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Forest HyperSoft Sets for Quality Measurement of Preschool Education in the New Era Utilizing MCDM Approach and Data Analytics

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Abstract: The assessment of preschool education quality has evolved in the new era, necessitating a comprehensive evaluation framework that encompasses pedagogical approaches, teacher effectiveness, learning environments, and institutional policies. This study explores the critical factors influencing preschool education quality, emphasizing the importance of holistic child development, parental engagement, and technology integration. By employing multi-criteria decision-making (MCDM) methodologies, we propose a MCDM methodology with the Entropy method to compute the criteria weights and the TOPSIS method to rank the alternatives. We use the Forest HyperSoft set to divide each criterion as a TreeSoft set. In each TreeSoft set we compute the criteria weights and rank the alternatives. This study uses four criteria and five alternatives. So, we have four TreeSoft sets.

Keywords: Forest HyperSoft Sets; MCDM Approach; Preschool Education; TOPSIS Methodology.

1. Introduction

Preschool education serves as the foundation for a child's cognitive, social, and emotional development, shaping their ability to learn and adapt in later academic stages. In the new era, characterized by rapid technological advancements, shifting pedagogical philosophies, and evolving societal expectations, the quality assessment of preschool education has become more complex yet essential. Traditional evaluation models, which primarily focused on academic preparedness, are being replaced with comprehensive frameworks that assess not only intellectual growth but also emotional intelligence, creativity, and adaptability. Given the increasing recognition of holistic child development, quality assessment in preschool education must incorporate modern teaching methods, inclusive learning environments, and data-driven decision-making processes[1], [2].

One of the primary challenges in evaluating preschool education quality is the diversity of educational approaches. Schools adopt varied pedagogical frameworks such as Montessori, Reggio Emilia, play-based learning, and STEM-integrated curriculums, each offering unique benefits. While structured learning environments foster early literacy and numeracy skills, child-centered models prioritize creativity and self-expression. As a result, quality assessment methods must be flexible enough to accommodate different teaching philosophies while maintaining core developmental benchmarks[3], [4]. Furthermore, the integration of digital learning tools and AI-driven assessment platforms adds another dimension to the evaluation process, necessitating a balance between traditional and technology-driven metrics.

Beyond classroom instruction, the role of educators, parents, and institutional policies plays a pivotal role in defining preschool education quality. Teacher competence, classroom engagement, and emotional support are crucial factors in fostering a positive learning environment. Additionally, parental involvement in a child's early education significantly enhances learning outcomes[5], [6]. Schools that actively engage families through workshops, digital communication platforms, and collaborative learning activities tend to witness better student performance and emotional well-being. Therefore, modern assessment frameworks should include parameters that evaluate teacher training, parental engagement, and administrative support as integral components of preschool education quality.

The learning environment and infrastructure also play a critical role in defining the effectiveness of preschool education. Safe, inclusive, and stimulating environments encourage children to explore and develop essential skills. Quality assessment models must consider factors such as classroom size, access to age-appropriate learning materials, physical activity opportunities, and child-friendly technology integration. Moreover, with increasing awareness of mental health and emotional resilience, modern preschools must ensure that their environments nurture social-emotional learning, peer interaction, and self-regulation abilities in young learners[7], [8].

In this evolving educational landscape, a standardized yet adaptable framework for preschool education quality assessment is essential for ensuring optimal learning outcomes. By integrating multi-criteria decision-making (MCDM) methodologies, schools and policymakers can evaluate preschool programs holistically, considering both quantitative performance indicators and qualitative developmental measures. This research aims to explore a structured approach to preschool education assessment, identifying key criteria that reflect modern educational priorities while ensuring scalability and inclusivity in diverse learning settings.

The number of studies using MCDM approaches in education research has grown dramatically since 2000. But utilizing MCDM techniques, this study is the first to look at the performance of Preschool education in new era[9], [10]. The Entropy Weight-TOPSIS was utilized in this study to rank the nations under investigation based on the weights of the factors influencing preschool education. Four criteria are used in this study[11], [12].

2. MCDM Approach

This section is divided into three stages. In the first stage, we compute the criteria weights by Entropy methods. In the second stage, we rank the alternatives using the TOPSIS methods. In the third stage, we use the Forest HyperSoft Set to divide each criterion into TreeSoft set.

First Stage

In this stage, we display the steps of the Entropy method to compute the criteria[13], [14].

Build the decision matrix.

We let three experts evaluate the criteria and alternatives by their opinions. Then we combine their opinions into a single matrix.

