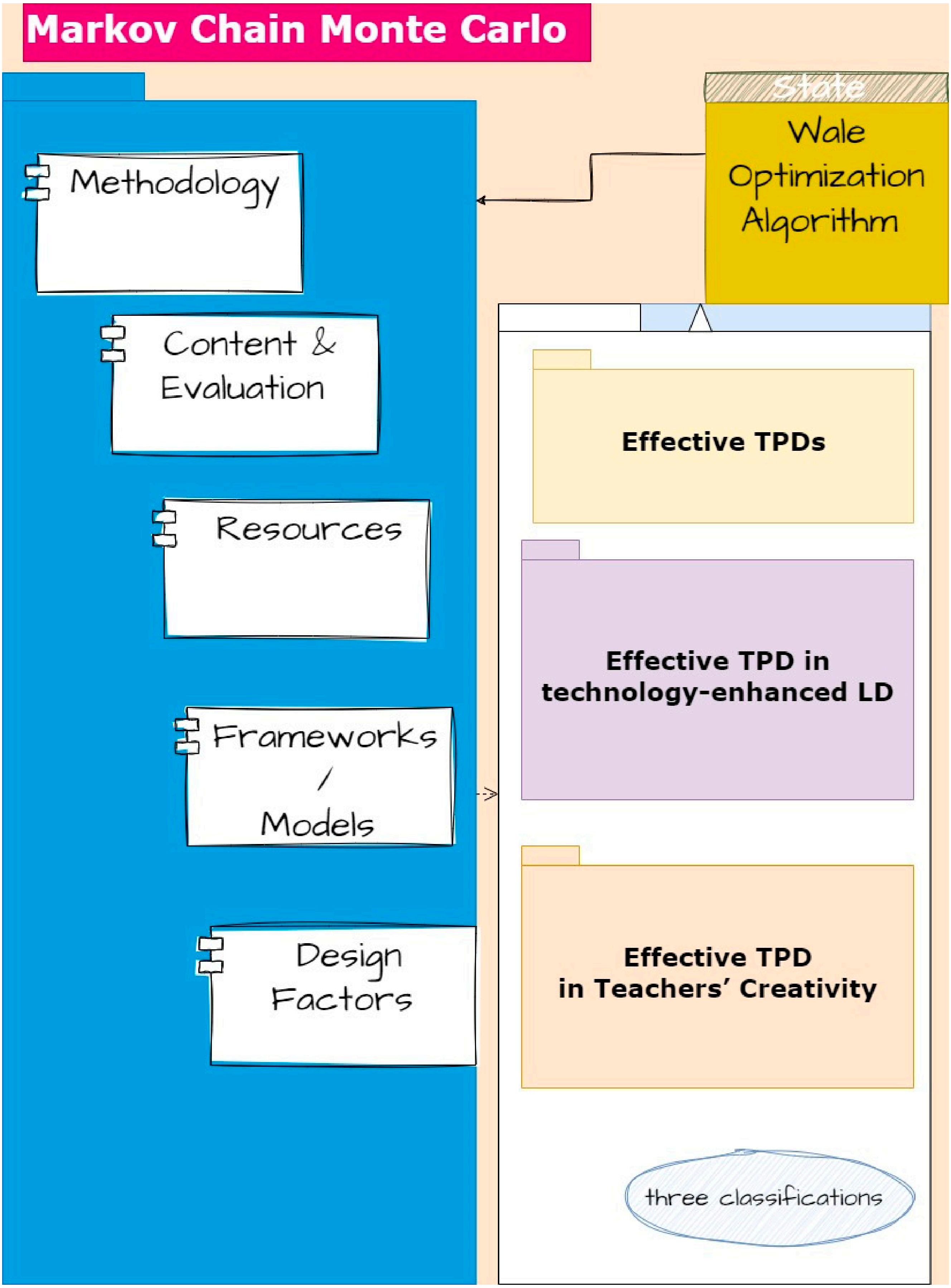

Figure 6. The whale optimization algorithm and Markov Chain Monte Carlo-based approach.

