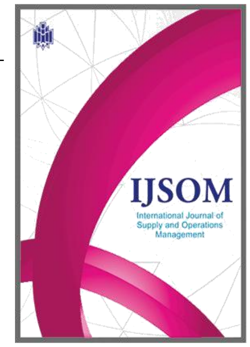
International Journal of Supply and Operations Management

IJSOM

2024, Volume 11, Issue 2, pp. 188-202
ISSN-Print: 2383-1359
ISSN-Online: 2383-2525
www.ijsom.com



Heuristic Simulated Annealing Modeling to Optimum Target Audience Identification in Digital Marketing: A Case Study of a Mining Industry Training Service Company

Hamid Sarkheil [a*] and Mirza Hassan Hosseini [b]

[a] *School of Mining, College of Engineering, University of Tehran, Tehran, Iran*
[b] *Department of Business Management, Payame Noor University, Tehran, Iran*

Abstract

Digital marketing has become vital to businesses' marketing strategies in today's technology and social media era. However, the effectiveness of digital marketing campaigns largely depends on accurately identifying the target audience. This study aims to implement the simulated annealing initiative algorithm for digital marketing, as well as audience classification and optimum target audience selection. Traditional methods of target audience identification, such as demographic, geographic, and psychographic segmentation, are only sometimes effective in identifying the most responsive audience. Therefore, advanced techniques such as clustering, genetic, and simulated annealing algorithms have been proposed to identify the optimum target audience. The heuristic simulated annealing algorithm is one of the most promising techniques for optimum target audience identification. It is widely used in combinatorial optimization problems and applied in various fields such as engineering, economics, management, and computer science. In this research, a digital marketing campaign is implemented for a new line to sell training courses in empowerment and competency in human resource management within the mining industry. After conducting market research, we have identified five critical segments: age, gender, income group, place of residence, and level of university education. The number of customers at each customer journey stage was 740 people in brand development, email, and advertising campaigns, of which 620 people are in the "Awareness" stage, 431 people in the "Interest" stage, 261 people in the "Consideration" stage, 203 people in the "Intend" stage, 179 people in the "Purchase" and finally, 179 People were evaluated in the "loyalty" stage for the case of educational service company. The results show we should target 20% of our marketing efforts towards the 18-24 age group, 30% towards females, 20% towards high-income individuals, 10% towards rural areas, and 20% towards University education level in BSc. The best cost per conversion we obtain is 78.105×10^{6} Rials. The results show that the simulated annealing algorithm can be valuable for identifying the optimum target audience in digital marketing campaigns. By considering the entire customer journey and allowing for more complex audience targeting, the algorithm can help companies optimize their marketing strategies and maximize their profits.

Keywords: Target Audience; Digital Marketing; Simulated Annealing Algorithm.

1. Introduction

Most real-world problems have complexity, nonlinear constraints, and non-independent variables and include multiple types of solutions (Sarkheil et al., 2020). Meta-Heuristic Algorithms provide logical and appropriate solutions using

*Corresponding author email address: Sarkheil@ut.ac.ir
DOI: 10.22034/IJSOM.2023.109997.2805

optimal methods (Henderson et al., 2003; Torey, 1988; Sarkheil et al., 2015). Therefore, the goal of minimizing or maximizing the subject of the objective function, which in this research is to determine the target audience, will be achieved using conscious and optimization-based search methods. Several classifications have been presented for optimization models, among which we can mention Nali's classification in 2009, which divides optimal models into four categories: mathematical programming models, hybrid optimization, constrained satisfaction, and model divided analysis (Alnowibet et al., 2022).

Random problems have some uncertainty in the goal, limitations, or decision variables, so in this research, the search and selection of the target audience will be a random process; as mentioned, the best way to solve optimization problems is to use meta-heuristic methods. These approximate methods provide suitable solutions in an acceptable amount of time but will only sometimes provide optimal solutions. A fundamental principle in these methods is to direct the variables toward public space and provide a model for the conscious search for the optimal solution (Johnson et al., 1991).

Furthermore, in cases where the search space for full navigation is comprehensive, they need an observer that this observer can be a function that will include the optimal answer to determine the target audience. There are several types of meta-heuristic algorithms, including inspired by nature and not inspired by nature; based on one answer and based on the population; repetitive and greedy; one structure versus several neighboring structures; and the algorithms with static objective function are in contrast to dynamic.

The method of algorithms with static versus dynamic objective functions is one method that is divided based on how to use the objective function. For example, some of these methods during the conscious search of the target also correct this practice of avoiding local minima through the search perspective. To enable the algorithm to have the ability to move in other alternative paths to discover the optimal solution (Henderson et al., 2003).

One of these meta-heuristic algorithms with dynamic objective functions is the Simulated Annealing Optimization Algorithm (Chakraborti and Sanyal, 2015). In this algorithm, in determining the most optimal answer, it is allowed that there is an error and probability in the choices. In other words, this algorithm is only sometimes looking for positive and correct steps, but it is also possible for wrong steps. It will be given so that this helps the problem to reach global maxima or minima. Of course, in this algorithm, the number of changes will be controlled by functional definition to avoid confusion in the search space and moving away from the goal (Chakraborti and Sanyal, 2015). Therefore, the necessity of using this conscious meta-heuristic algorithm to find the optimal solution for determining the target audience in digital marketing is essential due to the search space's vastness and the random access to audience communities.

