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RESEARCH ON GRA, PSI AND MOORA METHODS FOR OPTIMAL 3D PRINTER SELECTION

NGHIÊN CỨU PHƯƠNG PHÁP PHÂN TÍCH XÁM (GRA), LỰA CHỌN CHỈ SỐ ƯU TIÊN(PSI) VÀ TỐI ƯU DỰA TRÊN PHÂN TÍCH TỶ LỆ (MOORA) TRONG LỰA CHỌN MÁY IN 3D

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Tóm tắt

This paper presents the application of MCDM methods to optimize the selection of 3D printers based on 8 technical criteria and prices of 7 individual printer models. Three methods are used, including GRA (Grey Relational Analysis), PSI (Preference Selection Index) and MOORA (Multi Objective Optimization on the Basis of Ratio Analysis) to compare and determine the optimal choice. The results show that all three methods identify Ender 3 V3 (P3) as the most optimal solution, although there is a difference in the ranking order of the remaining solutions. This difference is mainly due to the difference in the data normalization process and the determination of the weights of each method. MOORA uses vector normalization, while PSI and GRA use max-min normalization. In addition, GRA and MOORA also consider the criteria in positive, negative and nominal directions, while PSI does not do this. The study confirms the applicability of MCDM methods in the problem of optimal machine selection.

Từ khóa: *MCDM, PSI, GRA, MOORA, 3D printer..*

Abstract

Bài báo trình bày ứng dụng các phương pháp MCDM để tối ưu lựa chọn máy in 3D dựa trên 8 tiêu chí kỹ thuật và giá cả của 7 mẫu máy in cá nhân. Ba phương pháp được sử dụng gồm GRA (Grey Relational Analysis), PSI (Preference Selection Index) và MOORA (Multi Objective Optimization on the Basis of Ratio Analysis) nhằm so sánh và xác định lựa chọn tối ưu. Kết quả cho thấy cả ba phương pháp đều xác định Ender 3 V3 (P3) là phương án tối ưu nhất, mặc dù có sự khác biệt trong thứ tự xếp hạng các phương án còn lại. Sự khác biệt này chủ yếu do sự khác nhau trong quá trình chuẩn hóa dữ liệu và xác định trọng số của từng phương pháp. MOORA sử dụng chuẩn hóa vector, trong khi PSI và GRA sử dụng chuẩn hóa max - min. Ngoài ra, GRA và MOORA còn xem xét các tiêu chí theo hướng tích cực, tiêu cực và danh nghĩa, trong khi PSI không thực hiện điều này. Nghiên cứu khẳng định tính khả dụng của các phương pháp MCDM trong bài toán lựa chọn tối ưu máy móc.

Keywords: *MCDM, PSI, GRA, MOORA, máy in 3D.*

1. Introduction

3D printing, commonly referred to as Additive Manufacturing, represents a transformative innovation of the Industry 4.0 era [1]. This technology enables the creation of physical objects by successively stacking layers of material based on digital models, and it has demonstrated its critical importance across numerous fields. Applications of 3D printing span medicine and dentistry, aerospace, automation, jewelry design, architecture, and fashion [2]. Within these domains, 3D printing optimizes manufacturing processes and facilitates the production of intricately shaped products that traditional manufacturing methods often cannot achieve [3].

The rapid expansion of the 3D printer market has led to an abundance of choices for users. However, selecting an appropriate 3D printer poses significant challenges due to the diverse and often conflicting evaluation criteria. These criteria encompass accuracy, layer thickness, printing speed, maximum product size, energy consumption, and cost [4]. The inherent trade offs among these factors for instance, lower cost printers frequently lacking high precision and durability add complexity to the decision making process.

To address these challenges, multi criteria decision making (MCDM) methods have been extensively employed as effective tools for supporting machine selection. Techniques such as the Technique for Order Preference by Preference Selection Index (PSI), Grey Relational Analysis (GRA), and Multi Objective Optimization On The Basis Of Ratio Analysis Method (MOORA) have proven particularly effective [5]. Several studies have substantiated the applicability and advantages of Multiple Criteria Decision Making (MCDM) techniques across different industrial sectors. Alpay et al. [6] and Stirbanovic et al. [7] have documented the effective application of MCDM methods in the selection of machinery for the mining industry. In a similar vein, Temiz et al. [8] and Ugur et al. [9] have provided compelling evidence of the benefits associated with utilizing MCDM approaches within the construction industry. Moreover, investigations conducted by Ertugrul et al. [10] have further corroborated the preference for MCDM techniques in resolving machinery selection challenges in the textile industry, ultimately enabling textile companies to optimize their production processes through the judicious selection of appropriate equipment.