Normalize the decision matrix

To guarantee that all characteristics are equal and in the same format, the Entropy Method must remove the impact and fluctuation of the index size on the criterion. The original matrix in the range of assessment outcomes is normalized for this purpose. The data in the decision matrix X was normalized. When working with various sizes and variable ranges, this is essential. Next, below Eq. is used to generate the normalized decision matrix.

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

Compute the entropy value.

We determined the entropy value (e_j) for each indication after normalizing the decision matrix. In existing literature, the normalized value is subjected to the entropy. In this stage, blow Eq. is used to calculate normalized values. yij is multiplied and added to the logarithm values of these values (ln(yij)). The following equation may be used to determine the entropy values (ej) using the normalized data. where k is equal to 1/ln(m).

$$e_j = -k y_{ij} \ln y_{ij} \tag{2}$$

Compute the criteria weights.

$$w_j = \frac{1-e_j}{\sum_{j=1}^{n} 1-e_j} \tag{3}$$

Second Stage

In this stage, we apply the TOPSIS method to rank the alternatives[15], [16].

Normalize the decision matrix.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \tag{4}$$

Compute the weighted decision matrix.

The normalized scores are then multiplied by the weight of each indication to determine the weighted scores by calculating the weighted decision matrix. Because each indicator has a distinct weight, the weighted normalized decision matrix is created by multiplying each indication's important weight by the normalized decision matrix's indicator values. The weight of each indication is shown by the w_j that the entropy approach yielded.

$$U_{ij} = w_j \times r_{ij} \tag{5}$$

Compute the positive and negative ideal solutions.

The two standards for each indicator, also known as the ideal positive and negative solutions, are calculated in this stage. While the negative ideal solution contains the lowest values for each characteristic, the ideal positive solution has the best value for each indication. Blow equations were used to determine the digital innovation performance indicators' positive and negative optimum solution points

$$A^+ = \left\{\max_i u_{ij}\, for\ positive\ criteria;\ \min_i u_{ij}\, for\ negative\ criteria\right\} \tag{6}$$

$$A^- = \left\{\min_i u_{ij}\, for\ positive\ criteria;\ \max_i u_{ij}\, for\ negative\ criteria\right\} \tag{7}$$

Compute the ideal distance and non-ideal distance

We compute the distance between each viable solution and the negative ideal solution and the ideal solution.

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(u_{ij} - u_j^+\right)^2} \tag{8}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(u_{ij} - u_j^-\right)^2} \tag{9}$$

Compute the relative degree of approximation

The last stage is ranking each alternative nation based on the degree of relative approach to the ideal answer using the below formula. The relative degree of approximation value is used to rank the evaluation item. The quality of the assessment item increases with the value.

$$G_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{10}$$

Third Stage

In this stage, we display the Forest HyperSoft set[17]s.

Let A be the collection of attributes, H be the non-empty subset of U, and U be the discourse universe.

Every characteristic has a range of levels.

Level 1 is the values of the sub-attributes.

Level 2 is the values of the sub-sub attributes:

Level n is the values of the n-sub attribute.

Every characteristic creates a tree soft set, and when all of these tree soft sets are combined, they create a forest HyperSoft set.

The forest HyperSoft set is defined as

$$G: P\big(Forest(A)\big) \rightarrow P(H) \tag{11}$$

Where $Forest(A) = \big\{Tree\ (A)\ and\ Tree\ (A) = \{A_{i1} | i1 = 1,2, \ldots\ldots\}\big\}$. Fig 1 shows the Forest HyperSoft set.

