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Co-Creation in Generic Educational Activities: A Swarming Framework

Gregory Gasteratos*, Eleni Vlachou, Panagiotis Gratsanis, Ioannis Karydis
Dept. of Informatics, Ionian University, 7 Tsirigoti Square
Kerkyra, 49132, Greece
{ggasteratos, elvlachou, pgratsanis, karydis}@ionio.gr

The flipped classroom model enhances student engagement by encouraging active participation and collaboration, wherein students co-create knowledge by collaborating to address complex educational tasks, fostering deeper interaction between students and teachers. Swarming, a nature-inspired approach, uses collective intelligence to solve complex problems effectively, similar to how students work together in the flipped classroom. The knapsack problem involves selecting a subset of items with maximum desirability while meeting specific constraints. In education, this can represent choosing the most relevant resources from a large corpus for a given research question while managing constraints like time or complexity. This work proposes a framework that maps the task of selecting educational resources to the knapsack problem, solving it through the Ant Colony Optimization (ACO) algorithm to leverage collaborative learning. Experimentation shows that the proposed solution is more suitable for this context, while ACO's sensitivity analysis demonstrates its effectiveness for the framework's needs.

Keywords: Educational framework, Co-creation, Swarming, Ant colony optimisation, Knapsack problem.

1. Introduction

Nowadays, emerging technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT) are fundamentally transforming education [1]. These advancements are reshaping how learning is delivered and supported, promoting a self-organising vision of education where technology plays an increasingly pivotal role [2].

The flipped classroom educational model has recently gained significant traction with its emphasis on active student engagement over passive information reception, fostering greater autonomy, collaboration, and teamwork among students [3]. In flipped classrooms, students often work in small groups to tackle complex challenges, bringing diverse skills and knowledge to collaboratively create solutions.

Education on natural disasters and emergency situations is crucial as it contributes to community preparedness and resilience, reducing the loss of human lives and material damage. Additionally, informing and educating citizens promotes timely and effective responses to crises, enhancing their ability to protect themselves and those around them.

*Corresponding author

Despite the variety of educational tasks students encounter, many share common elements, such as identifying relevant resources, updating cognitive models through study, and producing outputs reflecting their understanding. This work models these generic tasks as an optimization problem, specifically the Knapsack problem [4]. This problem involves selecting the most valuable subset of items from a larger set while adhering to specific constraints, such as time and complexity.

Swarming, inspired by the collective behavior of social insects like ants and bees, offer effective solutions for complex problems through decentralised, self-organised collaboration [5]. Ant Colony Optimisation (ACO) is one such approach [6], leveraging the natural behavior of ants to identify optimal solutions efficiently [7].

In this paper, we propose a framework that integrates educational tasks with ACO to harness the co-creational benefits of the flipped classroom paradigm. By mapping educational challenges to the Knapsack problem and solving them using ACO, we aim to enhance the collaborative and creative aspects of learning.

Related research on the combination of the aimed to aspects of the proposed framework is scarce, but the individual aspects have indeed received significant attention. Co-creativity and its multi-domain provenance and effect has been explored academically since the early 1950s' [8,9], while in the context of education since 2008 [10,11]. The flipped classroom paradigm has been ground-breaking in educational domains, which is nowadays considered as a clear form of co-creation [12,13,14]. Given the mapping of the co-creative educational task to the Knapsack problem, the Swarming & Ant Colony Optimisation methods lend themselves as promising approaches to develop effective solutions [15,7,16,6].

1.1. *Motivation & Contribution*

Despite the obvious complementarity of the three pillars leading to the key theme of the work, educational task modeling to combinatorial optimisation solved by swarming methods, to the best of our knowledge, existing bibliography has not shone light on this amalgamation. Moreover, the prevailing of the new paradigm for educational methods, as addressed through the flipped classroom model, has been a significant and necessary development that despite its popularity still requires further exploration as to its implementation and efficiency. In addition, one of the main tenets of the flipped classroom model, the collaboration aspect, is addressing a, now more than ever, important aspect of the human condition, the ability to creation and co-creation. Latest developments in the domain of generative artificial intelligence have pushed the envelope of neural networks from pattern matching, to style learning to art-generating AI raising a litany of questions on the matter of creativity. Nevertheless, co-creativity is valuable tool for promoting creative and effective solutions to complex problems wherein the "collective intelligence" of co-creators is the required driving force.

Still, modeling of educational scenarios and the subsequent application of efficient and effective methodologies to address said needs is far from trivial. In order to address these requirements, this work proposes a framework that models the generic educational task of identifying a subset of literary works, best meets the task's requirements, from a large corpus, for some constraint, and maps it to the Knapsack problem that is then solved using the ACO swarming algorithm in order to take advantage of the co-creational advantages of the flipped classroom paradigm. Accordingly, the key contributions of this work can be summarised as follows:

- modelling of a generic part of numerous educational activities into a combinatorial optimisation,
- framework proposal that amalgamates the aforementioned modeled educational activity with a collaborative solution based on swarming methodologies wherein the mapping of characteristics of the 3 pillars of the framework are defined

The rest of the paper is organised as follows: Section 2 explores related work on the intersection of key pillars of education, co-creativity, the amalgamation of education & co-creativity, swarming & the Ant Colony Optimisation and the Knapsack problem with same of its various solutions. Section 3 presents the proposed framework for the combination of a generic education task modeled as the Knapsack problem that is subsequently addressed with the ACO algorithm. Section 4 discusses the setup used for the experimentation, the results of the experiments and the evaluation of the results obtained. Section 5 describes the limitations associated with the proposed model. While the framework demonstrates significant potential in enhancing educational outcomes through swarming methodologies, several challenges must be addressed. Finally, the paper is concluded in Section 6.

2. Background and related work

Several methodologies have been researched to support and enhance the learning process through swarming techniques, including collaborative learning, personalised learning, and gamification among others.

Collaborative learning refers to the process of working with groups of learners to achieve a common goal, as opposed to learning alone [17]. Vygotsky's social constructivism theory underpins this concept, positing that learning is inherently a social process enhanced by interaction and knowledge exchange among learners [18]. Research [19] has identified the benefits of collaborative learning, such as heightened motivation and engagement, improved communication and interpersonal skills, and enhanced critical thinking and problem-solving abilities. Depending on the kind of communication desired, it can be done by using a variety of methods, including online platforms, face-to-face meetings, or even a combination of both. It has been found that collaborative learning has a number of benefits, including improved motivation and engagement among learners, improved communication and interpersonal skills, and increased ability to think critically and solve problems [20].

The concept of personalised learning in education refers to an instructional approach aiming to adapt the learning experiences to reflect unique needs, interests, and abilities of individual learners, and to ensure these aspects are met. This approach often involves providing a range of tools and strategies, thereby granting students greater autonomy and control over their learning journey [21]. Recent studies suggest that personalised learning can significantly improve educational outcomes by aligning instructional methods with individual learning preferences and pacing. However, more empirical evidence is required on the long-term impacts of personalised learning on student achievement and how best to implement these strategies across diverse educational settings [22]. Additionally, research should focus on the technological and pedagogical challenges in scaling personalised learning effectively.

Gamification applies game design principles and mechanics to educational activities to engage and motivate students. By incorporating elements such as points, badges, leaderboards etc. into curricula, gamification aims to make learning more enjoyable and stimulating. Research [23] shows that gamification can significantly increase student engagement and motivation. Nonetheless, there are critical gaps in understanding the balance between gaming elements and educational content to avoid potential distractions from learning objectives [24]. Future research should investigate the types and combinations of game mechanics that are most effective for different age groups and subjects. Additionally, there is a need to explore the long-term effects of gamification on learning retention and academic performance.

2.1. *Education*

In the field of AI, swarm intelligence has become a critical development direction as an emerging research area that has the potential to revolutionise the way education and learning are being delivered [25]. Wong & Looi [21] introduce the concept of swarm intelligence, for developing adaptive learning systems that can adjust the difficulty of learning materials in accordance with the performance of students. This leads to a more personalised and engaging learning environment. The authors, however, acknowledge that the design of the swarm needs to be carefully considered to ensure that it is effective at achieving the learning goals.