Beyond identifying the most efficient 3D printer, the application of these MCDM methods seeks to leverage the technical parameters of existing printers as a foundation for designing new models. By analyzing and referencing existing machines, this approach aims to contribute to advancements in 3D printing technology, specifically the development of printers that better meet practical needs in terms of performance, cost, and functionality.

This study applies three prominent MCDM methods, GRA, PSI, and MOORA, for analysis and comparison. GRA, based on gray system theory, is particularly suitable when data is lacking or noisy; PSI has a simple calculation process, allowing the construction of a priority index from normalized data; MOORA applies vector normalization and separates criteria into “benefits” and “costs,” making it easy to handle criteria with different units of measurement. Combining the three methods allows cross comparison of results and assessment of the stability of rankings, thereby increasing the objectivity of the study. The investigation focuses on evaluating seven popular personal 3D printers from various manufacturers, including Anycubic Kobra 2, Elegoo Neptune 4, Ender 3 V3, Dewang ENTER 3 PRO, Mingda D2, Prusa i200, Mi-ho BLU-3. Using eight technical and price criteria, this study aims to rank these printers and make recommendations for optimal selection.

2. Mothodology

The problem of machine selection frequently manifests as a MCDM challenge, wherein the incorporation of multiple criteria introduces diverse perspectives and intensifies the complexity of the underlying information. The principal objective of MCDM methods is to assist decision makers in systematically organizing and synthesizing pertinent information, thereby optimizing the decision making process and reducing the likelihood of erroneous choices through the comprehensive satisfaction of the established criteria.

The GRA method is particularly advantageous in situations characterized by incomplete or noisy data, as it facilitates effective information access and analysis even under conditions of limited data availability [11]. However, GRA often encounters challenges in the determination of criterion weights, a factor that can markedly influence the final ranking of alternatives. MOORA method is recognized for its simplicity, computational efficiency, and ability to accommodate heterogeneous criteria, rendering it a valuable tool for multi criteria decision making [12]. Nevertheless, similar to GRA, MOORA necessitates a prior process of data normalization and the accurate determination of criterion weights. Meanwhile, the PSI method offers the advantages of conceptual simplicity and the capacity to integrate diverse pieces of information, particularly in scenarios where weight determination is problematic [13]. Despite these strengths, PSI is subject to limitations concerning data sensitivity and its effectiveness in reflecting complex interrelationships among criteria. In general, these methods all have their own advantages and disadvantages, and the use of any method has trade offs.

2.1. PSI method

The PSI method is implemented through the following basic calculation steps:

1. Determine the set of criteria and alternatives to be evaluated, from which a decision matrix with corresponding values is established.

2. Normalize the decision matrix: Convert the initial values into unitless values to ensure similarity between different criteria.

+ The larger the criteria, the better the ranking is

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determined:

$$R_{ij} = \frac{x_{ij}}{x_j^{max}} \quad (1)$$

+ The smaller the criteria, the better the ranking is determined:

$$R_{ij} = \frac{x_j^{min}}{x_{ij}} \quad (2)$$

3. Determine the average value of the standardized data:

$$R = \frac{1}{n}\sum_{i=1}^{n} R_{ij} \quad (3)$$

4. Determine the deviation of the standardized value:

$$\phi_j = \left(1 - V_j\right) \quad (4)$$

Where V_j is the preferred value from the average value: $V_j = \sum_{i=1}^{n}(R_{ij} - R)^2$

5. Determine the overall preference

$$\Psi_j = \frac{\phi_j}{\sum_{j=1}^{m} \phi_j} \quad (5)$$

6. Calculate the PSI value

$$I_j = \sum_{j=1}^{m}(R_{ij} \times \Psi_j) \quad (6)$$

7. In the last step, based on the calculated PSI value, the alternatives are ranked from high to low or vice versa, depending on the nature of the index to make the final choice.