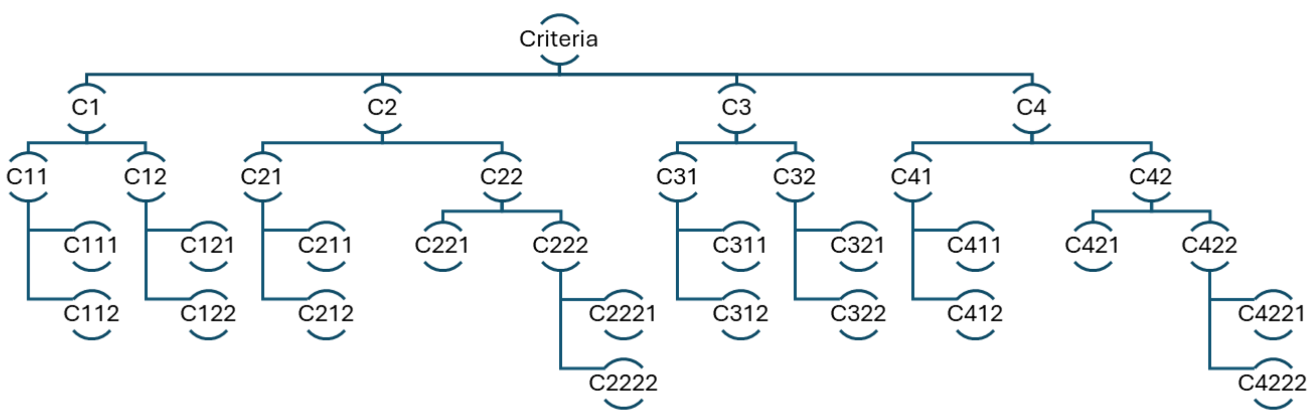

Fig 1. The Forest HyperSoft set.

3. Results and Discussion

This section shows the results of the forest HyperSoft set based on a set of criteria and alternatives. We apply the entropy method to compute the criteria weights and TOPSIS method to rank the alternatives. Three experts are invited to evaluate the criteria and alternatives. The experts are used scale between 0.1 to 0.9. This study uses four main criteria and five alternatives. Four criteria are presented in Fig 2.

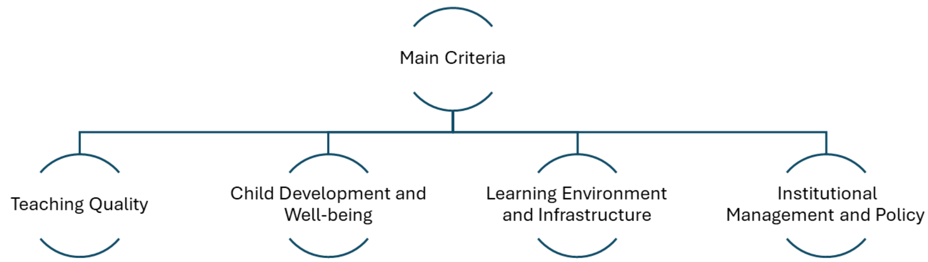

Fig 2. Main criteria.

First Criterion

We apply the Entropy method and TOPSIS method based on the first criterion. Fig 3 shows the sub criteria with values for first criterion.

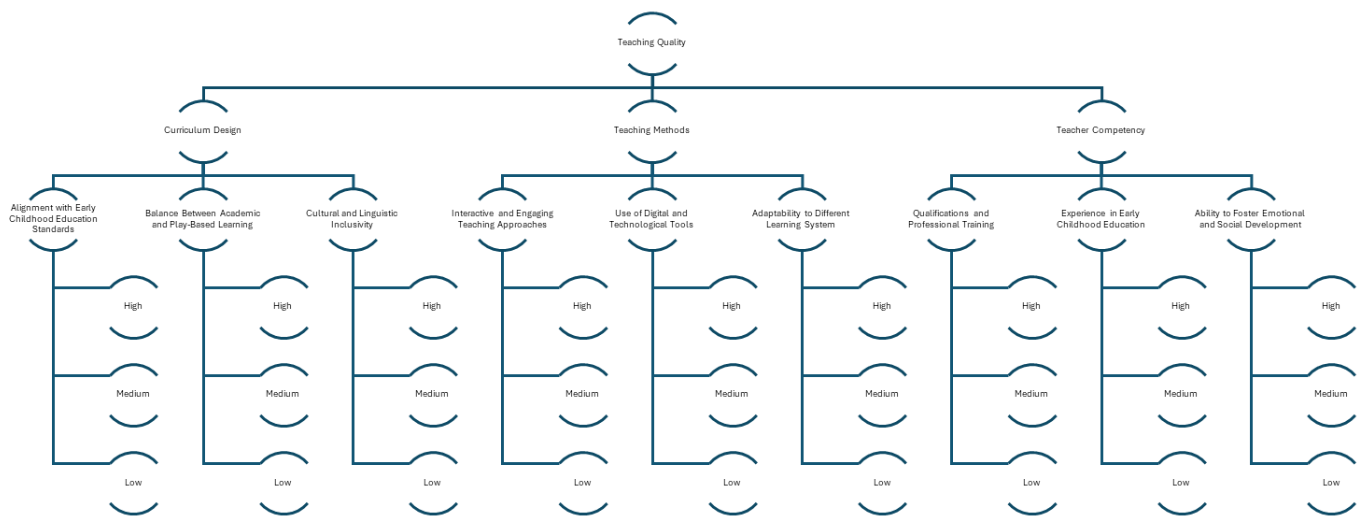

Fig 3. The first criterion with values.