In another study, Kurilovas et al. [26] propose an improved swarm-based approach to recommend appropriate learning scenarios based on learners' preferences. Learners are divided into different groups based on their preferences and a swarm optimisation algorithm then finds the most appropriate learning scenarios. Based on learners' preferences, their proposed approach provides a promising solution for meeting the task of recommending suitable learning scenarios to learners. It is important to note, however, that more research is required to determine whether their proposal is effective and if it is scalable for large data-sets [27].

Menai et al. [28] argue that traditional methods of curriculum sequencing have limitations that can be overcome by using swarm intelligence algorithms. They propose a new curriculum sequencing algorithm (SwarmRW) that uses swarm intelligence to solve the problem of the curriculum sequencing, based on the Ant Colony Optimisation and highlight the potential for this method.

Swarm intelligence algorithms are increasingly used in education research and practice, especially in personalised learning and adaptive assessment. While their use in education is still in its early stages, these approaches have shown promising results in improving students' learning outcomes and providing personalised and adaptive learning experiences.

2.2. *Co-creativity*

Co-creativity is a concept that has been explored by several researchers in different fields, from education to design, and from arts to technology. At its core, co-creativity refers to collaborative and participatory practices that involve individuals working together to create something new and innovative [8,9].

One of the earliest accounts of exploring co-creativity in the context of education was written by Anna Craft in 2008 [10]. Craft addressed the implications of studying collaborative creativity for education and identified the importance of fostering a supportive environment for creativity to thrive. An example of the use of co-creativity in education can be found in the work of Alexander Schmoelz, who explored the potential of co-creativity in playful classroom activities [11]. Schmoelz argued that co-creativity can promote engagement, motivation, and creativity among students, and suggested practical strategies for implementing co-creative activities in the classroom. Another example of the use of co-creativity in education is in the work of Astutik [29,30], who investigated the effectiveness of Collaborative Creativity Learning (CCL) models in developing scientific creativity skills among secondary school students. Astutik's research found that CCL models, which involve collaborative and participatory learning activities, can promote creativity and scientific thinking among students. In the field of design, the work of Vyas et al. [31] explored the collaborative practices that support creativity in design. Therein, the authors argued that co-creativity can promote diverse perspectives, idea generation, and innovation in design, and provided examples of successful co-creative design practices. The potential of co-creativity in the arts is also explored by Zeilig et al. [32]. Therein, the authors investigated the use of co-creative arts' interventions for people with dementia, and posited that co-creativity can provide a meaningful and enriching experience for individuals with dementia, promoting social inclusion and well-being. In [33], Sanabria's work on enhancing 21st century skills with augmented reality (AR) emphasised the importance of co-creativity in technology-mediated learning environments. Their research lead to the conclusion that a gradual immersion method can foster collaborative creativity in AR-based learning activities. The work by Satama et al. [34] explored the embodied subtleties of collaborative creativity in dance, providing insights into how organisations can learn from dance to promote co-creativity in their work environments.

These examples highlight the versatility and potential of co-creativity as a concept that can be applied across various fields and contexts. Whether in education, design, technology, or the arts, co-creativity can promote, and is ultimately based on, collaboration, participation, and innovation, making it a valuable tool for promoting creative and effective solutions to complex problems.

2.3. *Inverted Classroom: A Form of Co-creation*

The flipped classroom model is considered a form of co-creation [12], as it involves a collaborative approach to learning between teachers and students. Students are given instructional material to review outside of class, freeing up class time for more live, interactive, and collaborative activities. This approach allows students to take more ownership of their learning and actively participate in the learning process.

According to a literature review by Roehl et al. [35], the flipped classroom model can promote student engagement and active participation and can lead to increased collaboration between teachers and students. Gomez-Lanier argues that flipped classroom promotes a greater understanding of course material as well as improves verbal, analytical skills and nurtures their creativity and adaptability to working with others. Carvalho and Goodyear [36] argue that the flipped classroom model can facilitate co-creation of knowledge by enabling students to take an active role in the learning process and by promoting collaboration among teachers and students, as well as between students themselves.

During interactive and collaborative activities in the flipped classroom, students can work together to co-create knowledge by sharing their ideas, insights, and perspectives [37]. Teachers can act as facilitators, guiding and supporting students as they work together to make sense of complex concepts and ideas. This collaborative approach to learning can lead to improved learning outcomes for students, as shown in a meta-analysis by Hew and Lo [13] which found that the flipped classroom model can improve student learning outcomes and that this improvement may be due in part to increased student engagement and active participation.

In addition to fostering collaboration between students, the flipped classroom model can also encourage co-creation between teachers and students [38]. Teachers can create instructional materials that are more tailored to the needs and interests of their students, while students can provide feedback and contribute their own ideas and insights to the learning process [14].

The flipped classroom model can promote a more collaborative and interactive approach to learning, where teachers and students work together to co-create knowledge and enhance the learning experience for everyone involved.

2.4. *Swarming & Ant Colony Optimisation*

To develop effective solutions for complex problems, it is important to also examine nature-based solutions, such as the principles of “swarm intelligence”. The concept of swarm intelligence can be traced back to the biological study of how insects interact with each other in a self-organised manner [15]. According to Du and Swamy [7], social insects (e.g. ants), use swarming to coordinate their activities and accomplish tasks such as foraging for food and building nests, that are otherwise deemed too complex for each unitary insect to accomplish. Combining swarm intelligence with algorithmic optimisation techniques has proven to be one of the most effective approaches to solving complex logistics, engineering, and finance problems [6].

ACO is a discrete optimisation approach that is based upon the ability of ants to collaborate in order to identify the shortest paths to targets [6]. The basic concept behind ACO is the use of artificial ants. These ants traverse paths on a graph whose nodes represent the components of the solution to a challenge. As ants traverse between nodes, they construct solutions to the problem at hand.

As part of the ACO approach, simulated pheromones are used to attract ants onto better trails / edges through graphs. Pheromones are chemicals ants release on their trails to attract other ants. As ants work together, they explore randomly and monitor chemicals left behind by other ants. This method of collaboration is known as stigmergy [16]. It is an effective way for ants to find a solution to complex problems by leveraging collective intelligence. Accordingly, ACO is a powerful tool in the field of artificial intelligence and is thus used to tackle a wide range of problems, from routing to scheduling and optimisation [6].

2.5. *Research Gap*

While there is significant research [15,7,16,6] on individual components of our proposed framework, the integration of these into a cohesive educational model remains underexplored. Existing literature extensively covers collaborative learning, personalised learning, and gamification as separate methodologies to enhance education. However, the combination of these approaches with swarming techniques [5], such as Ant Colony Optimization (ACO) [6], and the mapping of educational tasks to optimisation problems like the Knapsack problem [4], has not been thoroughly investigated. Current studies highlight the benefits of collaborative learning in fostering social interaction and knowledge exchange, but they do not explore optimising these interactions through advanced algorithms. Similarly, while personalised learning effectively tailors experiences to individual needs, its integration with co-creational processes and swarming intelligence remains unexplored. Therefore, our work aims to fill this gap by proposing a framework that combines these methodologies.

2.6. *Knapsack Problem*

The "Knapsack Problem" is the challenge of filling a fixed-sized sack with the most valuable items, and as per Smith-Miles et al. [4], is:

> *We are given a set of n items, each item i having an integer profit z_i and an integer weight w_i. The problem is to choose a subset of the items such that their overall profit is maximised, while the overall weight does not exceed a given capacity C.*

This can be expressed, as per [4], using the equation $max \sum_{i=1}^{n} z_i x_i$ with constraints $\sum_{i=1}^{n} w_i x_i \leq C$ where C is the total knapsack load capacity; z_i is the profit on an object i; w_i is the weight of an object i; C,z_i, and w_i are all integers and positive numbers; and $x_i = 0$ when an object i has not been loaded into a knapsack or $x_i = 1$ when an object i has been loaded into a knapsack.

In this paper, we are focusing on the most commonly used case, the "0-1 knapsack problem", which restricts the number of copies of each item to zero or one. This variation is better suited for our scenario whereby students pick academic papers only once in order to complete a specific task.

There are several variations of solutions for the knapsack problem [39], ranging from examining all combinations of items, to dynamic programming algorithms to swarming algorithm solutions, as described in the sequel.