2.2. GRA method

GRA method has emerged as one of the most widely adopted methods in MCDM. Serving as a quantitative tool within the framework of gray system theory, GRA is particularly adept at managing imprecise and incomplete information. The computational procedure of GRA can be delineated through the following sequential steps:

1. Construct the initial decision matrix

2. Normalize the decision matrix: The criteria have different units of measurement and value ranges, so the values need to be converted to unitless form. The normalization formula depends on the nature of the criteria:

+ For criteria with the nature of *"maximization"*:

$$X_i^* = \frac{X_i - min\ X_i}{max\ X_i - min\ X_i} \quad (7)$$

+ For criteria with the nature of *"minimization"*:

$$X_i^* = \frac{max\ X_i - X_i}{max\ X_i - min\ X_i} \quad (8)$$

3. Determine the reference chain:

$$X_0^* = \max X_i^*(k)\,,\ k = 1,2,\ldots,n \quad (9)$$

4. Calculate the absolute distance between the reference chain and the object chains:

$$\Delta_{min} = min|X_0^* - X_i^*|$$
$$and\ \Delta_{max} = max|X_0^* - X_i^*| \quad (10)$$

5. Calculate the gray relation coefficient

$$\gamma_i = \frac{\zeta\Delta_{max} + \Delta_{min}}{\zeta\Delta_{max} + \Delta_i} \quad (11)$$

With the value Δ_i being the skewed series, ζ being the distinguishing coefficient ranging from 0 to 1.

6. Calculate the combined gray relation index

$$\Psi_i = \sum_l^z w_i.\gamma_i \quad (12)$$

Where w_i is the weight of the targets to the gray relation. This weight can be determined by the Principal Component Analysis (PCA) method as follows:

+ The coefficient correlation matrix is determined

$$R_{il} = \left(\frac{Cov\left(y_p(q),\left(y_p(l)\right)\right)}{\sigma_{yp}(q)\times\sigma_{yp}(l)}\right); q = 1,2,\ldots k \quad (13)$$

+ The correlation coefficient of the array is used to determine the eigenvectors and the eigenvalues are shown:

$$V_{ji}(R_{il} - \lambda_l I_n) = 0 \quad (14)$$

Where λ_l is eigenvalues, V_{ji} is eigenvectors corresponding to the eigenvalues, l = 1,2,..k.

+ The uncorrelated principal component is determined:

$$Z_{jk} = \sum_{i=1}^{n} Y_j \times V_{ji} \quad (15)$$

Z_{jk} represent the kth principal component. Since the eigenvalues and principal components are arranged in descending order based on the variance they explain, the eigenvalue corresponding to the first principal component accounts for the largest contribution to the overall variance.

7. Rank the alternatives: Based on the Ψ_i value of each alternative, rank from high to low. The alternative with the highest Ψ_i is considered the optimal alternative according to the evaluation criteria of the problem.

2.3. MOORA method

The calculation steps of MOORA are summarized as follows:

1. Construct the initial decision matrix

2. Normalize the decision matrix

$$X'_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}};\ j = 1,2,\ldots n \quad (16)$$

3. Calculate the weighted matrix:

$$Y_{ij} = w_j \times X_{ij}^{\prime} \quad (17)$$

Where the weight can be determined by the Entropy or PCA method.

4. Determine the overall evaluation index of each alternative: Divide the criteria into two groups with I_{max} being the set of benefit criteria (to be maximized) and I_{min} being the set of cost criteria (to be minimized)

$$S_i = \sum_{j \in I_{max}} Y_{ij} - \sum_{j \in I_{min}} Y_{ij} \quad (18)$$

5. Rank the alternatives: The highest S_i is considered the optimal choice according to the proposed criteria.

3. Results and discussion

The seven printers selected for this study represent a cross section of personal printers currently available on the market. They were chosen not only for their widespread availability but also for their relevance to everyday consumer needs. The printing material used by these printers is PLA, which is a common material that can be printed in open spaces and is less demanding on the environment. The evaluation of these printers was based on a set of criteria derived from the specifications that manufacturers typically highlight to assist customers in making informed purchasing decisions. These specifications, which are often reflective of consumer priorities, serve as the foundation for assessing the performance and suitability of each printer. The eight criteria of the seven printers are listed in Table 1.

Where:

+ 7 printers including Anycubic Kobra 2 (P1), Elegoo Neptune 4 (P2), Ender 3 V3 (P3), Dewang ENTER 3 PRO (P4), Mingda D2 (P5), Prusa i200 (P6), Mi-ho BLU-3 (P7)

+ 8 criteria including: C1 is layer thickness (mm), C2 is maximum printing speed (mm/s), C3 is power capacity (W), C4 is maximum temperature of extruder (ºC), C5 is net weight (kg), C6 is printing accuracy (mm), C7 is printing volume = LxBxH (cm^3), C8 is cost (million VND).