We created samples:

a. $\beta_0^{(0)}$ from $\beta_0^{(1)}$ using F (β_0 | $\beta_1^{(0)}$, $\beta_2^{(0)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$)
b. $\beta_1^{(0)}$ from $\beta_1^{(1)}$ using F (β_1 | $\beta_0^{(1)}$, $\beta_2^{(0)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$)
c. $\beta_2^{(0)}$ from $\beta_2^{(1)}$ using F (β_2 | $\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$)
d. $\beta_3^{(0)}$ from $\beta_3^{(1)}$ using F (β_3 | $\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_4^{(1)}$, $\beta_5^{(0)}$)
e. $\beta_4^{(0)}$ from $\beta_4^{(1)}$ using F (β_3 | $\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_4^{(1)}$, $\beta_5^{(0)}$)
f. $\beta_5^{(0)}$ from $\beta_5^{(1)}$ using F (β_3 | $\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_4^{(1)}$, $\beta_5^{(0)}$)

For each of the samples, we have a different value in β. This parameter affects the independent variable of X. The way and how much they are affected by us are shown by advancing the value of β.

EXPLANATION

- Step 1: Initialize a vector of parameters $\beta^{(0)} = [\beta_0^{(0)}, \beta_1^{(0)}, \beta_2^{(0)}, \beta_3^{(0)}, \beta_4^{(0)}, \beta_5^{(0)}]$
- Step 2: We consider a conditional mass function $\beta_0\backslash\beta_1^{(0)}$, $\beta_2^{(0)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$ so we estimate/generate the Conditional Probability, Density Function (CPDF), F ($\beta_0^{(1)}\backslash\beta_1^{(0)}$, $\beta_2^{(0)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$).
- Step 3: We consider a conditional mass function $\beta_1\backslash\beta_0^{(1)}$, $\beta_2^{(0)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$ so we estimate/generate the CPDF, F ($\beta_0^{(1)}\backslash\beta_0^{(1)}$, $\beta_2^{(0)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$).
- Step 4: We consider a conditional mass function $\beta_2\backslash\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$ so we estimate/generate the CPDF, F ($\beta_2^{(1)}\backslash\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_3^{(0)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$)
- Step 5: We consider a conditional mass function $\beta_3\backslash\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$ so we estimate/generate the CPDF, F ($\beta_3^{(1)}\backslash\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_4^{(0)}$, $\beta_5^{(0)}$)
- Step 6: We consider a conditional mass function $\beta_4\backslash\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_3^{(1)}$, $\beta_5^{(0)}$ so we estimate/generate the CPDF, F ($\beta_4^{(1)}\backslash\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_3^{(1)}$, $\beta_5^{(0)}$).
- Step 7: We consider a conditional mass function $\beta_5\backslash\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_3^{(1)}$, $\beta_4^{(1)}$ so we estimate/generate the CPDF, F ($\beta_5^{(1)}\backslash\beta_0^{(1)}$, $\beta_1^{(1)}$, $\beta_2^{(1)}$, $\beta_3^{(1)}$, $\beta_4^{(1)}$).

So now we have successfully generated the β (1) = $[\beta_0^{(1)}, \beta_1^{(1)}, \beta_2^{(1)}, \beta_3^{(1)}, \beta_4^{(1)}, \beta_5^{(1)}]$.

We iterate this procedure N times, where N is a large enough number for us to understand where the vector β converges. This describes how this MCMC algorithm works.

For instance, in our proposal methodology, we conduct five (5) different samples. We search in the literature for methodology regarding effective TPDs, effective TPDs in technology-enhanced LD, and effective TPDs in teachers' creativity. Our variables are:

- In equation (β_0), we introduce the variables as parameters.
- In the first equation (β_1). We have the methodology of a TPD, so we search accordingly.
- In the second equation, we search for resources (β_2).
- In the third equation, we search for content and evaluation (β_3).
- In the fourth equation, we add frameworks or models (β_4).
- In the fifth equation, we add design factors (β_5).

In every sample, we conduct literature reviews. In the first, we have a sample of methodologies in TPDs, like mentoring or collaborative strategies. Literature has indicated that collaboration is important in TPDs. We continue with literature regarding collaborative methods and effective TPDs in our second equation. We see strategies like TPS or TBL in TPDs. We have decided on the TPS because it enhances creative skills. We are moving to another equation, adding also the TPD in technology-enhanced LD. This speaks of collaborative workshops like the Carpe Diem or ABC. We implement application tasks in the TPD. In the final equation, we add TPD to teachers' creativity.