We select the best values in the sub criteria as

$C_{1111} \times C_{1121} \times C_{1132} \times C_{1211} \times C_{1221} \times C_{1233} \times C_{1311} \times C_{1321} \times C_{1333}$

We build the decision matrix. We let three experts evaluate the criteria and alternatives by their opinions. Then we combine their opinions into a single matrix.

Eq. (1) is used to normalize the decision matrix as shown in Table 1.

Then we compute the entropy value using Eq. (2)

Then we compute the criteria weights using Eq. (3)

Table 1. Normalized values by Entropy method.

	C_{1111}	C_{1121}	C_{1132}	C_{1211}	C_{1221}	C_{1233}	C_{1311}	C_{1321}	C_{1333}
A_1	0.163214	0.215356	0.214298	0.235988	0.163214	0.215356	0.214298	0.235988	0.2183
A_2	0.166785	0.216178	0.132909	0.191747	0.166785	0.216178	0.132909	0.191747	0.1897
A_3	0.190186	0.207348	0.214298	0.235988	0.190186	0.207348	0.214298	0.235988	0.2022
A_4	0.244114	0.170422	0.208335	0.143798	0.244114	0.170422	0.208335	0.143798	0.1963
A_5	0.235701	0.190697	0.230161	0.192478	0.235701	0.190697	0.230161	0.192478	0.1936

Then we apply the TOPSIS Method.

We normalize the decision matrix using Eq. (4) as shown in Table 2.

Then we compute the weighted decision matrix using Eq. (5) as shown in Table 3.

Then we compute the positive and negative ideal solutions using Eqs. (6 and 7).

Then we compute the ideal distance and non-ideal distance using Eqs. (8 and 9).

Then we compute the relative degree of approximation using Eq. (10).

Table 2. Normalized values by TOPSIS method.

	C_{1111}	C_{1121}	C_{1132}	C_{1211}	C_{1221}	C_{1233}	C_{1311}	C_{1321}	C_{1333}
A_1	0.359802	0.479739	0.472281	0.520104	0.359802	0.479739	0.472281	0.520104	0.487467
A_2	0.367673	0.48157	0.292912	0.422598	0.367673	0.48157	0.292912	0.422598	0.423575
A_3	0.419261	0.461901	0.472281	0.520104	0.419261	0.461901	0.472281	0.520104	0.451589
A_4	0.538143	0.379641	0.45914	0.316922	0.538143	0.379641	0.45914	0.316922	0.438355
A_5	0.519598	0.424807	0.507242	0.424211	0.519598	0.424807	0.507242	0.424211	0.432288

Table 3. Weighted Normalized values by TOPSIS method.

	C_{1111}	C_{1121}	C_{1132}	C_{1211}	C_{1221}	C_{1233}	C_{1311}	C_{1321}	C_{1333}
A_1	0.051443	0.018513	0.075905	0.078828	0.051443	0.018513	0.075905	0.078828	0.005998
A_2	0.052569	0.018583	0.047077	0.064049	0.052569	0.018583	0.047077	0.064049	0.005212
A_3	0.059945	0.017824	0.075905	0.078828	0.059945	0.017824	0.075905	0.078828	0.005557
A_4	0.076942	0.01465	0.073793	0.048033	0.076942	0.01465	0.073793	0.048033	0.005394
A_5	0.074291	0.016393	0.081524	0.064294	0.074291	0.016393	0.081524	0.064294	0.005319

Second Criterion

We apply the Entropy method and TOPSIS method based on the second criterion. Fig 4 shows the sub criteria with values for the second criterion.