3.1. PSI method calculations

The criteria presented in the decision matrix (Table 1) were processed using the PSI method, with the resulting data detailed in the tables below. In the initial stage, the collected data were normalized by distinguishing between criteria that are "larger is

Table 1. Information on 3D printer criteria

No.	C1	C2	C3	C4	C5	C6	C7	C8
P1	0.3	300	400	260	8.5	0.1	12100	5.9
P2	0.4	250	350	300	8.9	0.1	13416	4.8
P3	0.3	250	300	260	7.2	0.1	12100	4.4
P4	0.4	180	270	250	10.5	0.1	12100	9.8
P5	0.4	100	320	230	9.8	0.05	13754	7.4
P6	0.3	120	240	265	12.5	0.05	8000	6.4
P7	0.4	200	240	260	8.2	0.1	14812	7.8

Table 2. Normalized value by PSI method

No.	C1	C2	C3	C4	C5	C6	C7	C8
P1	1.00	1.00	0.60	0.87	0.85	0.50	0.82	0.75
P2	0.75	0.83	0.69	1.00	0.81	0.50	0.91	0.92
P3	1.00	0.83	0.80	0.87	1.00	0.50	0.82	1.00
P4	0.75	0.60	0.89	0.83	0.69	0.50	0.82	0.45
P5	0.75	0.33	0.75	1.00	0.73	0.50	0.93	0.59
P6	1.00	0.40	1.00	0.88	0.58	1.00	0.54	0.69
P7	0.75	0.67	1.00	0.87	0.88	0.50	1.00	0.56

Table 3. Values of the deviation parameters and the overall preference

No.	C1	C2	C3	C4	C5	C6	C7	C8
V_j	0.11	0.35	0.14	0.03	0.12	0.21	0.13	0.23
ϕ_j	0.89	0.65	0.86	0.97	0.88	0.79	0.87	0.77
ψ_j	0.13	0.10	0.13	0.15	0.13	0.12	0.13	0.12

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better" and those that are "smaller is better," as outlined in Equations (1) and (2). Specifically, criteria C1, C3, C5, C6, and C8 are intended to be minimized, while criteria C2, C4, and C7, being benefit criteria, are to be maximized. The normalized results are displayed in Table 2. Subsequently, the parameters listed in Table 3 were determined using Equations (3), (4), and (5). Equation 7 was used to determine the PSI value to evaluate and rank the alternatives. The PSI value results are shown in the summary Table 12.

3.2. GRA method calculations

In the GRA method, data normalization similarly requires distinguishing between criteria that need to be maximized and those that need to be minimized, akin to the approach utilized in the PSI method. However, beyond the standard objective of standardizing data collected from diverse sources, an additional motivation for normalizing data within a smaller range is the broad variability inherent in the original decision matrix. Thus, normalization enhances consistency and interpretability when the raw data span a wide range.

The normalization steps in the GRA procedure are implemented via Equations (7) and (8), the results are shown in Table 4. Subsequently, the reference sequence and absolute value matrix are derived using Equations (9) and (10), contingent upon whether each criterion is characterized as a benefit or cost (Table 5). Following these calculations, the GRA correlation coefficient matrix is obtained through Equation (11) and the results are shown in Table 6. In this calculation procedure, the distinguishing coefficient (ζ) applied is 0.5 to adjust the uniform sensitivity between the reference value and the observed value.

Subsequently, determining the grey relational grade necessitates the specification of criterion weights. In multi criteria problems, each criterion may exhibit a distinct level of importance, thereby

Table 4. Normalized value by GRA method

No.	C1	C2	C3	C4	C5	C6	C7	C8
P1	1.00	1.00	0.00	0.43	0.75	0.00	0.60	0.72
P2	0.00	0.75	0.31	1.00	0.68	0.00	0.80	0.93
P3	1.00	0.75	0.63	0.43	1.00	0.00	0.60	1.00
P4	0.00	0.40	0.81	0.29	0.38	0.00	0.60	0.00
P5	0.00	0.00	0.50	0.00	0.51	1.00	0.84	0.44
P6	1.00	0.10	1.00	0.50	0.00	1.00	0.00	0.63
P7	0.00	0.50	1.00	0.43	0.81	0.00	1.00	0.37