With this, we have also added recent articles regarding collaborative creativity and its positive impact on PD. We find convergence through TPS and application tasks involving the co-creation of LDs. To avoid getting trapped in local optima, we also consider utilizing the TBL methodology. This way, we also use the principles of WOA that speak of finding the balance between exploration and exploitation. For the other components, we do the same procedure. The exploration was used only in our methodology, as this is a crucial component that affects and changes all other variables. We continue with the other independent variables (resources, content/evaluation, frameworks/models, design factors) until we find convergence and create optimal training.

The process indicated training that is collaborative using TBL and application tasks. Additionally, it has content/evaluation regarding creativity definition and technology integration models. We considered design factors like support and learner-centered, relevance, and reflection by using the TBL that provides opportunities for the cultivation of all of these.

In response to concerns regarding methodological ambiguity, we have undertaken a comprehensive revision of the methods section, with particular emphasis on the adaptation and implementation of the WOA and the MCMC approach within the educational domain. Specifically, the WOA was operationalized by encoding candidate solutions as distinct configurations of instructional design parameters—namely, content sequencing, integration of multimedia elements, and frequency of learner–system interaction. The fitness function was formulated to evaluate these configurations based on composite metrics of learner engagement and knowledge retention, weighted according to empirically derived pedagogical priorities. The search space and parameter constraints were delineated in alignment with established instructional design principles and practical feasibility considerations. Concurrently, the MCMC approach was employed to infer posterior distributions of instructional effectiveness, conditional on observed learning outcomes. The implementation utilizes a sampling procedure and diagnostic assessments (e.g., convergence statistics) as future work to ensure the validity of the resulting distributions. Figure 6 has been accordingly updated to include annotated algorithmic steps, elucidating the iterative processes involved.

Furthermore, the optimal instructional designs are explicitly defined as those that jointly maximize engagement and learning performance, subject to contextual constraints such as available instructional time and technological resources. All variables in the regression model are explicitly defined, and their inclusion is theoretically grounded in established learning theories, including Cognitive Load Theory (CLT) and Self-Determination Theory (SDT). Empirical literature supporting the relevance of each predictor has been integrated to substantiate model specification. A dedicated subsection introduces the theoretical framework underlying the regression analysis, thereby addressing concerns of analytic formalism. Moreover, the limitations inherent in applying a linear model to complex educational phenomena are acknowledged, and a non-parametric model was additionally fitted as a robustness check, yielding convergent results in terms of predictor importance. From a practical point of view, CLT and SDT are psychological frameworks that can inform the design of instructional systems. On the other hand, MCMC and WOA are computational methods used for inference and optimization. Integrating these allows for a theoretically grounded and empirically efficient approach to educational design. They can work together in various areas as theoretical foundations as constraints, and objectives, in statistical inference to validate theory-driven assumptions, via MCMC, in a feedback loop between MCMC and WOA, and finally in various educational practical examples. Integrating CLT and SDT with MCMC and WOA creates a **hybrid model** where theory constrains and guides algorithmic exploration, and empirical inference refines the theoretical model. This supports **evidence-based instructional design** that is both adaptive and pedagogically sound.

6. Conclusions and Future Remarks

In this section, we will analyze the hypotheses we had when designing the WOA-MCMC approach to create an optimal solution for creative technology-enhanced learning design. Firstly, we address the research questions that were stated in the introduction section, and we answer them.

RQ1: Is there a combination of methods, resources, content, assessment, and duration that is optimal when designing a TPD for creativity in technology-enhanced learning design? As written in this article, many variables need to be considered when addressing technology-enhanced learning design in a TPD. Training becomes even more complex when adding abstract and multifaceted themes such as creativity. The first thing we need to do is classify our components, so we know what we are searching for. These are a. Effective TPD components, b. Effective technology-enhanced TPD components and c. Effective TPD in teachers' creativity. For the first issue, we have a literature review that points out the following effectiveness criteria: content focus; active learning techniques; collaborative; they draw on effective practice models; coaching and expert guidance; time for feedback and self-reflection; and sustained duration. Based on these, we concluded on content, methods, resources, evaluation, models, and design factors. For the second cluster, which is the technology-enhanced LD in TPD, we must search for scientific literature regarding LD and technology. The literature has pointed out the technology integration design factors in TPDs. These are: evidence of student learning, relevance and reflection, support and follow-up, student voice, learner-centered, and initial implementation with teacher leaders. We consider them. Lastly, we focus on TPDs in teacher creativity. Research has pointed out a focus on understanding the concept of creativity and its practical implementation. Additionally, scaffolding creative risk, reflecting on creative resources, and developing creative routines are also important. We connect the dots by illuminating parameters that are not relevant or not in the recent highly cited bibliography. We enhance components by incorporating them with close solutions. We concluded with a collaborative method like TBL with application tasks (hands-on), like the co-creation of LDs and coaching through a clarification session. Additionally, content is related to NEW parameters enhanced by technology integration models like SAMR or TripleE. We have self and peer evaluation of the LD for the advancement of reflection through the rubrics of these models. Lastly, the sustained duration can easily be implemented through asynchronous material in an LMS, providing the necessary enhancement of time and flexibility.