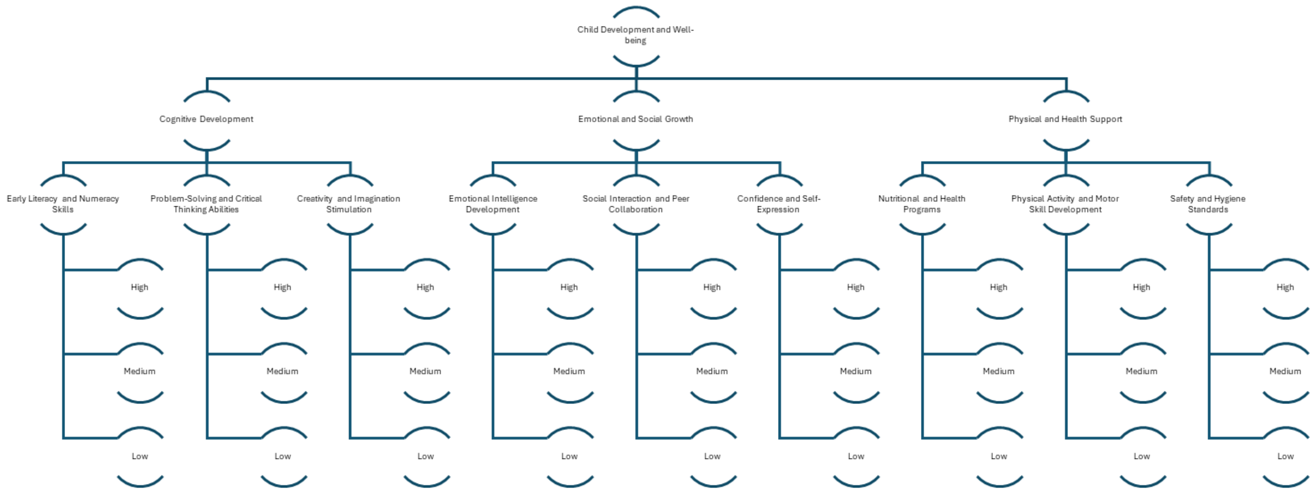

Fig 4. The second criterion with values.

We select the best values in the sub criteria as

$C_{2111} \times C_{2121} \times C_{2132} \times C_{2211} \times C_{2221} \times C_{2233} \times C_{2311} \times C_{2321} \times C_{2333}$

We normalize the decision matrix as shown in Table 4.

Table 4. Normalized values by Entropy method.

	C_{2111}	C_{2121}	C_{2132}	C_{2211}	C_{2221}	C_{2233}	C_{2311}	C_{2321}	C_{2333}
A_1	0.195612	0.205014	0.212628	0.237659	0.196682	0.208592	0.212628	0.231799	0.218274
A_2	0.180209	0.208884	0.181514	0.192231	0.19005	0.22841	0.181514	0.203518	0.189665
A_3	0.183012	0.188714	0.187848	0.204945	0.206295	0.187686	0.187848	0.183866	0.202209
A_4	0.211098	0.208007	0.178004	0.160219	0.184346	0.194235	0.178004	0.180924	0.196284
A_5	0.230069	0.189381	0.240007	0.204945	0.222627	0.181077	0.240007	0.199892	0.193567

Then we apply the TOPSIS Method.

We normalize the decision matrix as shown in Table 5.

Then we compute the weighted decision matrix as shown in Table 6.

Table 5. Normalized values by TOPSIS method.

	C_{2111}	C_{2121}	C_{2132}	C_{2211}	C_{2221}	C_{2233}	C_{2311}	C_{2321}	C_{2333}
A_1	0.435526	0.457957	0.472234	0.527337	0.4388	0.464773	0.472234	0.516197	0.487467
A_2	0.40123	0.466604	0.403133	0.426539	0.424005	0.508931	0.403133	0.453217	0.423575
A_3	0.407471	0.421547	0.417199	0.454749	0.460248	0.418193	0.417199	0.409454	0.451589

A_4	0.470005	0.464643	0.395336	0.355508	0.41128	0.432785	0.395336	0.402902	0.438355
A_5	0.512244	0.423037	0.533042	0.454749	0.496684	0.403467	0.533042	0.445143	0.432288

Table 6. Weighted Normalized values by TOPSIS method.

	C_{2111}	C_{2121}	C_{2132}	C_{2211}	C_{2221}	C_{2233}	C_{2311}	C_{2321}	C_{2333}
A_1	0.018512	0.004689	0.031387	0.04136	0.009807	0.016253	0.031387	0.020817	0.005998
A_2	0.017054	0.004777	0.026794	0.033454	0.009476	0.017797	0.026794	0.018278	0.005212
A_3	0.01732	0.004316	0.027729	0.035667	0.010286	0.014624	0.027729	0.016513	0.005557
A_4	0.019978	0.004757	0.026276	0.027883	0.009192	0.015134	0.026276	0.016248	0.005394
A_5	0.021773	0.004331	0.035429	0.035667	0.0111	0.014109	0.035429	0.017952	0.005319

Third Criterion

We apply the Entropy method and TOPSIS method based on the third criterion. Fig 5 shows the sub criteria with values for the third criterion.