To illustrate the 0-1 knapsack problem in our educational context consider a student with a time budget of 7 hours ($C = 7$) selecting papers to read from the following collection Table (1):

Paper	**Reading Time (hrs)**	**Educational Value**
A	3	8
B	2	6
C	4	9
D	1	3
E	5	10

Table 1. The Knapsack Problem in a educational model.

If educational value represents our profit z_i and reading time represents our weight w_i, the optimal solution would be to select papers A, B, and D (total time: 6 hours, total relevance: 17), rather than just selecting paper E (time: 5 hours, relevance: 10). We can see from this that an optimization strategy is required, not just a selection based on high educational values.

It's important to note that the 0-1 knapsack problem is NP-hard, meaning that as the number of items increases, the computational complexity grows exponentially. In practical educational settings with numerous resources to choose from, this makes exhaustive search methods impractical, necessitating heuristic approaches like ACO that can find near-optimal solutions efficiently, even if they don't guarantee the absolute optimal solution. A more detailed discussion follows in section 2.6.3.

This simple example demonstrates how the knapsack problem directly maps to educational resource selection challenges, where students must maximize learning value while respecting time constraints.

2.6.1. *The Brute-force Solution*

In order to address the requirements of the 0-1 knapsack problem one might resort to a methodology that evaluates all alternative potential solutions and then keep (one of) the best. This approach requires the non-repeating combination of sampling

r of n discrete elements as per the equation $C(n,r) = \frac{n!}{r!*(n-r)!}$.

Moreover, given the requirements of the Knapsack problem to allow one or more elements to be selected, the combinations of all scenarios $\forall r \in [1,n]$ must be considered leading to the evaluation of the number of combinations using the equation $\|\mathbf{combinations}\| = \sum_{r=1}^{n} C(n,r)$.

As this method does not utilise any optimisation, the number of combinations it has to examine, even for relatively low numbers of N elements is significantly high.

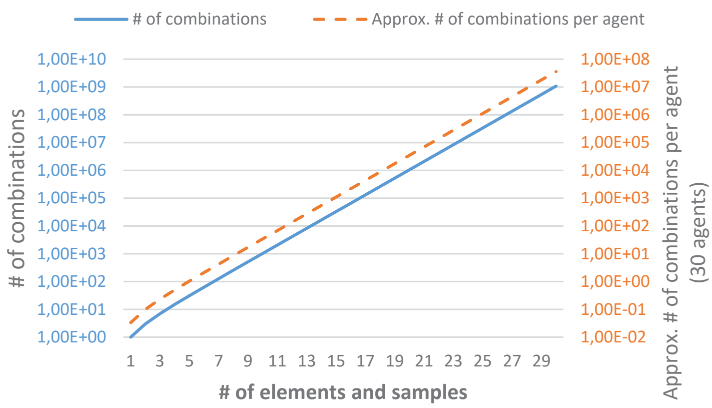


Fig. 1. Number of combinations for one or 30 examining entities (agents) where distinct elements and the number of samples are equal and vary in the range of 1 to 40.

Figure 1 presents the number of combinations for one or multiple agents when the number of distinct elements and the number of samples are equal for values ranging from 1 to 40, leading to maximum numbers of combinations reaching values near 10^{12}. Herein, the term agent refers to the elements to be included in the knapsack, in a form of parallelisation of the task, where the volume of combinations to be examined are with high approximation equally split between them.

This very high number of combinations is mainly the result of the numerous alternatives of the number r of elements to be sampled from the discrete elements while the most significant contributors are the ranges of r in the center of its distribution, as shown in Figure 2, and mostly around 30%-70%.

As far as the form of parallelisation in the examination processes with multiple agents, the number of concurrent examining agents does indeed significantly affect the number of combinations per agent but given the relatively high number of combinations to be examined altogether, the combinations per agent still remain quite large, as shown in Figure 3 where the number of distinct elements and the number of samples are both equal to 40. Accordingly, the brute-force solution to the Knapsack problem, despite the fact that it always reaches the best solution(s), becomes prohibitively expensive for relatively small quantities of discrete elements in terms of the sheer number of combinations that must be evaluated.

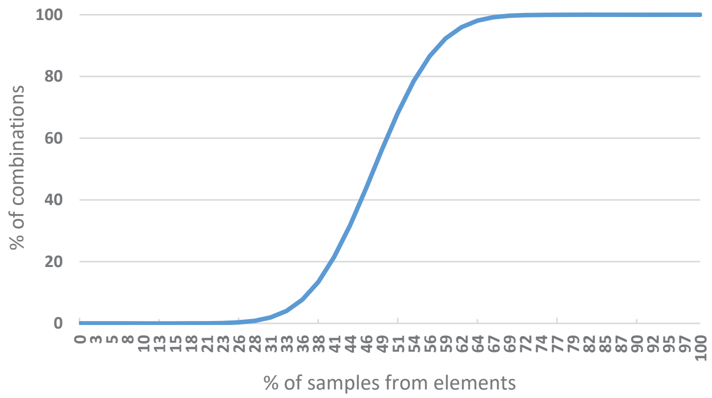


Fig. 2. The percentage of contribution attributed to varying sampled elements of all the discrete elements (% of samples from elements).

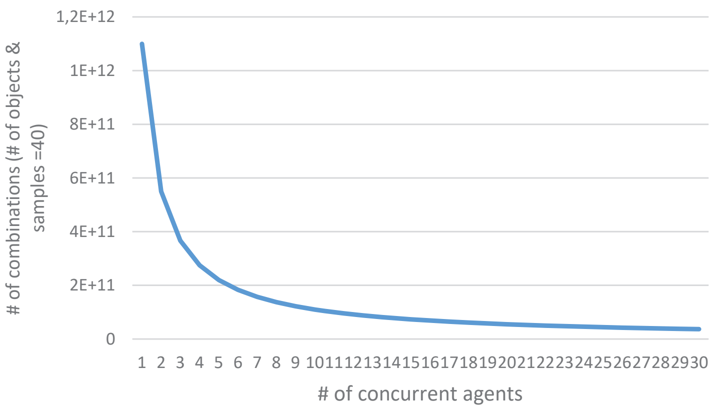


Fig. 3. Number of combinations with 40 distinct elements and 40 samples, evaluated for a varying number of concurrent agents within the range of 1 to 30.

2.6.2. *Dynamic Programming Solution*

Another way to solve the 0-1 Knapsack problem, is to use the Dynamic Programming (DNP) algorithm which works on the principle of using a table to store the answers to solved subproblems. Whenever a subproblem is surfaced again, the answer can be looked up in the table rather than being computed again. As a result, dynamic programming-designed algorithms are incredibly efficient.

Unfortunately, herein, it cannot be applied to our educational model, i.e. map it to students co-creating solutions by accessing informative resources / papers. Nevertheless, it is used herein as a point of reference to obtain exact solutions comparing the results to other algorithms for the solutions for the Knapsack problem, such as the ACOK algorithm, discussed in the sequel (Section 2.6.3).

2.6.3. *ACOK Algorithm Solution*

The knapsack problem's NP-hard nature offers valuable teaching opportunities. First, students experience firsthand how problem complexity grows exponentially, providing intuitive understanding of computational complexity theory. This experiential learning helps solidify abstract theoretical concepts through practical engagement.

The significant gap between exact methods like dynamic programming and approximation methods such as ACO at different problem scales demonstrates the tradeoffs between solution quality and computational efficiency. Students gain appreciation for why approximation algorithms are often necessary in practice, even when they don't guarantee optimal solutions.

Perhaps most importantly for our framework, NP-hard problems highlight the value of collective intelligence approaches, as they create scenarios where distributed problem-solving can effectively explore large solution spaces. When individual comprehensive exploration becomes impractical, swarm-based approaches demonstrate their particular strengths.

In this work, to solve the 0-1 Knapsack problem, we will employ the ACO algorithm and compare it against the brute-force method, as described in Section 2.6.1. Due to the long duration of the brute-force algorithm and the fact that the ACO algorithm does not always guarantee a 100% optimal [40] solution, we use the aforementioned dynamic programming algorithm, as described in Section 2.6.2, to obtain the exact solution so we have a fixed target for comparison.

As described in section 2.6.2 a DNP approach to solve the 0-1 Knapsack problem cannot be applied to our educational model meaning that a different approach is needed. On the other hand, ACO as described in section 2.4 employs a probabilistic technique to explore the solution space efficiently. This stochastic process helps in escaping local optima, which is a common issue in combinatorial problems such as the 0-1 Knapsack problem [41,42].