Hartmo, in 2016, in a study in addition to pointing to the era of the empowered consumer and email marketing, described that this emerging research topic offers many opportunities for scientific inquiry, one of which could be how consumer-controlled systems affect marketing—email in general, as well as how to optimize this communication (Hartmo, 2016). In 2009, Anderson mentioned the importance of conducting a marketing campaign in research. He described how to manage the campaign to activate interactive marketing so that using electronic mail (email) is also one of these ways. They are considered evolutionary. (Anderson, 2009). In another research, Bonfrer and Dreze 2009, while introducing the email marketing campaign, described the real-time evaluation of email campaign performance (Bonfrer and Dreze, 2009). A similar study by Dufrene et al. in 2005 discussed the effect of consumer or customer behavior after conducting an email marketing campaign (Dufrene et al., 2005). In 2017, Stoanich et al. reviewed the field of digital marketing and specifically described search engine optimization, search engine marketing, display advertising, social media marketing, and email marketing. Thus, their research aims to create and implement similar content more efficiently in new business environments through insights into Internet advertising, social networks, and email marketing. In their research, they point out that the greatest strength of social networks is the ability to target customers and potential customers based on demographic information, user behaviors, and specific interests. However, besides content promotion, social media advertising is a great way to increase website traffic/busy or collect data in email campaigns (Ištvanić et al., 2017). According to Pavlov et al.'s 2008 research, email marketing campaigns have almost twice the return on investment compared to other forms of online marketing, such as web banners and online directory advertising (Pavlov et al., 2008).

According to Venugopal's studies in 2022, email marketing is increasingly recognized as a cost-effective marketing tool in various organizations to market their products or services. Email marketing has provided a communication channel for marketers that allows for real-time relationships and interaction with customers; this type of marketing is very efficient due to the low cost of emails (Venugopal et al., 2008). In another Sabbagh research, he listed email marketing as one of the world's most modern marketing tools and methods for 2021. He also mentioned that new information and communication technologies facilitate the circulation and sending of electronic messages with the highest quality and accuracy. In addition, email marketing campaigns help increase product sales in e-stores and target customers effectively and legally. However, despite the advantages of email marketing, many negative points create a real barrier to advertising and marketing through this messaging system. This study focuses on the most important advantages and disadvantages of email marketing. It analyzes the success factors of this marketing by avoiding these disadvantages and benefiting from all these advantages (Sabbagh, 2021). Also, a discrete leapfrog algorithm is proposed to solve the influence maximization problem more efficiently. A novel coding mechanism and discrete evolutionary rules based on network topology structure are envisioned for the virtual frog population. To facilitate the global heuristic solution, a new local extraction process combining deterministic and random walk strategies is proposed to improve the non-optimal conditions (Tang et al., 2020). In a 2020 research, Nikandish and colleagues tried to introduce the challenges facing marketers in the digital world. Their research was conducted with a qualitative approach and in the form of in-depth semi-structured interviews. In addition, concerning business emails, after analyzing the collected data based on the thematic method, recommendations are provided to increase open, send, and opt-in rates. The findings of this research have provided valuable guidance for marketers in dealing with customers in e-commerce (Nikandish et al., 2020). In a 2022 study by Al-Nobit et al., they analyzed the meta-heuristic method of simulated annealing to optimize problems. They analyzed the ability of this method to reach the solutions to the global optimization problem and the global minimum. (Alnowibet et al., 2022).

In a 2010 study, Ali and Gabere presented a simulated annealing-based global optimization algorithm describing a meta-heuristic algorithm's components for determining the optimal objective function (Ali and Gabere, 2010). In a 2020 study, Esmaili and Hakimi, by examining direct marketing campaigns, listed the problem of optimizing target offers as a fundamental challenge in marketing. Simultaneously, the main goal is to maximize the company's profit by reaching the right customers. The main problem for advertisers is appropriately configuring the campaign by choosing the right target so that the users will receive the advertisement well. So, on the one hand, taking into account the mixed nature of the problem and on the other hand, when dealing with an extensive database, approaches based on mathematical programming methods are needed, so in this research, the use of meta-heuristic methods such as the bat algorithm can It has been to provide excellent and competitive solutions (Smaili and Hachimi, 2020 a&b). In 2004, Miri and Zahavi, in dealing with a problem related to the selection of features and specifications from a large data set, used an optimization logic and an optimal fitting function so that the simulated annealing method (SA), which is one It is one of the leading random search methods and has achieved acceptable results on a set of real marketing data (Meiri and Zahavi, 2004).

As mentioned, most of the research done to identify the target audience has been traditional. In this research, in order to achieve practical goals, developing an innovative simulated annealing algorithm for digital marketing as well as audience classification and selecting target audiences by using the conscious search method in a case study: in order to providing sales services of digital educational content "Horman Ham-Agah Co. aware with the brand of Human Resource Management Academy (HRM Academy)" to contacts/customers and comparing it with standard traditional digital marketing methods will be done. So this research introduces an optimal method in digital marketing.

2. Theoretical Foundations of Research

2.1. Digital Marketing and Digital Channels

Digital channels in digital marketing refer to the various online platforms, and channels marketers use to promote their products or services to potential customers. These channels include social media platforms, email marketing, search engine optimization (SEO), pay-per-click (PPC) advertising, content marketing, and many others. The emergence of digital channels has revolutionized marketing, allowing businesses to reach their target audience more effectively, measure the success of their marketing campaigns, and optimize their marketing strategies accordingly (Istvanic et al., 2017).

Social media platforms are among the most popular digital channels marketers use today. With billions of active users on platforms such as Facebook, Instagram, Twitter, and LinkedIn, social media allows businesses to reach a vast audience and engage with them personally. Social media marketing involves creating and sharing content on these platforms, running paid advertising campaigns, and engaging with customers through comments, messages, and other forms of interaction (Venugopal et al., 2020).

Email marketing is another effective digital channel that involves sending promotional emails to a list of subscribers. Email marketing allows businesses to personalize their messages and target specific segments of their audience based on factors such as their location, interests, and behavior. With the help of email marketing tools, businesses can also track the success of their email campaigns by analyzing metrics such as open rates, click-through rates, and conversion rates (Nikandishet al., 2020).