Table 5. Absolute distance between the reference chain and the object chains

No.	C1	C2	C3	C4	C5	C6	C7	C8
P1	0.00	0.00	1.00	0.57	0.25	1.00	0.40	0.28
P2	1.00	0.25	0.69	0.00	0.32	1.00	0.20	0.07
P3	0.00	0.25	0.38	0.57	0.00	1.00	0.40	0.00
P4	1.00	0.60	0.19	0.71	0.62	1.00	0.40	1.00
P5	1.00	1.00	0.50	1.00	0.49	0.00	0.16	0.56
P6	0.00	0.90	0.00	0.50	1.00	0.00	1.00	0.37
P7	0.00	0.50	1.00	0.43	0.81	0.00	1.00	0.37

Table 6. GRA relational coefficients

No.	C1	C2	C3	C4	C5	C6	C7	C8
P1	1.00	1.00	0.33	0.47	0.67	0.33	0.56	0.64
P2	0.33	0.67	0.42	1.00	0.61	0.33	0.71	0.87
P3	1.00	0.67	0.57	0.47	1.00	0.33	0.56	1.00
P4	0.33	0.45	0.73	0.41	0.45	0.33	0.56	0.33
P5	0.33	0.33	0.50	0.33	0.50	1.00	0.76	0.47
P6	1.00	0.36	1.00	0.50	0.33	1.00	0.33	0.57
P7	0.33	0.50	1.00	0.47	0.73	0.33	1.00	0.44

Table 7. Eigenanalysis of the covariance matrix

No.	C1	C2	C3	C4	C5	C6	C7	C8
Eig.	0.22	0.17	0.07	0.05	0.04	0.01	0.00	0.00
Prop.	**0.39**	0.30	0.12	0.09	0.07	0.02	0.00	0.00
Cum.	0.39	0.69	0.81	0.90	0.98	1.00	1.00	1.00
Eigenvectors								
C1	**0.40**	0.08	-0.51	0.15	-0.06	0.34	0.36	-0.03
C2	**0.45**	-0.48	-0.37	0.34	-0.19	-0.52	-0.08	0.46
C3	**-0.35**	0.19	0.47	-0.10	-0.22	0.17	-0.09	0.73
C4	**0.17**	-0.34	-0.06	-0.61	-0.57	0.10	0.38	-0.02
C5	**0.34**	-0.04	0.46	0.03	0.12	-0.57	0.55	-0.19
C6	**-0.46**	0.66	-0.39	-0.28	0.12	-0.34	0.25	0.29
C7	**-0.07**	-0.20	0.09	0.30	0.35	0.38	0.57	0.31
C8	**0.40**	-0.37	-0.11	-0.56	0.66	-0.01	-0.14	0.18

Table 8. Criterion weights calculated by PCA method

No.	C1	C2	C3	C4	C5	C6	C7	C8
w_i	0.162	0.199	0.119	0.028	0.116	0.210	0.005	0.162

reflecting its relative priority in the overall evaluation. In practice, weights can be established through various means, including expert judgment (AHP, Entropy, PCA, etc.), past experience, or statistical data. In this study, the weights were derived using the PCA method with the support of Minitab software to ensure that the relative significance of each criterion is accurately captured, thus enabling a more comprehensive evaluation and precise ranking within the multi criteria context.

Table 7 presents the uncorrelated principal components, along with their corresponding eigenvalues and eigenvectors, derived through Equation (14). Notably, the first principal component (PC1) accounts for 39.2% of the overall variance. Consequently, the eigenvectors associated with PC1 were extracted and squared to obtain the relative weights for each response. The product of the relative weights according to their respective GRCs produces the GRGs. The resulting GRGs are shown in Table 12 for comparison with the results produced by the other methods.

3.3. MOORA method calculations

The outcomes of the procedures conducted with the MOORA method are summarized as follows. In the initial phase, a dimensionless normalized matrix is generated by applying Equation (16), with results displayed in Table 9.

Subsequently, the Entropy method is employed to determine the weights of the responses, as reported in Table 10. The weighted matrix (Table 11) is then computed using Equation (17). Finally, the corresponding S_i values and rankings of the alternatives are presented in Table 12 for comparative analysis with the other two methods.

3.4. Ranking of alternatives

The ranking indices calculated by the three methods PSI, GRA, MOORA and the rankings of the corresponding alternatives are summarized in Table 12 below. All three analysis methods result in the optimal choice being option P3 (ie Ender 3 V3 printer) as it is ranked first in all three methods. However, the ranking order of the alternatives is somewhat different for each method.