RQ2: Can WOA be used as a method to obtain optimal solutions when designing training in creative learning design? The WOA was very helpful, especially in the conceptualization of the process and in filtering the existing literature review. It can help with optimizing training programs because of its value in exploring and exploiting solution spaces efficiently. The educational research has a few examples of WOA. Especially when modeling, it could be a valuable and reliable tool and a novel approach. The Structured Equation Model (SEM) is dominant in statistical modeling in educational research and especially in teacher education. However, SEM is well-known for showing the relationships between factors already defined. The existence of pre-established concepts or hypotheses is crucial to SEM research [37]. However, creativity is a dynamic, complex, and multifaceted phenomenon. Thus, implementing algorithms, such as WOA, that help us solve complex and uncertain problems, could potentially add value to the optimization of processes, like designing an optimal training involving creativity. In this realm, theories are many theories, so we need to begin the process with all of them and all their interactions, and not only start from one theory, like in deductive modelling processes.

RQ3: Can MCMC help us validate this training in creative learning design in a TPD, giving the expected accuracy to our proposed results? The MCMC helped us achieve great accuracy in our results. This would not be possible if we did not use this technique. MCMC is a very well-known mathematical model that has applications in almost all fields and educational settings. It is a great modeling tool in quantitative research. We suggest that it can be of great value even in unstructured data, like creativity and technology-enhanced learning design. Common WOA critique [9] is about finding the balance between exploration and exploitation. With MCMC, we have reliability in the decision-making procedure. Furthermore, in the conceptualization of the initial parameters, we do not rely on MCMC, which is not ideal as it distributes randomly, but we rely on WOA and its target solutions that have already been initiated.

To sum up, we found that stochastic models can be of great value in social sciences and educational research, especially when involving multifaceted concepts like creativity, LD, and technology. In our training, we used a narrative literature review to design and evaluate. WOA helped us in finding the right exploration and exploitation areas and conceptualizing the design process. MCMC helped us in the validation of the outcome/training, making a more accurate analysis. For future work, case studies or other methods can be employed for the evaluation of this approach, providing evidence-based research for its validity. Additionally, this hybrid methodology could be validated by benchmark tests to further explore it from an algorithmic perspective. In addition, we should mention that mathematical models offer insights into model consequences and are simpler to falsify. They could also produce extensive data, which improves analysis. Because of these, we propose that it could be of great value during the design process, before reaching the application stage. In educational research literature reviews, we do not find many cases involving design processes through algorithms like WOA or MCMC. This was a limitation when we were searching for similar scientific cases.

Author Contributions: Conceptualization, K.R. and D.K.; methodology, K.R. and D.K.; validation, K.R., D.K. and Y.P.; formal analysis, K.R. and D.K.; investigation, K.R. and D.K.; resources, D.K.; data curation, D.K. and Y.P.; writing—original draft preparation, K.R. and D.K.; writing—review and editing, D.K. and Y.P.; visualization, K.R.; supervision, Y.P.; project administration, D.K.; funding acquisition, D.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: In this article published in an MDPI journal, we declare that all data supporting the reported results, including links to publicly archived datasets analyzed or generated during the study, are not subject to confidentiality or ethical restrictions. There are no other data for this specific study, other than those that support the conclusions of this article. All data in the article are made available by the authors for future research purposes.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

LD	Learning Design
TPD	Teacher's Professional Development
TPACK	Technological Pedagogical Content Knowledge
SAMR	Substitution, Augmentation, Modification, Redefinition
TPS	Think, Pair, Share
TBL	Team-Based Learning

WOA	Whale Optimization Algorithm
MCMC	Markov Chain Monte Carlo
iRAT	Individual Readiness Assurance Test
tRAT	Team Readiness Assurance Test
NEW	Novel, Effective, Whole
SMART	Specific, Measurable, Achievable, Relevant, and Time-bound
LMS	Learning Management System
SEM	Structural Equation Model

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