Furthermore, in ACO, pheromone trails represent the learned quality of solutions [6]. When applied to the 0-1 Knapsack problem, these trails can effectively highlight promising item selections, helping to explore effective solutions more efficiently.

By combining, the use of the 0-1 Knapsack problem within the ACO framework not only enhances the efficiency and effectiveness of solving the knapsack problem but also enriches the ACO algorithm with practical problem-solving capabilities.

Taking advantage of this hybrid approach for our framework, we utilise a ported version of the standard ACO algorithm tailored for the 0-1 knapsack problem 2.6 (ACOK). The main procedure is described in Algorithm 1.

An artificial ant's probabilistic solution building process is biased by pheromones and heuristic variables (α, β) in ACO. The ants' movements are determined by stochastic local decision policies based on two composite parameters, namely, the pheromones and the attractiveness of the path leading to an, also, attractive

Algorithm 1 ACOK - ACO tailored for the 0-1 knapsack problem

```
antCount ← number of ants
cycles ← number of cycles
initialise a global solution
for i = 1 to cycles do
    create antCount ants
    for all ant in ants do
        ant creates a local solution
        if local solution's profit > global's profit then
            make the local solution global
        end if
    end for
    evaporate
    update pheromones
end for
```

edge [43]. Each ant incrementally constructs a solution to the problem by moving iteratively in various directions. In the process of completing a solution, the ant changes the pheromone value on the visited items, aiming at providing pheromone information to guide future ants.

In more detail, each ant moves from one state i to another state j according to a transition probability rule p_j [43], as shown in Eq. (1).

$$p = \begin{cases} \frac{\tau_j^{\alpha} \mu_j^{\beta}}{\sum_{j \in N_i} \tau_j^{\alpha} \mu_j^{\beta}} & , \ for\ j \in N_i \\ 0 & , \ for\ j \notin N_i \end{cases} \tag{1}$$

The α parameter is responsible for controlling the impact of the pheromone trail τ_j, i.e. the collective memory of the colony. Increasing the value of α, ants are more likely to follow pheromone trails that other ants have previously followed. Parameter β controls the impact of the heuristic information (attractiveness μ_j), which is local information available to the ants regarding the problem. Increasing β, ants are more likely to choose paths that appear to be more promising based on the characteristics of the problem. The neighbourhood N_i of state i is composed of items that can be used for the construction of a partial solution. The attractiveness μ_j refers to the problem-specific heuristic information that is used by the ants to evaluate the desirability of an item from the neighbourhood N_i being added to the N_i solution under construction. z_j is the profit and w_j is the weight of the selected item j. Accordingly, the attractiveness [43] can be expressed as per the equation $\mu = \frac{z_i}{w_j^2}$.

When a solution has been found, each ant deposits an amount Δ_τ of pheromone τ on all the items included in the solution following the pattern using the equation $tau = \tau + \Delta\tau$.

The amount Δ_τ of pheromone deposited on each item is proportional to the quality of the solution that the ant has found [43]. This is shown in the equation $\Delta\tau = f(Q) = \frac{1}{1+\frac{z_{best}-z}{z_{best}}}$.

Finally, a mechanism of evaporation, as far as pheromones are concerned, is incorporated into the process of ACO and respective implementation of algorithms to avoid fast convergence to a sub-optimal solution [43]. The strength of evaporation is controlled by the parameter ϱ which represents the evaporation rate. The evaporation is calculated using the equation $\tau = \varrho\tau, \varrho \in (0, 1)$.

3. Proposed method

This paper introduces and examines a framework (Algorithm 2) for educational scenarios where a teacher/enabler maps the educational task at hand to a distributed and decentralised process during which students cooperate to solve a challenge or, more generally, perform an educational task. As a result, students themselves co-create the solution, meaning that the solution they develop is a result of their collective output.

Algorithm 2 Educational Swarming Framework

```
teacher sets the educational task to a flipped classroom
teacher sets a time limit
studentCount ← number of students in the flipped classroom
cycles ← number of cycles
initialise a global solution
for i = 1 to cycles do
    for all student in students do
        student selects a subset of items based on time availability,
            reading capacity, and content complexity
        student evaluates each source by relevance, reference/cite count
        student creates a local solution
        if local solution's score > global's score then
            make the local solution global
        end if
    end for
    students's memory retention decreases (evaporation)
    students form collective memory (pheromones update)
end for
```

In swarm learning, the teacher/enabler plays a different role compared to traditional teaching approaches [44]. The teacher is not necessarily an instructor, but rather more of a facilitator with primary responsibility to support and guide students as they work collaboratively in order to learn. The teacher/enabler should first identify the educational task / goal they want to achieve through their teaching. This could involve defining the learning objectives, outcomes, and/or competencies they want their students to develop. In examining the integral part of education, i.e. the students, and more specifically a class of students seeking out new knowledge, we observe that it is directly related to the ant colony paradigm and that makes ACO an ideal candidate for a swarming approach for the aforementioned task.

One of the key initial activities of students is identifying information relating to the educational task. To achieve this, students are expected to examine sources to gather as much information about the subject in question. Each source is evaluated by both students and peers of its authors. The relative quality of a source depends on how well it meets the student's informational needs. Additionally, students' evaluation of a source requires a thorough examination of the source's content, including its bibliography thus affecting the whole examination process by adding more resources. Moreover, by citing a source within their own work, the peers of the source's authors in addition to providing references where due, they indirectly provide a measurement of evaluation, much like in the manner PageRank does when evaluating web pages [45].

The process of selecting papers that contribute most to the task at hand represents a well-defined problem domain as already discussed in Section 2.6, the Knapsack problem that dates back to the early works of the mathematician Tobias Dantzig [46]. To address the mapped educational challenge with the Knapsack problem using the aforementioned swarming solutions, the ACO approach, which is a generic approach rather than a specific algorithm, it needs to be tailored to the particular problem under consideration i.e. education. To achieve this goal, we use the Knapsack problem as an intermediary.

As described in Section 2.6, the knapsack problem attempts to select the subset of items with maximum desirability while satisfying a constraint on the total weight of the items [47]. Within the context of learning, the knapsack problem can be applied to the selection of resources that address the educational challenge, i.e. to select a subset of resources from a large corpus that is relevant to a specific research question or topic, based on factors such as time availability, reading capacity, and content complexity. For example, given a set of papers with associated relevance scores, citation counts, and a limited amount of time to be devoted to reading, a student will have to determine the subset of papers that maximises the overall relevance or information gained based on the time limit and reading capacity constraints.

Accordingly, the proposed framework utilises the notions of (a) the Knapsack problem as a generic methodology to identify the best subset of resources that maximise their value while adhering to a (weight) constraint, (b) the ACO swarming algorithm that is inspired by ants for the task of identifying the aforementioned subset, and (c) the educational domain wherein one of the common processes includes the examination of educational resources in order to address an educational need. The fusion of these notions is based on a mapping between their key characteristics, as shown in Figure 4.

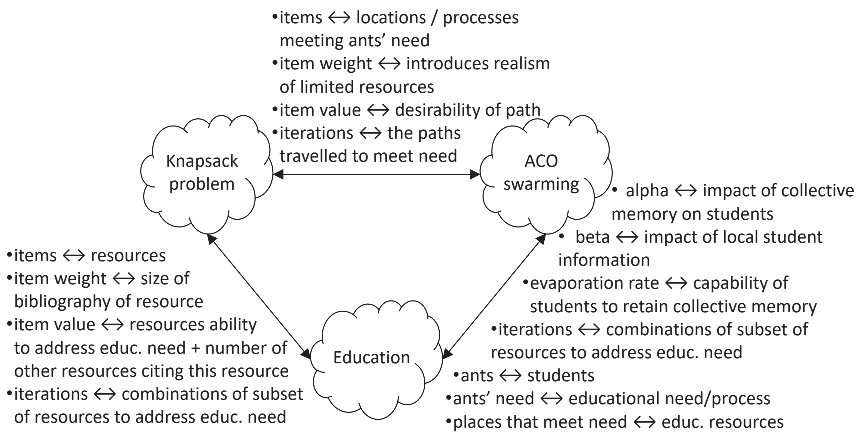


Fig. 4. Mapping between key notions of the Knapsack problem, the ACO swarming algorithm, and a generic educational process.