In all three methods, P3 emerges as the most suitable alternative; however, the variations in the ranking order can be attributed to differences in the normalization procedures adopted by each method. Specifically, the MOORA method is highly sensitive to the selected normalization technique, employing a vector based normalization, whereas the PSI and GRA methods rely on a max-min normalization approach, which is a form of linear normalization. Another noteworthy source of discrepancy arises from the extent to which each method considers various types of criteria namely, positive, negative, and nominal during the normalization phase. In contrast to both MOORA and GRA, the PSI method does not make this distinction between different criterion types.

Despite the variation in their respective normalization techniques, the PSI and MOORA

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Table 9. Normalized value by MOORA method

No.	C1	C2	C3	C4	C5	C6	C7	C8
P1	0.31	0.54	0.49	0.36	0.34	0.40	0.37	0.32
P2	0.42	0.45	0.43	0.42	0.35	0.40	0.41	0.26
P3	0.31	0.45	0.37	0.36	0.29	0.40	0.37	0.24
P4	0.42	0.32	0.33	0.35	0.42	0.40	0.37	0.54
P5	0.42	0.18	0.39	0.42	0.39	0.40	0.42	0.41
P6	0.31	0.21	0.29	0.37	0.50	0.20	0.24	0.35
P7	0.42	0.36	0.29	0.36	0.33	0.40	0.45	0.43

Table 10. Criterion weights calculated by Entropy method

No.	C1	C2	C3	C4	C5	C6	C7	C8
w_i	0.06	0.35	0.09	0.01	0.08	0.12	0.08	0.20

Table 11. The weighted matrix

No.	C1	C2	C3	C4	C5	C6	C7	C8
P1	0.018	0.188	0.046	0.005	0.029	0.049	0.031	0.063
P2	0.024	0.156	0.040	0.006	0.030	0.049	0.034	0.052
P3	0.018	0.156	0.035	0.005	0.024	0.049	0.031	0.047
P4	0.024	0.113	0.031	0.005	0.035	0.049	0.031	0.105
P5	0.024	0.063	0.037	0.006	0.033	0.049	0.035	0.080
P6	0.018	0.075	0.028	0.005	0.042	0.024	0.020	0.069
P7	0.024	0.125	0.028	0.005	0.028	0.049	0.038	0.084

Table 12. Ranked Alternatives

No.	PSI method		GRA method		MOORA method	
	PSI	Rank	*GRG*	Rank	S_i	Rank
P1	0.797	3	0.668	3	0.0187	2
P2	0.804	2	0.549	4	0.0018	3
P3	0.856	**1**	0.726	**1**	0.0195	**1**
P4	0.702	7	0.420	7	-0.0962	6
P5	0.720	6	0.538	5	-0.1187	7
P6	0.773	5	0.709	2	-0.0803	5
P7	0.790	4	0.516	6	-0.0439	4

methods conduct the bulk of their calculations directly on alternative level data, which contrasts with GRA's operation on the overlapping segments of the alternatives. Consequently, while the PSI and MOORA outcomes may differ in certain scenarios, their resultant rankings frequently align more closely with one another than with those of GRA.

In addition, the weighting methods used in GRA and MOORA lead to different rankings. When considering the print area size criterion as the print area increases, costs may rise, and the machine becomes more cumbersome, but it can accommodate a wider range of applications. In contrast, machines with smaller print areas are typically more compact and affordable, yet limited in product size. This result may require adjustment by analytical methods or expert judgment to adjust the weighting for this criterion.

MCDM processes can therefore assist in identifying the best performance alternative, providing valuable insights into the relative importance and interactions of different criteria. This information can guide manufacturers and product designers in prioritizing features for development or refinement.

4. Conclusion

This investigation has demonstrated the effective application of MCDM methods to identify the optimal 3D printer, using eight criteria across seven commercially available models. All three methods produced consistent outcomes, indicating that the P3 printer is the most advantageous choice. Variations in the ranking of other alternatives are attributed to methodological differences in normalization and weighting processes. The results of this study confirm that PSI, GRA, and MOORA are both suitable and robust tools for decision making problems characterized by multiple, often conflicting, criteria. Furthermore, the methodology can be extended with additional MCDM approaches and weighting techniques, such as SAW or AHP to perform similar comparative analyses and select optimal alternatives in related applications.

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