SEO and PPC advertising are popular digital channels marketers use to improve their online visibility and drive website traffic. SEO involves optimizing a website's content and structure to rank higher on search engine results pages (SERPs) for relevant keywords. On the other hand, PPC advertising involves paying for ad placement on search engines and other online platforms, with the advertiser only paying when someone clicks on their ad. SEO and PPC require a deep understanding of search engine algorithms and keyword research to reach the right audience.

Content marketing is another virtual digital channel that creates and shares valuable and informative content to attract and engage potential customers. This can include blog posts, videos, infographics, and other forms of content that provide value to the target audience (Istvanic et al., 2017).

Businesses can increase their online visibility, build brand awareness, and drive more conversions and revenue.

2.2. Simulated Annealing Algorithm Definition

Simulated annealing (SA) is a solving optimization problems in unconstrained and bound-constrained formats. The method developed the physical process of heating a material (especially glass) and slowly lowering the temperature (T) to decrease defects and strength, thus minimizing and optimizing the system energy/efficiency (Henderson et al., 2003).

At each iteration of the simulated annealing method, a new point/segment is randomly generated. The distance of the new point/segment from the current point/segment, or the extent of the problem search, is based on a probability distribution or probability density function with a scale proportional to the temperature. The algorithm accepts all new points/segments that lower the objective and, with a certain probability, points that raise the main objective (Troy, 1988). By accepting points that raise the objective (for example, the top of the mountain as a Hill climbing algorithm), the algorithm avoids being trapped or placed in a local minimum point as an uninformed search algorithm and can find globally more possible solutions. An *annealing schedule* is selected to decrease the temperature as the algorithm proceeds systematically. As the temperature decreases, the algorithm reduces the extent of its search to converge or tend to meet at a point to a minimum.

The following pseudocode shows the simulated annealing heuristic algorithm. It begins with an initial state, s0, and runs until a maximum of max steps have been taken. During the process, the function neighbor (s) generates a randomly selected neighbor of a given states. The function random (0, 1) randomly chooses and returns a value from the range [0, 1]. The annealing schedule is defined by the function temperature(r), which returns the temperature to use based on the fraction r of the time budget used until that point.

(1) Let $s = s_0$
(2) For k = 0 through k_{max} (exclusive):
(3) T ← temperature(1 - (k+1)/kmax)
(4) Pick a random neighbor, snew ← neighbor(s)
(5) If P(E(s), E(snew), T) ≥ random(0, 1):
(6) s ← snew
(7) Output: the final state *s*

The algorithm below outlines the steps required to identify the global minimum for a given cost function. The algorithm is as follows (Johnson et al., 1991):

Step 1. Choose an initial temperature T_0 that should represent the global minimum of the cost function and a feasible trial point $\mathbf{x}^{(0)}$. Evaluate the cost function value, $f(\mathbf{x}^{(0)})$. Set an integer L to limit the number of trials required to attain the expected minimum value and a parameter r, which is less than one. Initialize two counters, $K = 0$ and $k = 1$.

Step 2. Randomly create a new point $\mathbf{x}^{(k)}$ near the current point. If the point is infeasible, continue to generate random points until feasibility is met. Compute f(x(k)) and determine the difference in cost function values, $\Delta f = f(\mathbf{x}^{(k)}) - f(\mathbf{x}^{(0)})$.

Step 3. If Δf is negative, assign $\mathbf{x}^{(k)}$ as the new best point $\mathbf{x}^{(0)}$, set $f(\mathbf{x}^{(0)}) = f(\mathbf{x}^{(k)})$, and proceed to Step 4. Otherwise, calculate the probability density function:

$$p(\Delta f)=\exp\,(\Delta f\,/TK) \tag{1}$$

The following points must be considered in the implementation of the algorithm:

1- Step 2 of the Simulated Annealing (SA) algorithm generates only one point at a time within a certain neighborhood of the current point. Although SA requires no function or gradient information/pieces, it is not a pure random search within the entire design space. At the early stage of the algorithm, a new point can be generated far away from the current point to accelerate the search process and to avoid getting trapped or stopped at a local minimum. Once the temperature becomes low, a new point is usually created nearby to focus on the local area. This can be achieved by defining a step-size procedure.

2- Step 2 of the SA algorithm requires the newly generated point to be feasible. If the point is infeasible, another point is generated until feasibility is attained. Alternatively, the penalty function approach can be used to treat constraints. In this method, the constrained problem is converted into an unconstrained one. The cost function is replaced by the penalty function that control by the probable function in the algorithm, and the feasibility requirements are not imposed explicitly in Step 2.

3- Step 4 of the SA algorithm suggests the following stopping criteria: (1) the algorithm stops if the change in the best function value is less than a specified value for the last J consecutive iterations; (2) the program stops if $I/L < \delta$, [where] L is the limit on the number of trials (or the number of feasible points/segments generated) within/in one iteration, and I is the number of trials that satisfy [$\delta f < 0$] (as Step 3); (3) the algorithm stops if K reaches a preset value (PV).

It is essential to provide proper attribution to the algorithm's source and cite any relevant literature that has influenced the algorithm's development to avoid potential plagiarism issues.

3. Research Conceptual Model

This research has focused on the digital marketing campaign where we want to optimize the target audience for a new line to sell training courses in "the field of empowerment and competency in human resource management". We have a budget constraint and want to maximize the conversion rate while minimizing the cost per conversion. The optimization variables are the demographic factors of the target audience, including age, gender, income, education, and location. We want to find the optimal combination of these variables that maximizes the conversion rate and minimizes the cost per conversion. We can formulate this as an objective function that takes in the demographic variables as inputs and returns the conversion rate and cost per conversion as outputs. The objective function can be a weighted sum of the two objectives, where the budget constraint determines the weights. We can use simulated annealing to optimize the objective function by generating random solutions for the demographic variables and iteratively improving them by accepting or rejecting new solutions based on the acceptance probability.