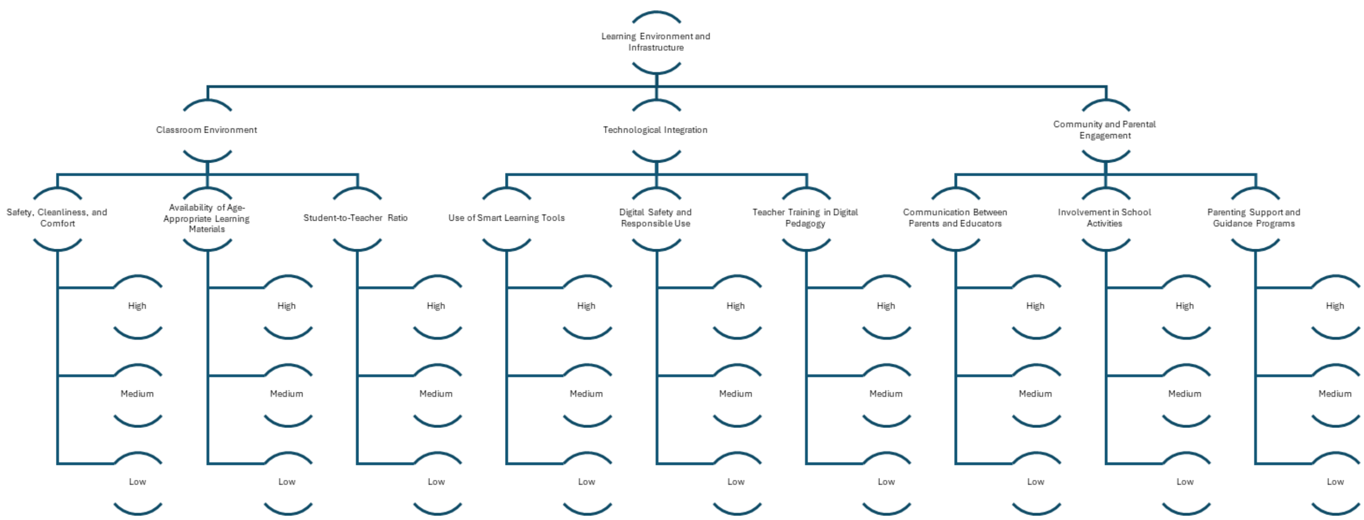

Fig 5. The third criterion with values.

We select the best values in the sub criteria as

$C_{3111} \times C_{3121} \times C_{3132} \times C_{3211} \times C_{3221} \times C_{3233} \times C_{3311} \times C_{3321} \times C_{3333}$

We normalize the decision matrix as shown in Table 7.

Table 7. Normalized values by Entropy method.

	C_{3111}	C_{3121}	C_{3132}	C_{3211}	C_{3221}	C_{3233}	C_{3311}	C_{3321}	C_{3333}
A_1	0.18935	0.1954	0.19958	0.221814	0.162445	0.189228	0.215629	0.194725	0.222029
A_2	0.1747	0.19909	0.17085	0.179415	0.178847	0.201505	0.172165	0.191316	0.176492
A_3	0.182721	0.211078	0.178693	0.221814	0.199457	0.210049	0.183335	0.199428	0.187944
A_4	0.234424	0.186265	0.229257	0.158613	0.207914	0.216527	0.205545	0.217902	0.210712

A_5	0.218805	0.208167	0.22162	0.218344	0.251337	0.182691	0.223326	0.19663	0.202823

Then we apply the TOPSIS Method.

We normalize the decision matrix as shown in Table 8.

Then we compute the weighted decision matrix as shown in Table 9.

Table 8. Normalized values by TOPSIS method.

	C_{3111}	C_{3121}	C_{3132}	C_{3211}	C_{3221}	C_{3233}	C_{3311}	C_{3321}	C_{3333}
A_1	0.420683	0.436492	0.443371	0.491798	0.359171	0.422291	0.479922	0.434944	0.494859
A_2	0.388136	0.444734	0.379547	0.397793	0.395436	0.44969	0.383183	0.427331	0.393367
A_3	0.405955	0.471513	0.396972	0.491798	0.441004	0.468757	0.408045	0.445449	0.41889
A_4	0.520826	0.416085	0.509301	0.351671	0.459702	0.483212	0.457477	0.486713	0.469636
A_5	0.486125	0.46501	0.492334	0.484105	0.555712	0.407703	0.497051	0.4392	0.452052

Table 9. Weighted Normalized values by TOPSIS method.