Using this framework, for the pillars "educational process" and "Knapsack problem", educational sources are mapped to items; the number of bibliographic entries within each source is mapped to the item weight; citations received by a source as well as the source's ability to address the informational need are mapped to the desirability of each item; and, the combinations of subsets of resources that must be examined to address the educational need are mapped to iterations.

For the pillars "Knapsack problem" and its "ACO swarming" approach: items are mapped to locations and/or processes that meet ants' needs (e.g. foraging); the item weight is mapped to the process of ACO that introduces realism by including constraints; the item value is mapped to the desirability of a path; and, iterations are mapped to the paths travelled by ants to meet their needs.

For the pillars "ACO swarming" approach and "educational setting": parameter Alpha (α) is mapped to the impact of collective memory on students' decisions; parameter Beta (β) is mapped to the impact of local student information; evaporation rate is mapped to the capability of students to retain a varying persistence collective memory; iterations are mapped to the combinations of subsets of resources that must be examined to address educational needs; ants are mapped to students; ants' needs are mapped to educational needs / processes; and, places where ants meet their needs are mapped to educational resources.

The selection of the specific attributes for each of the constituent pillars / processes was done on the basis of the significance of the attributes, on each respective domain. The pair-wise interrelation was achieved based on the definition / description of the attributes, as shown in Figure 4.

4. Experimental evaluation

4.1. *Experimental Setup*

To explore the capabilities of the ACOK algorithm, we built a simulation model, that allowed us to test the algorithm in various scenarios and perform sensitivity analyses on its input parameters to assess their impact on effectiveness. The simulation model was implemented in the .NET framework using C#. The machine characteristics that we run the tests are, Intel Quad Core i7-6820HK CPU @ 2.70GHz with 16 GB RAM. To obtain a simulation model that is as realistic as possible, the experiments were conducted using graphs directly obtained from Connected Papers [48] via their REST API.

Through Connected Papers, researchers are able to locate relevant academic papers based on the field of study in which they are interested (see example in Figure 5). For the purposes of this work, the graphs experimented on where based on papers that research ICT methodologies for the reduction of risks and vulnerabilities closely related to climate change (e.g. flood risk, risk of fire, erosion, landslides and landslides). This selection was made as a preparation for future application of the proposed framework in various levels of educational institutions to promote / educate on issues of the climate crisis.

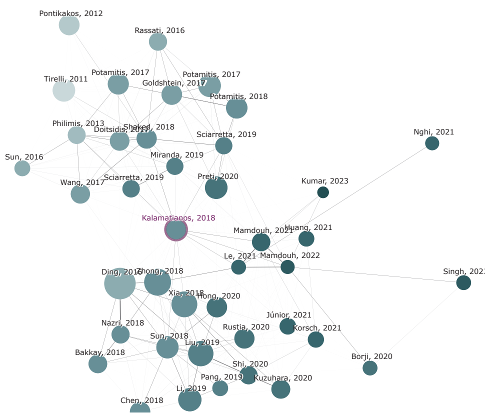


Fig. 5. An example of Connected Papers graph.

We tested the simulation model using a set of three graphs with 20, 30 and 40 papers respectively. For each graph, we run a test scenario with the ACOK algorithm parameters set as follows:

- Number of Iterations: 5, 10, 100, 1000
- Number of Ants: 1, 2, 4, 6, 8, 10, 15, 20, 25, 30, 50, 100
- Evaporation Rate: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1
- Alpha: 0, 1, 2, 3, 4, 5
- Beta: 0, 1, 2, 3, 4, 5

The test scenario for each graph produced 17,280 results that measured the success rate of that particular combination of parameter values compared against the optimal solution obtained from the dynamic programming algorithm.

Furthermore, to validate the fact that ACOK, despite inherent stochasticity, produces results very close to DNP, we ran the Wilcoxon Signed-Rank Test [49] for the "Solution Score" obtained from ACOK and DNP over 50 different scenarios (graphs obtained from Connected Papers) as shown in Table (2).

Table 2: Best solution score per graph in ACOK & DNP.

#	Graph id	ACOK Score	DNP Score
1	00acc6bf481d6d81995d231e7931113ccc9aa31d	9.59	9.61
2	0dc223480bd521f6eae897f1e4b5fcb2bd81b765	7.66	7.73
3	173d1555d3efc60956acda6c85165292546c5c38	7.92	8.01
4	18f8bf0d001fcbc01f8f83ca3c6bfc520d779ad8	8.53	8.55
5	19d56eebdac34f0848e00c8fce6ee96ba8dad362	8.28	8.34
6	1a8002f88748cce5f40d374141a31a50e2c0a245	8.14	8.22
7	1bbd7c193475b84f8acb113898146fbac90d5572	6.73	7.46
8	1cdd1948bb6895454b1bb009062a896cbded6b58	8.49	8.58
9	25a6ea8e7b5edd05a71b1dd91f26b5741ebaf28e	8.30	8.32
10	25eecb89bed586cb7066d0b3dfd12dbe120c0f8a	8.62	8.66
11	2e399cac4022ac52072e98d6e310c2e61b6f5b0d	9.59	9.72
12	365b62472d95de8a203fa513e80f491b5323ab42	8.24	8.34
13	36bbca69c74376f5e0190458a6b794bb01066106	8.64	8.69
14	3d877065e079f54ce1a97b6231b94def687dbb76	7.50	7.52
15	416c081bdb82251ae402bbd5222ade49d56db134	8.72	8.72
16	432672fafe125435b43f891fa97496985a719b15	7.79	8.01
17	4e54dfc251d987e0da5286163814b9989a37cd2d	6.18	10.45
18	59fd232f314d1db75c38dce15f906a1789f46826	8.40	8.43
19	5e1234229e59cbc48420601832ed08180f21642f	8.06	8.09
20	5fb9176fa0213c47d1da2439a6fc58d9cac218b6	9.04	9.04
21	65d20c4926407068298220540769dd6ff77a33d2	8.10	8.27
22	73750e1a1c9a6645cb0c8948c119143b6d3c5c05	8.90	9.73
23	790dfacaeb70f9f0fcb2c98ec61ac216f28f6ab5	8.88	8.91
24	7964e723b7afd36c5824f2c27cbcd18e02f5d16c	8.61	8.61
25	7d561845fef639cbe428d182d414dff4f9c7a60e	7.24	7.28
26	7dde44a178a64f4562988ef8883b37488c2a6569	8.57	8.60
27	858b3c532ceb73ba7ad00cb3ba55b9a161f86e3a	6.59	6.68
28	870d8a90ebc2860bbdd6a261c906555e9b1eb333	8.79	8.88
29	8813f772eff9573e5e6d671d42ebc0bff1594889	7.90	7.94
30	88779c23a367a652ff6989c3047c0f624627d222	10.49	10.61
31	8954928ac7ff9529931f501d6ae7e3121104fe8e	9.07	9.10
32	8cd688bf2e4532be29a74bd7e2922e1774d5e03f	8.60	8.66
33	923a15c8519e8db3cb18665346d6fe1d38760255	8.43	8.51
34	9ddaca07ea4c96e9effab2954aee9b719cb1eb23	8.19	8.40
35	a01a3c061644f6d140e643ec2f0ad33ee188baf3	7.08	7.21
36	a7394c3e226a698719b56a5a57989a01200e23ee	8.32	8.33
37	b8cadd2bcd8f1166562f2bba5f64ec0528e29033	8.42	8.44
38	bd1ee8194a092c65a2ce832ddd0b4fa65a70b74e	7.64	7.70
39	c367dc3b1efd1b32a3532d3f6334cf6560784342	8.58	8.58
40	c54b5737ffc1da720a3dd51615587d34892f81ad	9.79	9.93
41	caf62f1c21a671e7226078e8287995012a92c14e	8.07	8.16

Table 2 (Continued)

#	Graph id	ACOK Score	DNP Score
42	cc2ba00bb0f54ee295a4df70ac6a58b41b8c5593	8.93	8.93
43	ce8a920b97748fe92ccd83b943a244b2111d1619	9.67	9.74
44	d48673b4a2279867c12d60a97797472507fb8706	8.32	8.47
45	db659897e9f3904277b8ec1188ac3f91ee5da7ed	8.60	8.60
46	df9c58bdedae83bbb184b84dea9a1b0d81f694b4	8.90	8.96
47	e5b5e0d1d692d5c07aba181f0ee08ac27bee3a3e	8.00	8.01
48	e639ab4ffe613877d0d6cf3a67aa7c1007cced34	9.39	9.50
49	ec3b84f36e1db7a53ac8bdeca0fd643cf8675e9d	7.63	7.73
50	f6e6fa5fe91ea5ca1747eaece5375f1898abea8d	9.09	9.09

The result received included (a) the sum of the ranks of the differences above zero (a.k.a. "statistic") with value 0, and (b) the "p-value" with value 0.999999994491044. This indicates that the paired samples are identical in terms of the rank sums of their differences, and there is no statistical evidence to suggest any difference between them. This situation usually occurs when the data in the paired samples (ACOK Score and DNP Score) are exactly the same or extremely close to each other, leading to a strong consistency with the null hypothesis of no difference. In other words, the data is consistent with the null hypothesis: any observed differences are likely due to random variation rather than a true effect.