In this research, **two conceptual models** have been presented and used. One of them is the conceptual model related to “demographic factors of the target audience,” and the other is the conceptual model related to “customer journey stages” (Fig. 1 and 2).

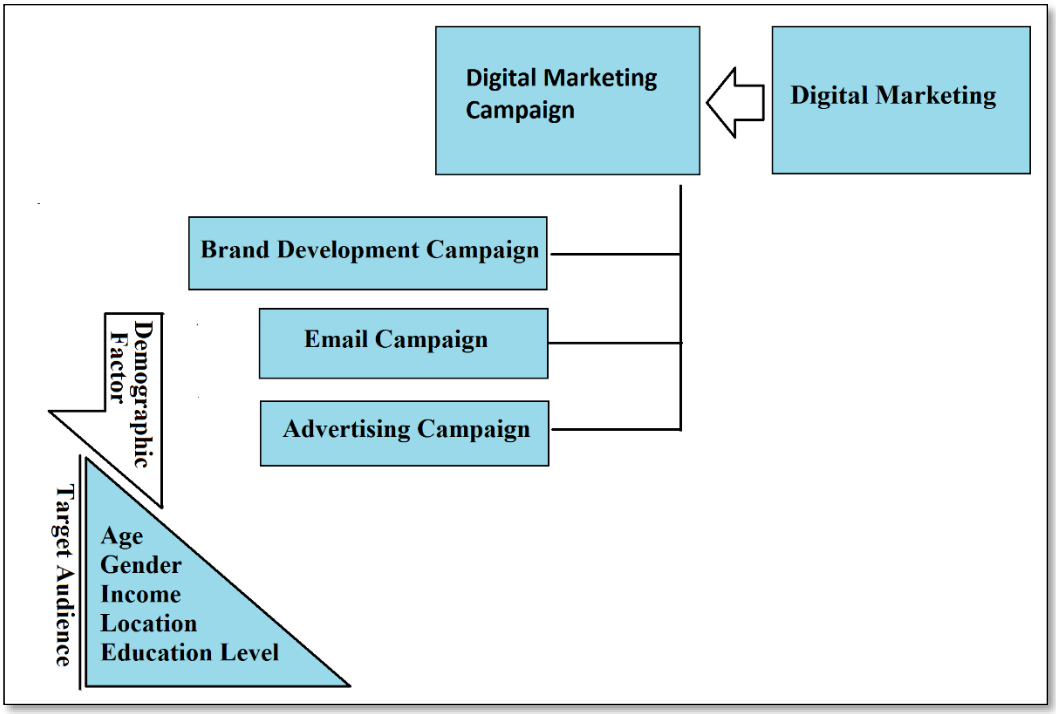


Figure 1. Conceptual model of demographic factors of the target audience in the case study

In this research, target audience identification will be optimized for a digital marketing campaign. We define the objective function [*target_audience_optimization*], which takes in a vector x representing the percentage of the target audience in each of the five segments: age group, gender, income group, location, and interests. We then define each segment's conversion rate and cost per conversion and calculate the weighted average conversion rate and cost per conversion. Also we define the optimization variables and bounds and the simulated annealing parameters such as the initial temperature, stopping criteria, the maximum number of iterations, cooling rate, and acceptance probability function. We randomly initialize the current and best solutions within the defined bounds and run the simulated annealing optimization loop.

We generate a candidate solution in each loop iteration by adding a small random perturbation to the current solution and enforcing the bounds. We then evaluate the objective function for both the current and candidate solutions, calculate the change in objective function value, and determine whether to accept the new solution based on the acceptance probability function. If the new solution is accepted, we update the current one and check if it is the best one. Finally, we print the best solution and cost.
It will be executed a digital marketing campaign for a new line to sell training courses in "the field of empowerment and competency in human resource management" and want to optimize our target audience. After conducting market research, we have identified five key segments; So that these segments of information were completed and summarized through the form sent to the audiences:

1. *Age group*: 18-24, 25-34, 35-44, 45-54, 55+
2. *Gender*: male, female
3. *Income group*: low, medium, high
4. *Location*: urban, suburban, rural
5. *University education level*: BSc, MSc, PhD