	C_{3111}	C_{3121}	C_{3132}	C_{3211}	C_{3221}	C_{3233}	C_{3311}	C_{3321}	C_{3333}
A_1	0.026824	0.004371	0.029118	0.043281	0.040024	0.008363	0.022639	0.004638	0.016201
A_2	0.024749	0.004453	0.024926	0.035008	0.044065	0.008906	0.018076	0.004557	0.012878
A_3	0.025885	0.004721	0.026071	0.043281	0.049143	0.009284	0.019248	0.00475	0.013714
A_4	0.033209	0.004166	0.033448	0.030949	0.051226	0.00957	0.02158	0.00519	0.015375
A_5	0.030997	0.004656	0.032333	0.042604	0.061925	0.008074	0.023447	0.004683	0.0148

Fourth Criterion

We apply the Entropy method and TOPSIS method based on the fourth criterion. Fig 6 shows the sub criteria with values for the fourth criterion.

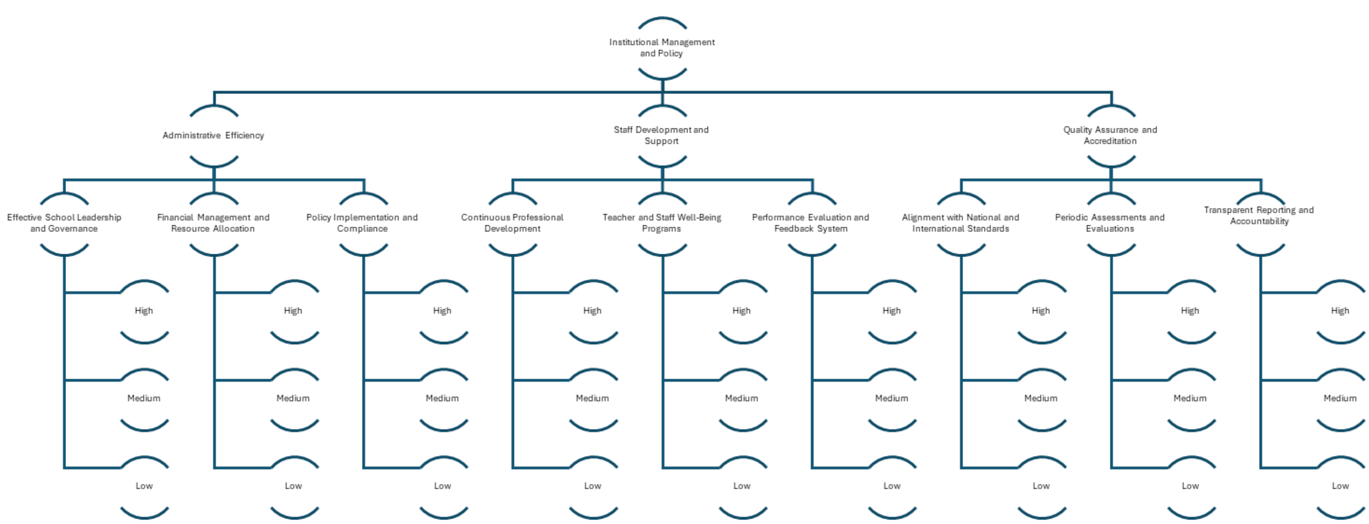

Fig 6. The fourth criterion with values.

We select the best values in the sub criteria as

$C_{4111} \times C_{4121} \times C_{4132} \times C_{4211} \times C_{4221} \times C_{4233} \times C_{4311} \times C_{4321} \times C_{4333}$

We normalize the decision matrix as shown in Table 10.

Table 10. Normalized values by Entropy method.

	C_{4111}	C_{4121}	C_{4132}	C_{4211}	C_{4221}	C_{4233}	C_{4311}	C_{4321}	C_{4333}
A_1	0.192184	0.206914	0.208483	0.215734	0.15922	0.210224	0.215845	0.226015	0.218601
A_2	0.177786	0.227303	0.168572	0.212873	0.207351	0.197373	0.154197	0.217984	0.182745
A_3	0.196196	0.189803	0.206752	0.220067	0.191816	0.214614	0.216837	0.179685	0.224136
A_4	0.220721	0.192758	0.192277	0.150233	0.21168	0.178867	0.199068	0.179685	0.187158
A_5	0.213114	0.183222	0.223916	0.201092	0.229933	0.198922	0.214054	0.196632	0.187359

Then we apply the TOPSIS Method.

We normalize the decision matrix as shown in Table 11.

Then we compute the weighted decision matrix as shown in Table 12.

Table 11. Normalized values by TOPSIS method.