4.2. *Sensitivity Analysis*

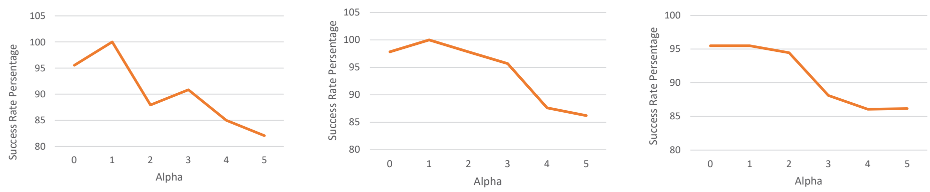
By focusing on the parameters Alpha (α), Beta (β), and Evaporation Rate (ϱ) in the range of the highest success rates, we attempted to examine the effect of these aspects of the experimentation on the utilised algorithm and subsequently, their effect on the solution received. For those instances, we examined the values for each of these parameters when the Success Rate (see section 4.3.1) was at its peak. We then kept two of those constant and examined more closely the impact of the third one on the Success Rate in turn. This produced the following results.

4.2.1. *Parameter Alpha*

Figure 6 shows that for values of Beta = 2 and Evaporation Rate = 0.8 we obtain the best (exact) solution when Alpha = 1 with the Success Rate being at its maximum (100%). On the other hand, we obtain the worst solution when Alpha = 5 with the Success Rate being at its lowest (82%). In general, we observe that we start with high Success Rates that decrease as Alpha increases, showing the tendency that lower values of Alpha achieve better results.

4.2.2. *Parameter Beta*

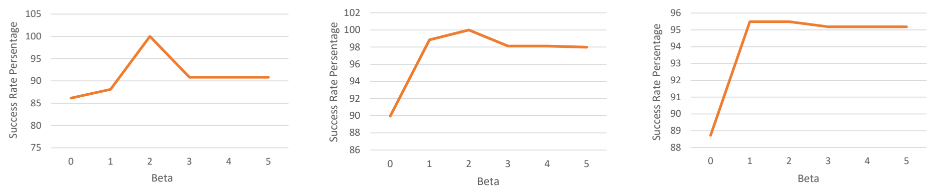
Figure 7 shows that for values of Alpha = 1 and Evaporation Rate = 0.8 we obtain the best solution when Beta = 2 with the Success Rate being at its maximum



(a) 20 Items (b) 30 Items (c) 40 Items

Fig. 6. Parameter testing - Alpha

(100%). On the other hand, we obtain the worse solution when Beta = 0 with the Success Rate being at its lowest (86%). In general, we observe that the results start with low Success Rates that increase as Beta increases until we reach somewhere in the middle of the values of Beta at which point we see a slight decreasing tendency leading to a plateau, showing the tendency that mid-range values of Beta achieve better results.

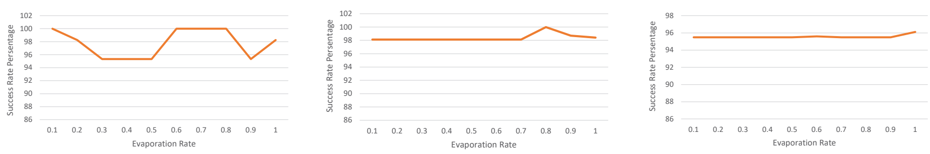


(a) 20 Items (b) 30 Items (c) 40 Items

Fig. 7. Parameter testing - Beta

4.2.3. *Parameter Evaporation Rate*

Figure 8 shows that for values of Alpha = 1 and Beta = 2 we obtain the best solution when the Evaporation Rate is close to 0.8 with the Success Rate being at its maximum (100%).



(a) 20 Items (b) 30 Items (c) 40 Items

Fig. 8. Parameter testing - Evaporation Rate

On the other hand, we obtain the worst solution when the Evaporation Rate is close to 0.4 with the Success Rate being at its lowest (94.7%). The fact that there is a small variation on the Success Rate when the number of items increase, is initially attributed to the relative small number of experiments performed in this work as well as to the specific characteristics of the current setup.

4.2.4. *Default parameter values*

Given the aforementioned results we selected as default values for Alpha, Beta and Evaporation Rate to be 1, 2, and 0.8 respectively. Based on our simulation model, the Number of Ants never exceeds the value of thirty which maps favourably to the paper's theme of the typical number of students in a class. Additionally, the maximum Number of Iterations to be executed, within which the solution is to be found, is selected to be 10 as, per our theme, most repetitive tasks larger than these are deemed to become exhausting and boring for the students participating in the experiments.

4.3. ***Evaluation Results***

We performed 2 sets of experiments each with 2 variations measuring: (a) Success rate, and (b) Number of iterations at which the optimal solution was found, both for varying number of items in the graph, and number of ants involved.

All scenarios were executed 10 times for each variation of the parameters to average the stochasticity of the heuristic process of the algorithm. After tuning the parameters as outlined in Section 4.2, we present their default values in Table 3. This process resulted in a dataset containing 18,000 entries.

Table 3. Parameters' value ranges

Parameter	Value / Range
Alpha	1
Beta	2
Evaporation Rate	0.8
Number of Iterations	1…20
Number of Ants	1…30
Items in graph	20, 30, 40

4.3.1. *Measuring Success Rate*

These experiments involve testing the impact of the number of items in the graph and the number of ants involved on the success rate. That is, the ACOK's average success rate against the exact solution produced by the DNP algorithm, as described in Section 2.6.2. Thus, we measure this as a percentage of the output produced by ACOK against DNP since, as already mentioned, the ACO algorithm does not always guarantee the exact solution [40] hence the use of the DNP algorithm.

4.3.2. *Maximum Success Rate per Items in a graph*

This experiment involves testing the impact of the number of items a graph contains and how this affects the process of finding the exact solution. Thus, we measure the maximum percentage of the success rate against DNP.

Examining the results shown in Figure 9, we observe that adding more items in a graph above the number 30, reduces the success rate slightly by 4%. However, the maximum success rate for all items still remains very high, above 96% given the performance of ACO.

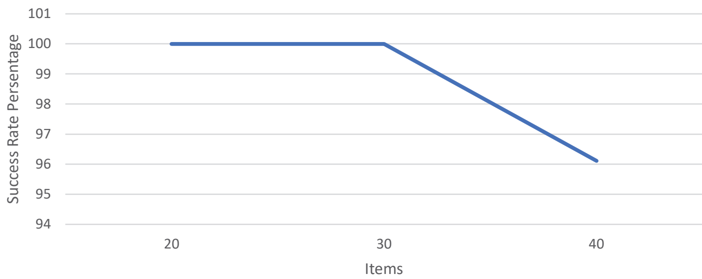


Fig. 9. Maximum Success Rate per Items in a Connected Papers graph

4.3.3. *Average Success Rate per Ant*

The next experiment tests the impact of the number of ants involved to find the exact solution. Accordingly, we measure the average percentage of the success rate against DNP's performance.

Examining the results shown in Figure 10, we observe that for all three classes of items (20, 30, 40 items), the results received present a similar evolution for varying number of ants, i.e. as a part of an s-shaped logistic increase.