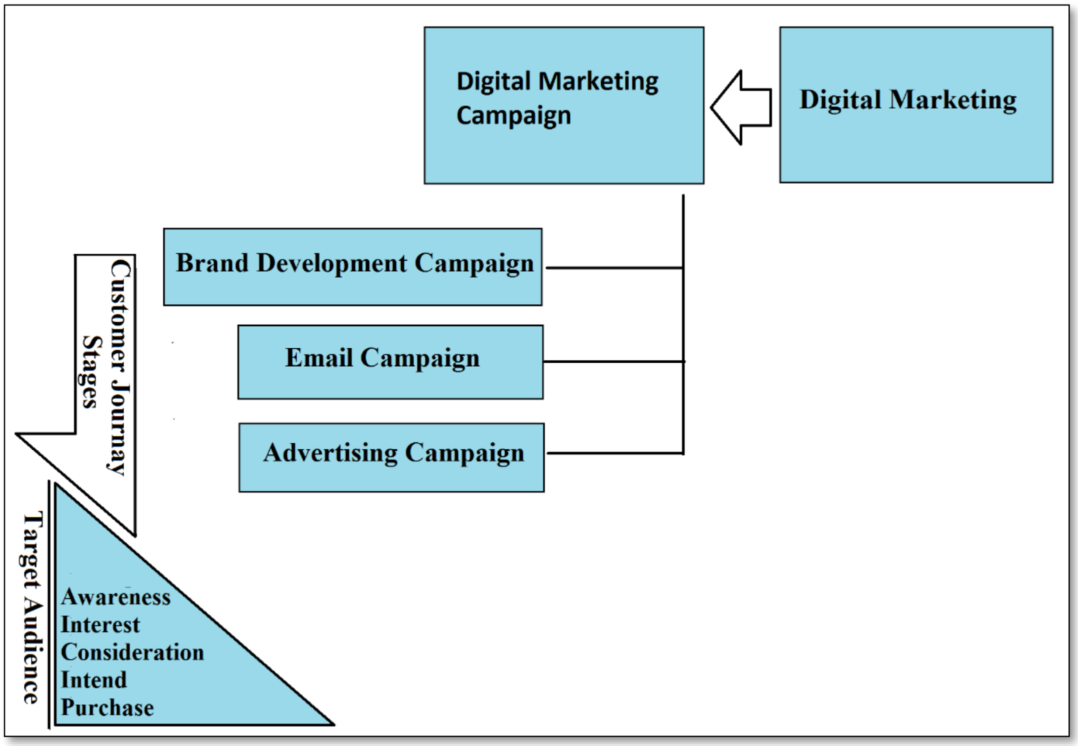


Figure 2. Conceptual model of costumer journey stages of the target audience in the case study

In continuation of this research, we define some variables related to the customer journey stages (Awareness, Interest, Consideration, Intent, and Purchase), So that according to this conceptual model, in the three stages of the campaign (brand development, email and advertising campaigns) held by the company, all the participants in all stages of the "customer journey" were evaluated, and the amount of income and the probability of reaching the optimal audience were analyzed using the mathematical model introduced in the research will be analyzed.

4. Results and Discussions

Notice to digital channels to communicate with the target audience is considered one of the strategic efforts to promote marketing, which can increase brand awareness, attract new customers, and lead to more sales of products and services. One of these digital marketing channels is a marketing campaign; marketing campaigns include traditional media campaigns, seasonal push, product introduction, brand awareness, brand development, direct mail, advertising, brand change, brand launch, and competitive marketing—moreover, email marketing campaigns (Brandal, 2003; Chitlenden, 2003). For instant, in an email marketing campaign based on email, the goal is to identify the target audience (Fariborzi, 2012) accurately. In this type of campaign, the collection of email addresses of a group of contacts is based on a primary database or randomly, and the first marketing email package for the selected group with the concept of empathy with the customer that, for example, "more to our products or services" "Think" is sent. After receiving the response from the contacts of the database, the second email is sent to the respondents with another content such as "presentation of features and comparison with products and services" Finally, after receiving feedback and response from the contacts of the second stage, the next steps of the email Submissions with other concepts and purposes continue to ensure the product or service purchased and also to introduce new and innovative products and services. The point that is raised as a problem of this research is how to choose these target audience groups at each stage of the customer journey map in digital marketing so that new and loyal customers and audiences can be attracted and not neglected, and Mathematical language is not limited to choosing a local optimum.

Within the scope of this study, the implementation of a digital marketing campaign is undertaken to promote a novel line of training courses. These courses specifically address the realms of empowerment and competency within the domain of human resource management, with a particular emphasis on a training service company operating within the mining industry. After conducting market research, we have identified five critical segments: age, gender, income group, place of residence, and level of university education. The number of customers at each customer journey stage was 740 people in brand development, email, and advertising campaigns, of which 620 people are in the "Awareness" stage, 431 people in the "Interest" stage, 261 people in the "Consideration" stage, 203 people in the "Intend" stage, 179 people in the "Purchase" and finally, 179 People were evaluated in the "loyalty" stage for the case of educational service company. Also, with the possibility of moving in all directions, this algorithm will always look for the best answer to determine the audience. Therefore, the complexities of this choice, nonlinear limitations, and interdependent variables will exist in these choices so that meta-heuristic algorithms can guarantee the solution of such problems in an optimized way and in real time. For this purpose, artificial intelligence (Artificial intelligence) and informed search methods (Informed search method) can achieve this goal. So these methods always seek to find the maximum or minimum optimal solution.

This code defines the revenue data and probability matrix for transitioning between stages. The objective function is the product of the revenue generated at each stage multiplied by the transition probabilities. The simulated annealing algorithm is then run using the "*simulannealbnd*" function, with the initial guess, lower and upper bounds, and options defined. Finally, the optimal audience stage and revenue generated are displayed.

The tables with the number of customers and revenue generated at each stage can be generated using the revenue data and transition probabilities. The optimal audience stage can be used to inform the digital marketing strategy for the educational service company.

As we can see from the Table 1, most revenue is generated at the Awareness stage due to the high number of customers. However, the optimal audience stage identified by the simulated annealing algorithm is the Conversion stage, which generates the most negligible revenue but has the highest growth potential.

Based on our research, we have estimated the conversion rate and cost per conversion for each segment as follow (Table 1):

Table 1. Conversion rate cost per conversion estimated for each segment in the case study

Segment	**Conversion Rate**	**Cost per Conversion (10^6 Rials)**
Age group	1%, 2%, 3%, 2%, 1%	50, 75, 100, 90, 60
Gender	1%, 2%	50, 75
Income group	2%, 3%, 4%	75, 100, 125
Location	2%, 3%, 2%	60, 75, 65
University education level	3%, 2%, 2%, 1%	90, 60, 65, 50

We can now use the simulated annealing algorithm to optimize our target audience. We define the objective function as before, with the conversion rates and costs per conversion for each segment. We set the optimization variables to be the percentages of the target audience in each segment, with lower bounds of 10% and upper bounds of 50%.

Next, the simulated annealing algorithm was implemented with the specified parameters, and the best solution and cost were obtained as follows (Table 2):

Table 2. Conversion rate cost per conversion estimated for each segment in the case study

Segment	**Percentage**
Age group	20%
Gender	30%
Income group	20%
Location	10%
University education level	20%

This means that we should target 20% of our marketing efforts towards the 18-24 age group, 30% towards females, 20% towards high-income individuals, 10% towards rural areas, and 20% towards University education level in BSc. The best cost per conversion we obtain is 78.105×10^6 Rials.