	C_{4111}	C_{4121}	C_{4132}	C_{4211}	C_{4221}	C_{4233}	C_{4311}	C_{4321}	C_{4333}
A_1	0.428484	0.461256	0.46417	0.478473	0.353546	0.46917	0.479264	0.50308	0.486923
A_2	0.396383	0.506708	0.375312	0.472127	0.46042	0.44049	0.34238	0.485203	0.407056
A_3	0.43743	0.423112	0.460318	0.488082	0.425926	0.478966	0.481466	0.399955	0.499251
A_4	0.492108	0.4297	0.42809	0.333199	0.470033	0.399188	0.442011	0.399955	0.416885
A_5	0.47515	0.408441	0.49853	0.445997	0.510564	0.443947	0.475287	0.437676	0.417333

Table 12. Weighted Normalized values by TOPSIS method.

	C_{4111}	C_{4121}	C_{4132}	C_{4211}	C_{4221}	C_{4233}	C_{4311}	C_{4321}	C_{4333}
A_1	0.012531	0.013911	0.020494	0.041838	0.025552	0.009155	0.035775	0.02295	0.018632
A_2	0.011592	0.015281	0.016571	0.041283	0.033276	0.008596	0.025557	0.022134	0.015576
A_3	0.012792	0.01276	0.020324	0.042678	0.030783	0.009347	0.035939	0.018245	0.019103
A_4	0.014391	0.012959	0.018901	0.029135	0.033971	0.00779	0.032994	0.018245	0.015952
A_5	0.013895	0.012318	0.022011	0.038998	0.0369	0.008663	0.035478	0.019966	0.015969

Finally, we obtain the criteria weights of each TreeSoft as shown in Table 13. Then we obtain the final ranks of each TreeSoft as shown in Table 14. Then we combine the ranks of the alternatives in single rank.

Table 13. Criteria weights of each TreeSoft Set.

	C_{4111}	C_{4121}	C_{4132}	C_{4211}	C_{4221}	C_{4233}	C_{4311}	C_{4321}	C_{4333}

First Criterion	0.143	0.039	0.161	0.152	0.143	0.039	0.161	0.152	0.012
Second Criterion	0.043	0.010	0.066	0.078	0.022	0.035	0.066	0.040	0.012
Third Criterion	0.064	0.010	0.066	0.088	0.111	0.020	0.047	0.011	0.033
Fourth Criterion	0.029	0.030	0.044	0.087	0.072	0.020	0.075	0.046	0.038

Table 14. Ranks of alternatives for each TreeSoft Set.

	First Criterion	Second Criterion	Third Criterion	Fourth Criterion	Combined
A_1	4	5	2	3	2
A_2	1	2	3	4	3
A_3	3	1	1	2	1
A_4	5	3	5	5	5
A_5	2	4	4	1	4

5. Conclusions

This study used two MCDM methods such as Entropy method to compute the criteria weights and ranking the alternatives. We use the Forest HyperSoft set to divided each criterion as TreeSoft set and we compute the criteria weights and ranking the alternatives in each TreeSoft set. We used four criteria and seven alternatives in this study.

The quality assessment of preschool education in the new era requires a multifaceted evaluation approach that moves beyond traditional academic indicators. This research highlights teaching methodologies, teacher competence, learning environments, parental involvement, and institutional policies collectively shape the effectiveness of early childhood education. By integrating holistic child development measures, assessment frameworks can ensure that preschools cater to both intellectual and emotional growth.

One of the key findings is that educational diversity must be respected in quality assessments. While structured academic models emphasize early literacy and numeracy, child-centric approaches such as Montessori and Reggio Emilia focus on creativity and social development. The study underscores that quality evaluation should balance structured learning with experiential, play-based, and digital learning elements, ensuring that children develop essential life skills alongside foundational knowledge.

Additionally, the research confirms that teacher quality and parental engagement significantly influence preschool learning outcomes. Schools that invest in continuous teacher training, personalized learning approaches, and parent-school collaboration initiatives demonstrate higher levels of student progress. As digital education tools become more prevalent, their role in adaptive learning and real-time assessment must be integrated into evaluation models while ensuring that child-friendly and ethical AI applications are prioritized.

A dynamic, data-driven approach to preschool education assessment is necessary to accommodate the evolving demands of modern education. By adopting multi-criteria decision-making models, educators and policymakers can implement a scalable, inclusive, and developmentally appropriate quality assessment framework, ensuring that preschool education remains effective, engaging, and aligned with the needs of future generations.

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