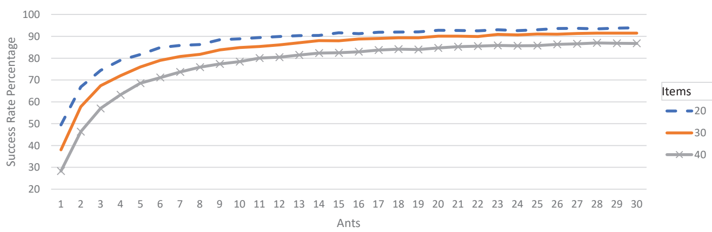


Fig. 10. Average Success Rate per Ant

For the class of 20 items (blue dashed line), the success rate for one ant is 50% and the 95th percentile is achieved for 9 ants with success rate 90%, while the class peaks at 30 ants reaching 95% success rate. For the class of 30 items (solid orange line), the success rate for one ant is 38% and the 95th percentile is achieved for 16 ants with success rate 88%, while the class peaks at 30 ants reaching 91% success rate. For the class of 40 items (x-marked gray line), the success rate for one ant is 28% and the 95th percentile is achieved for 22 ants with success rate 85%, while the class peaks at 30 ants reaching 87% success rate.

4.3.4. *Measuring number of iterations needed*

The next set of experiments concentrates on how the number of ants and the number of items in a graph affect the number of iterations needed to reach the optimal solution.

4.3.5. *Average number of iterations the best result found at*

In the first experiment of this set, we examine the average number of iterations in which the optimal solution is found by varying the numbers of ants.

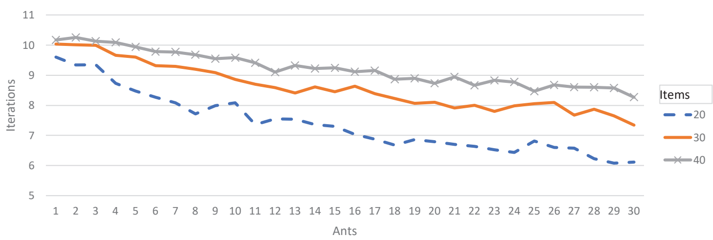


Fig. 11. Average number of iterations at which the best result was obtained.

From the results received in this experiment, as shown in Figure 11, we observe that for all three classes of items (20, 30, 40 items), the results received present a similar evolution for varying number of ants, i.e. a near linear decrease.

For the class of 20 items (blue dashed line), for one ant the average number of iterations at which the best result is found is 9.6 , the inclination of the slope is 350°, while the class achieves the best result for 30 ants in iteration 6. For the class of 30 items (solid orange line), for one ant the average number of iterations at which the best result is found is 10, the inclination of the slope is $352, 5°$, while the class achieves the best result for 30 ants in iteration 7,4. For the class of 40 items (x-marked gray line), for one ant the average number of iterations at which the best result is found is 10,2, the inclination of the slope is 353°, while the class achieves the best result for 30 ants in iteration 8.3.

4.3.6. *Maximum number of iterations the best result found at*

In the last experiment of this set, we examine how the number of items in a graph and the number of ants affect the number of iterations needed to reach an optimal solution. According to the results, as shown in Figure 12, we observe that for all four classes of number of ants (1, 10, 20, 30), the results received exhibit high variability. For the class with 1 ant (blue long-dashed line) the results for the maximum number of iterations the best result was found at are constant at 20 iterations. For the class with 10 ants (solid orange line) the results for the maximum number of iterations the best result was found at are constant at 19 iterations for up-to 30 items while for 40 items the result increases to 20 iterations.

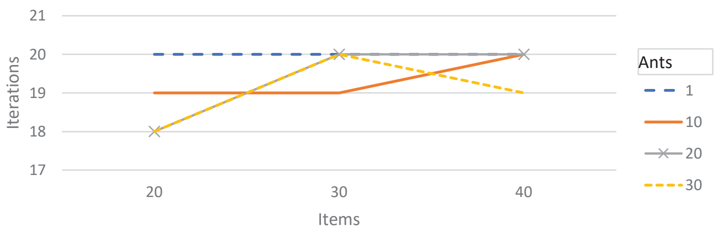


Fig. 12. Maximum number of iterations at which the best result was obtained.

For the class with 20 ants (x-marked gray line) the results for the maximum number of iterations the best result was found at for 20 items are 18 iterations, while for 30 and 40 items are constant to 20 iterations. For the class with 30 ants (yellow short-dashed line) the results for the maximum number of iterations the best result was found at for 20 items are 18 iterations, for 30 items are 20 iterations and 40 items are 19 iterations.

4.4. *Discussion*

For the “Average Success Rate per Ant” experiment (see Section 4.3.3, Figure 10), we observe that for all three cases and for one ant, all three alternatives of the graph size present the worst success rate of their respective examination. The results increase in an exponential manner as more ants are incorporated into the experiment, reaching approximately 90% on average for 30 deployed ants. The result’s explanation presents as straightforward since the introduction of more ants allows more combinations to be processed within a set number of iterations; hence the possibility of finding the best solution with a higher success rate is also increased. Moreover, we observe that for smaller search spaces, i.e. having fewer items to process, the success rate is higher than for larger search spaces (i.e. graphs with 20 items as opposed to graphs with 40 items).

For the “Average number of iterations the best result found at” experiment (see Section 4.3.5, Figure 11), we observe that the maximum number of iterations at which we find the most optimal solution, peaks at approximately 10 iterations (averaged values). We also observe that as more ants are added to the colony, up to a total of 30, iterations are almost consistently decreasing with the minimum value reaching 6 iterations. It follows that as more workers (ants) are added, the parallelism of the process increases and thus fewer iterations are required, as expected. Moreover, we observe that the size of the graph, representing the search space, affects proportionately the iteration at which the identification of the most optimal solution is made at, for a given size of workers, again as expected.

In addition, for the "Maximum number of iterations the best result found at" experiment (see Section 4.3.6 - Figure 12), we observe that for 1 ant the number of iterations remains constant at 20, whereas for the remaining ants, the number of iterations decreases as more ants participate in the process. We also observe that the maximum number of iterations required for each graph never exceeds the 20 iterations regardless the number of ants. Moreover, an interesting point arises when examining the worst-case scenario: a graph with a large number of items (40) and only one ant. Despite this challenging setup, only 20 iterations are needed, which is significantly fewer than the exhaustive brute-force method that requires many orders of magnitude more iterations, as discussed in Section 2.6.1.

Finally, while our results demonstrate the effectiveness of the ACO approach, it's important to acknowledge how the algorithm's stochastic nature might influence educational implementations. The variability in success rates, particularly with fewer ants, presents both challenges and opportunities in classroom settings. This variability mirrors real-world problem-solving where groups often arrive at different yet viable solutions.

In educational practice, this variability can be leveraged as a learning opportunity. When different student groups (representing different ant colonies) arrive at varied solutions, instructors can facilitate comparative discussions about the relative merits of each approach. These discussions can deepen understanding of both the subject matter and the problem-solving process itself. Additionally, the improvement patterns observed as more ants are added illustrates the value of collaboration and diverse perspectives in addressing complex problems.

To address potential frustration that might arise when students don't immediately find optimal solutions, instructors implementing this framework should emphasize the iterative nature of the learning process. Structured reflection activities where students analyze the performance of different parameter settings can transform the algorithm's variability into lessons about persistence and methodical improvement. This approach treats suboptimal initial solutions not as failures but as valuable data points in the learning journey.

4.5. *Real-World Experimental Validation*

To bridge the gap between simulation-based validation and practical educational implementation, we conducted a preliminary real-world experiment with students from a Greek secondary school. This experiment establishes a foundational prototype that demonstrates the feasibility of applying our framework in authentic educational settings.

4.5.1. *Experimental Design*

The real-world validation involved $1 * 2 + 3 * 2 + 6 * 2 = 30$ students distributed across different group configurations and two distinct scenarios that aligned with our simulation parameters (Table 3). The first scenario presented students with 20 academic articles, and the second scenario required evaluation of 40 articles. Each scenario challenged students to collaboratively select the most relevant subset of articles for a given educational task while operating within time and complexity constraints, following the principles of our proposed swarming framework. The full set of parameters are presented in Table 4.