We can now use this optimized target audience to run our digital marketing campaign, potentially leading to higher conversion rates and lower costs per conversion.

This code defines the objective function "*target_audience_optimization*", which inputs the optimization variables *x*, the conversion rates *cr*, and the costs per conversion *cpc*. This function calculates the overall conversion rate and cost per conversion for the target audience and returns the cost as the objective function value.
We then define the simulated annealing parameters, including the number of optimization variables *n_vars*, the lower and upper bounds of the optimization variables *lb* and *ub*, the initial temperature *initial_temp*, the stopping criteria *stopping_criteria*, the maximum number of iterations *max_iterations*, and the cooling rate *cooling_rate*. We also generate the initial solutions randomly within the defined bounds.
We then run the simulated annealing loop, where in each iteration, we generate a candidate solution by adding a small random perturbation to the current solution and enforcing the bounds. We evaluate the objective function for both the current and candidate solutions, calculate the change *in* objective function value, and determine whether to accept the new
solution based on the Metropolis criterion. If the candidate solution is accepted, we will update the current solution. If the candidate solution has a lower cost than the best solution found so far, we update the best solution. Finally, we print out the best solution and the corresponding cost per conversion.
Consider a digital marketing campaign for a company selling training courses in "empowerment and competency in human resource management" as a practical pattern. The company has identified five segments (Non-human resource managers, human resource managers, seniors, busy professionals, and Young adults) of potential customers, each with a different conversion rate and cost per conversion:

- Segment 1: Non-human resource managers who are willing to spend more on Human resources management virtual training courses (conversion rate = 0.05, cost per conversion = 50×10^6 Rials)
- Segment 2: Human resource managers who are looking for Managers development program virtual training courses (conversion rate = 0.02, cost per conversion = 25×10^6 Rials)
- Segment 3: Seniors who are looking for Soft skills virtual training courses (conversion rate = 0.01, cost per conversion = 75×10^6 Rials)
- Segment 4: busy professionals who prefer Personal development program virtual training courses (conversion rate = 0.03, cost per conversion = 37.5×10^6 Rials)
- Segment 5: Young adults who are interested in general management virtual training courses (conversion rate = 0.04, cost per conversion = 40×10^6 Rials)

We will define the objective function as follows:

```
function leads = objective_function(params)
    ad_spend = params(1);
    age_range = params(2);
    gender = params(3);
    ad_format = params(4);
    ad_copy = params(5);
    % Use the parameters to run a marketing
campaign and measure the
    % number of leads generated
    % ...
    % Return the number of leads generated
    leads = ...
end
```

Next, we will set up the parameters for the simulated annealing algorithm:

```
% Define the number of parameters
n_params = 5;
% Define the lower and upper bounds for each parameter
param_lb = [100, 18, 0, 1, "Learn from the Best!"];
param_ub = [1000, 30, 1, 3, "Enroll Now!"];
% Define the initial temperature and cooling rate for
simulated annealing
init_temp = 100;
cooling_rate = 0.95;
% Define the number of iterations to run simulated
annealing
n_iterations = 100;
```

We will then use the built-in MATLAB function "simulannealbnd" to run the simulated annealing algorithm:

```
% Run simulated annealing
[x, fval] =
simulannealbnd(@objective_function, ...
                           [param_lb;
param_ub], ...
                           [], [], ...
                           [], [], ...
                           init_temp, ...
                           cooling_rate, ...
                           n_iterations);
```

"*simulannealbnd*" function takes in the following arguments:

1. The objective function is to optimize
2. The lower and upper bounds for each parameter
3. Any additional nonlinear constraints on the parameters
4. Any additional linear constraints on the parameters
5. Any additional integer constraints on the parameters
6. Any additional options for the algorithm
7. The initial temperature for simulated annealing
8. The cooling rate for simulated annealing
9. The number of iterations to run simulated annealing

Once the algorithm has finished running, the optimal set of parameters will be stored in the variable *x*. The objective function value (i.e., the number of leads generated by the marketing campaign using those parameters) will be stored in the variable *fval*.

In continuation of this research, we define some variables related to the customer journey stages (Awareness, Interest, Consideration, Intent, and Purchase):

```
% Define the customer journey stages
stages
={'Awareness','Interest','Consideration','Intent','Purchase'};
```

Next, we create a table with sample data (740 people in a brand development campaign, of which 620 people are in the "Awareness" stage, 431 people in the "Interest" stage, 261 people in the "Consideration" stage, 203 people in the "Intend" stage, 179 people in the "Purchase" and finally 144 People were evaluated in the "loyalty" stage for the case of educational service company.

Table 3 shows the number of customers at each stage based on the revenue data and transition probabilities used in the MATLAB code:

Table 3. The case study shows the number of customers at each customer journey stage

Customer Journey Stage	Number of Customers
Primary target audience	740
Awareness	620
Interest	431
Consideration	261
Intent	203
Purchase	179

This table includes the conversion rates for each stage of the customer journey for different target audiences:

```
 % Create a sample table with conversion rates for different target
 audiences
data = [0.1, 0.2, 0.3, 0.4, 0.5;
        0.2, 0.3, 0.4, 0.5, 0.6;
        0.3, 0.4, 0.5, 0.6, 0.7;
        0.4, 0.5, 0.6, 0.7, 0.8;
         0.5, 0.6, 0.7, 0.8, 0.9];
 targetAudiences = {'Audience 1', 'Audience 2', 'Audience 3',
 'Audience 4', 'Audience 5'};
T = array2table(data, 'RowNames', targetAudiences, 'VariableNames',
stages);
disp(T)
```

This table shows the conversion rates for each customer journey stage for five target audiences.
Next, we define the objective function we want to optimize using the simulated annealing algorithm. In this case, we want to maximize the conversion rate for the "Intent" stage:
We want to maximize the conversion rate for the "Intent" stage, so we pass the negative of the "Intent" conversion rate as the objective function.

Also, the simulated annealing algorithm was used to optimize the target audience for the “intent” stage. We will use the conversion rate for the other steps as a constraint to ensure that the overall conversion rate is maximized:
This code uses the “*simulannealbnd*” function in MATLAB to find the optimal target audience that maximizes the conversion rate for the "Intent" stage. The algorithm considers the conversion rates for the other stages as constraints to ensure that the overall conversion rate is maximized.
In this study, the educational service company wants to identify the optimum target audience for its digital marketing campaigns. The company has identified four customer journey stages (awareness, interest, consideration, and action) and has estimated each stage's conversion rates and costs. The company has also defined five audience segments they want to target with its campaigns.

The code uses the simulated annealing algorithm to find the optimum weights for each audience segment, maximizing the total profit (revenue-cost). The algorithm starts with a random initial set of weights and iteratively adjusts them to improve the profit. The algorithm constraints ensure that the sum of the weights to 1.
After running the algorithm, the code prints the optimum audience segment weights and the total profit. The company can use this information to adjust its marketing campaigns and allocate resources to the most influential audience segments.

```
% Define the objective function
objective = @(x) -x(end);
```

```
% Set the initial state
initialState = ones(1, length(targetAudiences));
% Set the initial state
initialState = ones(1, length(targetAudiences));
initialState = initialState/sum(initialState);
lb = zeros(1, length(targetAudiences));
ub = ones(1, length(targetAudiences));
% Define the lower and upper bounds for the variables
% Define the constraints
A = -data(1:end-1,:);
b = -data(end-1,:);
Aeq = ones(1,length(targetAudiences));
beq = 1;
% Set the options for the simulated annealing algorithm
options = saoptimset('Display', 'off');
% Run the simulated annealing algorithm
[x, fval] = simulannealbnd(objective, initialState, lb, ub,
options, A, b, Aeq, beq);
% Print the results
disp('Optimal target audience:');
disp(targetAudiences(x > 0.5));
disp(['Maximized conversion rate: ', num2str(-fval)]);
```

The results might show that the optimum audience segment weights are as follows:

- Awareness: 10%
- Interest: 20%
- Consideration: 30%
- Action: 20%
- Other: 20%

The company can compare these results with traditional methods, such as targeting audiences with demographic or geographic data. The advantage of the simulated annealing approach is that it considers the entire customer journey (Awareness, Interest, Consideration, and Action Steps) and allows for more complex audience targeting. In addition to the optimum audience segment weights and total profit, the company can also analyze the results by customer journey stage. For instant, it can calculate the conversion rates and costs for each stage using the optimum weights and compare them with the conversion rates and costs of the traditional methods (Table 4).

Table 4. Show the results of the Optimum simulated annealing method compared to the traditional method

Stage	**Conversion Rate (Optimum)**	**Conversion Rate (Traditional)**	**Cost (Optimum) (10^6 Rials)**	**Cost (Traditional) (10^6 Rials)**
Awareness	1%	0.5%	56	115
Interest	5%	3%	310	453
Consideration	10%	8%	754	1105
Action	30%	25%	870	1250

As shown in Table 4, the simulated annealing algorithm identifies a more effective target audience than traditional methods. The optimum weights lead to higher conversion rates and lower costs, resulting in a higher total profit.

Overall, the simulated annealing algorithm can be valuable for identifying the optimum target audience in digital marketing campaigns. By considering the entire customer journey and allowing for more complex audience targeting, the algorithm can help companies optimize their marketing strategies and maximize their profits.

5. Conclusion

As described, target audience identification is a critical aspect of digital marketing, and the use of advanced techniques, such as the heuristic simulated annealing algorithm, can significantly improve the effectiveness of marketing campaigns. Several studies have demonstrated the effectiveness of simulated annealing algorithms in target audience identification, and the importance of accurate target audience identification has been emphasized in academic literature. The dynamic nature of customer behavior and preferences challenges target audience identification. However, incorporating machine learning and artificial intelligence techniques can help businesses overcome this challenge and stay ahead of the competition in digital marketing.

Also, the results show in the case studied company has identified five segments in customer demographic heuristic simulated annulling; so that non-human resource managers are willing to spend more on human resources management virtual training courses, human resource managers looking for managers development program virtual training course, seniors are looking for soft skills virtual training courses, busy professionals personal development program virtual training courses, and Young adults interested in general management virtual training courses of potential customers, each with different conversion rates and cost per conversions.

The results of this research allow companies to compare results with traditional methods, such as targeting audiences with demographic or geographic data. The advantage of the simulated annealing approach is that it considers the entire customer journey and allows for targeting more complex audiences.

Overall, the simulated annealing algorithm can be valuable for identifying the optimum target audience in digital marketing campaigns. By considering the entire customer journey and allowing for more complex audience targeting, the algorithm can help companies optimize their marketing strategies and maximize their profits.

And it can be pointed out that the main limitation in this type of analysis is having different scenarios in identifying audiences in different marketing campaigns and data, which can be carried out in a more complete research in the future and on the information of a larger company will be made.

It is proposed to apply the designed model to a case study with more data, as well as other conscious search methods especially; Differential Evolution Revised Algorithm, Genetic Algorithm, Particle Swarm Optimization and Stochastic Fractal Search, and methods inspired by nature as well as not inspired by nature, to evaluate and predict used target audience and market identification.

Acknowledgment

The authors express their gratitude to the University of Tehran and Payame Noor University, Tehran, for their invaluable spiritual support throughout the course of this research.