Table 4. Parameters' value ranges in real-world experimentation

Parameter	Value / Range
Alpha	1
Beta	2
Evaporation Rate	0.8
Number of Iterations	10
Number of Ants	1, 3, 6
Items in graph	20, 40

4.5.2. *Prototype Implementation*

Recognizing the complexity of developing a comprehensive online platform capable of handling extensive article management, user reviews, and real-time ACOK algorithm implementation, we designed a streamlined prototype that captures the fundamental elements of our framework. The prototype is currently accessible at `https://softwareexelixis.com/acok` and provides an interactive environment for educational resource selection.

Rather than overwhelming students with complete academic articles, our implementation presents article titles accompanied by dynamically calculated Preference Index scores. These scores are generated through the ACOK framework, incorporating both ACO pheromone trail mechanics and Knapsack problem optimization principles. This approach maintains the essential decision-making processes while reducing cognitive overhead during the selection phase.

Students engage in an iterative selection process where they review available article titles and their corresponding preference indices, make selections based on perceived relevance to the educational task, and observe how their collective choices influence subsequent selections. The framework automatically manages the collaborative aspects, handling pheromone trail updates and cross-group communication without requiring explicit coordination from participants.

4.5.3. *Prototype Rationale and Future Development*

This prototype serves as the foundation for more sophisticated implementations. In fully developed systems, students would access complete articles through integrated online platforms, provide comprehensive ratings and reviews throughout their exploration of the articles' corpus, receive advanced algorithmic support based on complete ACOK implementation, and benefit from sophisticated pheromone trail modeling that captures nuanced preferences and peer discoveries.

4.5.4. *Preliminary Observations*

The preliminary results from this real-world validation reveal several important findings regarding practical implementation. Figure 13 presents the success rates achieved across different group sizes for two scenario configurations: 20 articles and 40 articles. The results demonstrate a clear positive correlation between group size and performance effectiveness. For the 20-article scenario, individual students achieved a 24% success rate, which increased substantially to 57% with three-student groups and reached 82% with six-student groups. The 40-article scenario showed a similar upward trend, with individual performance at 17%, three-student groups achieving 58%, and six-student groups reaching 70% success rates.

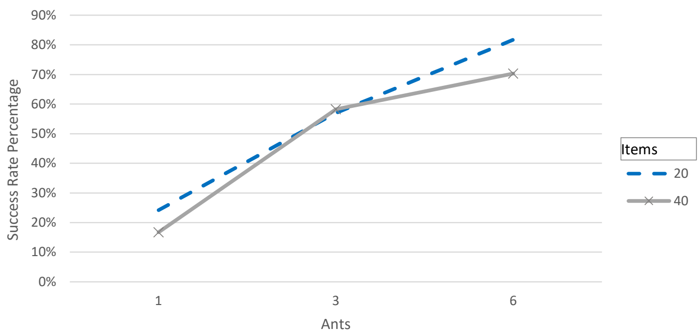


Fig. 13. Preliminary results from real-world validation.

These empirical findings align closely with the patterns observed in our simulation results shown in Figure 10, where larger ant colonies consistently outperformed smaller ones in identifying optimal solutions. The real-world data exhibits the same s-shaped logistic growth pattern characteristic of collaborative optimization processes, confirming that increased group size enhances collective problem-solving capabilities.

It should be noted that our simulation methodology required executing each scenario ten times per parameter variation to account for the stochastic nature of the heuristic algorithm, as detailed in Section 4.3. Such extensive repetition proves impractical when working with human participants in educational settings, where time constraints and participant availability impose natural limitations. Despite conducting single-run experiments rather than multiple iterations, our real-world results demonstrate remarkable consistency with the averaged simulation outcomes, suggesting that the collaborative human intelligence exhibits similar optimization characteristics to the algorithmic approach.

While our pilot study was necessarily limited in scope regarding the maximum number of participants due to practical constraints of the educational setting, the observed trend strongly suggests that the theoretical predictions from our ACOK simulation would continue to hold with higher student numbers.

Students exhibited clear learning patterns across iterations, with later selections showing improved alignment with educational objectives, supporting the effectiveness of the collaborative refinement process embedded in our framework. The consistency between simulation and real-world results supports both the accuracy of our computational model and the practical applicability of swarming principles in educational contexts. Notably, the performance improvement from individual to group work demonstrates the tangible benefits of collaborative approaches, even within the constraints of our simplified prototype implementation.

Perhaps most significantly, despite the simplified implementation, students successfully engaged with the swarming-inspired selection process, indicating that theoretical frameworks can be meaningfully translated into practical educational applications. The automatic handling of collaborative elements by the framework eliminated coordination difficulties while preserving the essential benefits of collective intelligence.

4.5.5. *Limitations and Future Work*

This prototype experiment represents an initial validation of core feasibility rather than a comprehensive real-world implementation. Future development priorities include creating robust online platforms that support full article access, sophisticated rating systems, and complete ACOK algorithm integration. Enhanced user experience design will focus on implementing intuitive interfaces that seamlessly blend algorithmic optimization with natural collaborative learning processes.

Comprehensive evaluation through extensive field trials across diverse educational contexts remains essential for refining the framework and validating its effectiveness at scale. The encouraging outcomes from this preliminary real-world validation reinforce confidence in the practical applicability of the proposed framework while providing valuable insights for subsequent development phases.

5. Limitations

While the proposed model demonstrates significant potential in enhancing educational outcomes through swarming methodologies, there are limitations that should be highlighted. Firstly, the complexity of implementing the model across diverse educational settings may vary due to differences in infrastructure, technological accessibility, and educator familiarity with advanced algorithms like ACO. Additionally, the effectiveness of the model heavily relies on the proper tuning of ACO parameters, which can be challenging and time-consuming without extensive expertise and experience, especially in the mapped setting of an educational scenario.

Furthermore, the model assumes students with a baseline level of digital literacy and collaborative skills, which might not be universally present. There is also risk that the competitive elements introduced by optimisation problems could overshadow collaborative learning goals if not carefully managed. Lastly, while the model has been validated through simulation, real-world educational environments may present unpredictable variables impacting its performance and scalability.

6. Conclusions

The meteoric popularity of the flipped classroom model [12] in recent years has been based on its ability to enhance students' engagement and promote learning through students' collaboration in order to address complex educational tasks [3], thus leading to the co-creation of knowledge. Such co-creation of knowledge is also observed in nature-based collaborative solutions [38], among others, in the form of swarming for efficient and effective tackling of complex problems. In swarming, as in co-creation, the key actors' "collective intelligence" emerges significantly more advanced than the sum of its units [5].

One of the key aspects of the flipped classroom model is the shift of class time activities to non-class time activities [36]. Thus, students initiate tasks such as examining the (suggested or at will) bibliography outside the classroom, thus prompting the generic educational task of the selection of educational resources that address a complex educational challenge with constraints [35]. A common such example is the selection of a subset of literature from a large corpus that is most relevant to a specific research question, while maintaining constraints such as time availability, content complexity, etc. This task is efficiently addressed by the Knapsack problem which attempts to select the subset of items with maximum desirability while satisfying a constraint on the selected items.

Building on the aforementioned aspects of an educational task modeled to combinatorial optimisation solved by swarming methods, in this work we propose a framework, (see Section 3), that models the generic educational task of identifying a subset of literary works that best meets the task's requirements from a large corpus, for some constraint, and maps it to the Knapsack problem that is subsequently solved using the ACO swarming algorithm in order to take advantage of the co-creational advantages of the flipped classroom paradigm.

Experiments with alternative solutions to the Knapsack problem (Section 4), such as brute-force and dynamic programming, indicate their inappropriateness to the requirements of the proposed framework, while experiments with ACO's sensitivity and key parameters indicate the effectiveness and efficiency of ACO to the proposed framework. Future research will focus on addressing the aforementioned limitations by developing comprehensive training programs for educators, creating more user-friendly interfaces for algorithmic applications, and conducting extensive field trials to refine the model under various educational contexts. Additionally, plans include mapping more generic and specific educational activities to the proposed framework, such as updating the students' cognitive model for a subject following the studying process and co-creating an output on the subject as an expression of their updated cognitive model and other input parameters. Moreover, experimentation with more swarming approaches is needed, given the requirement of co-creative solutions, to test their effectiveness and efficiency. In addition, we plan experimentation with multidimensional data and other (competing) swarming approaches. Finally, applying the proposed framework at various levels of educational institutions will help promote and educate on issues of the climate crisis.

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