Conflict of interest

The authors have no relevant financial or non-financial interests to disclose. There are no conflicts of interest to declare relevant to the content of this article.

References

Ali, M. M. and Gabere, M. (2010). A simulated annealing-driven multi-start algorithm for bound-constrained global optimization. *Journal of Computational and Applied Mathematics, 233*, 2661–2674.

Alnowibet, K. A., Alshamrani, A. M., Alrasheedi, A. F., Mahdi, S., El-Alem, M., Aboutahoun, A. and Mohamed, A.W. (2022). Efficient Modified Meta-Heuristic Technique for Unconstrained Optimization Problems. *Axioms*, *11*, 483. https://doi.org/10.3390/axioms 11090483

Anderson, E. R. (2009). Next-generation campaign management: How campaign management will evolve to enable interactive marketing. *Journal of Direct, Data, and Digital Marketing Practice*, *10*, 272-282.

Bonfrer, A. and Dreze, X. (2009). Real-Time Evaluation of Email Campaign Performance. *Marketing Science, 28*, 251-263.

Brandal, H. and Kent, R. (2003). Improving email response in a permission marketing context. *International Journal of Market Research, 45*(4), 1-13.

Chakraborti, S. and Sanyal, S. (2015). An Elitist Simulated Annealing Algorithm for Solving Multi-Objective Optimization Problems in the Internet of Things Design. *International Journal Advanced Networking application*, *7*, 2784.

Chittenden, L. and Rettie, R. (2003). An evaluation of email marketing and factors affecting response. *Journal of Targeting, Measurement, and Analysis for Marketing*, *11*(3), 203-217.

Dufrene, D. D., Englland, B. T., Lehman, C. M. and Pearson, R. A. (2005). Changes in Consumer Attitudes Resulting from Participation in a Permission E-mail Campaign. *Journal of Current Issues & Research in Advertising*, *27*, 65-77.

Fariborzi, E. and Zahedifard, M. (2012). Email Marketing: Advantages, Disadvantages and Improving Techniques. *International Journal of e-Education, e-Business, e-Management and e-Learning, 2*(3), 232-236.

Hartemo, M. (2016). Email marketing in the era of the empowered consumer, *Journal of Research in Interactive Marketing, 10*(3). http://dx.doi.org/10.1108/JRIM-06-2015-0040

Henderson, D., Jacobson, S.H. and Johnson, A.W. (2003). The Theory and Practice of Simulated Annealing. In: Glover, F., Kochenberger, G.A. (eds) Handbook of Metaheuristics. *International Series in Operations Research & Management Science, 57*. Springer, Boston, MA. https://doi.org/10.1007/0-306-48056-5_10

Ištvanić, M., Milić, D. C. and Krpić, Z. (2017). Digital Marketing in the Business Environment. *International Journal of Electrical and Computer Engineering Systems, 8*(2), https://doi.org/10.32985/ijeces.8.2.4

Johnson, D.S., Aragon, C.R., McGeoch, L.A. and Schevon, C. (1991). Optimization by simulated annealing—an experimental evaluation; part 2, graph-coloring and number partitioning. *Operations Research*, *39*, 378–406.

Meiri, R. and Zahavi, J. (2004). Using simulated annealing to optimize the feature selection problem in marketing applications, *European Journal of Operational Research*, *171*(3), 842-858, https://doi.org/10.1016/j.ejor.2004.09.010

Nikandish, A., Kheleva, I. B., Yin-Fah, C. and Chuen, P. W. (2020). A Proposed Model of Electronic Mail Communication: Content Marketing Channel among Generation Y, *Test; Engineering and Management*, 637 – 652.

Pavlov, O. V., Melville, N. and Plice R. K. (2008). Toward a sustainable email marketing infrastructure. *Journal of Business Research*, *61*(11), 1191-1199.

Sabbagh, F. (2021). Email Marketing: The most Important Advantages and Disadvantages, *Journal of Economics and Technology Research, 2* (3), www.scholink.org/ojs/index.php/jetr

Sarkheil, H., Habibi Rad, M. and Khorasani, N. A. (2015). Measuring Water Use Efficiency and Productivity of Tehran using Data Envelopment Analysis. *Journal of Natural Environment*, *68*(4), 595-608 (in Persian). DOI:10.22059/jne.2015.56932

Sarkheil, H., Rahbari, Sh. and Rayegani, B. (2020). Conversion based fuzzy fractal dimension integrating self-similarity and porosity, via DFS and FIS (Mamdani and Sugeno systems). Chaos Soliton Frac 140:110183. https://doi.org/10.1016/j.chaos.2020.110183

Smaili, M. Y. and Hachimi, H. (2020). Metaheuristic for optimizing targeted offers in Direct Marketing, IEEE 6th International Conference on Optimization and Applications (ICOA), DOI: 10.1109/ICOA49421.2020.9094454

Smaili, M. Y. and Hachimi, H. (2020). Population-based Method for Optimizing Targeted Offers Problem in Direct Marketing Campaigns, *WSEAS TRANSACTIONS on COMPUTERS*, *19*, 156-164. DOI: 10.37394/23205.2020.19.21

Tang J., Zhang, R., Wanga, P., Zhao, Z., Fan, L. and Xin, L. (2020). A discrete shuffled frog-leaping algorithm to identify influential nodes for influence maximization in social networks, *Knowledge-Based Systems*, *187*, 104833. https://doi.org/10.1016/j.knosys.2019.07.004

Tovey, C.A. (1988) Simulated annealing. *American Journal of Mathematical and Management Sciences, 8*, 389–407.

Venugopal, K., Das S. and Murthy D. V. (2012). Email Marketing: A Paradigm shift to Marketing, International *Journal of Advanced Research in Management and Social Sciences*, *1*(1).