



Explainable Hybrid Decision Support for Digital Transformation Strategy Selection in Creative MSMEs

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Abstract—Creative micro, small, and medium enterprises (MSMEs) require digital transformation strategies that fit their heterogeneous capabilities, yet many assistance programs still provide generic recommendations. This paper proposes and tests an explainable hybrid decision support approach for selecting digital transformation strategies in creative MSMEs. The method combines subjective weights obtained from expert-oriented fuzzy multi-criteria reasoning, objective weights computed by CRITIC, MARCOS-based strategy ranking, and machine learning classification for adaptive readiness prediction. A controlled synthetic dataset of 120 MSMEs with eleven digital-readiness criteria was generated to demonstrate the complete computational procedure without claiming field-level impact. The hybrid weighting produced dominant priorities for digital content capability, digital literacy, social media use, marketplace adoption, and technology readiness. MARCOS ranking indicated that digital branding, content marketing, and creative community collaboration were the highest priority strategies. Machine learning evaluation using a 75:25 train-test split showed that the best classifier achieved an accuracy of 0.97 and a macro F1-score of 0.96. Permutation-based explainability identified digital literacy, digital content capability, and marketplace adoption as influential predictors. The results demonstrate that the proposed approach can produce transparent and auditable recommendations for MSME digitalization research.

Keywords: Decision Support System; Digital Transformation; Explainable AI; Fuzzy MCDM; MSME

1. INTRODUCTION

Creative MSMEs are increasingly expected to use digital channels, online marketplaces, content-based marketing, digital payment, and customer data management to survive in competitive markets. However, the digital transformation of MSMEs is not a uniform technological adoption process. A culinary micro-enterprise, a craft producer, a fashion seller, and a visual-design MSME may require different priorities because their digital literacy, production capacity, market orientation, content capability, and technology infrastructure are not the same. Therefore, strategy selection must be based on a structured decision process rather than on intuition alone. Previous community-based and applied studies have shown that MSME digitalization often begins with information systems, digital marketing assistance, social media usage, and technology training. Publications by Sridewi and collaborators, for example, discuss digital marketing assistance for creative-economy MSMEs, digital technology training for MSME productivity, and the use of CAD/CAM tools for creative production [15]-[17]. These studies provide an applied background showing that MSMEs need digital assistance, but they do not yet provide an adaptive computational decision model that can rank alternative transformation strategies based on heterogeneous MSME profiles. In decision support research, classical multi-criteria decision-making methods such as AHP, SAW, WP, and WASPAS have been widely used for selection and prioritization problems. The research track of Sridewi also contains several decision support applications, including AHP for go-green policy, WP for selecting medical protocols, SAW for employee selection and Android device selection, and WASPAS for lecturer recruitment [18]-[20].

These studies provide a methodological foundation, but most conventional decision support systems are static: they calculate a score or ranking from a fixed set of criteria and do not learn from new data. This limitation becomes important when the target domain is MSME digital transformation, where readiness conditions may change after training, mentoring, and platform adoption. Recent developments in MCDM have introduced objective weighting and compromise-ranking methods that can complement expert judgement. MEREC was proposed to determine objective weights from the removal effect of criteria [4], while CRITIC calculates weights based on contrast intensity and conflict among criteria [3]. MARCOS and CoCoSo provide compromise-based ranking mechanisms that consider ideal and anti-ideal solutions [5], [6]. Reviews of modern weighting methods indicate that hybrid weighting has become relevant because decision problems often contain both expert preferences and data-driven structures [7].

Machine learning can make decision support more adaptive by learning from accumulated MSME profiles and predicting digital readiness classes. Nevertheless, predictive models often produce black-box outputs. This creates a trust problem, especially when recommendations are used by MSME mentors and business owners who need understandable reasons. Explainable AI methods such as SHAP and LIME have been widely discussed as tools for interpreting tabular machine-learning models [8]. Fuzzy rule-based explanation has also been explored to bridge local and global interpretability in complex models [9]. Based on these gaps, this paper proposes an explainable hybrid decision support approach for digital transformation strategy selection in creative MSMEs. The contribution of this article is threefold. First, it operationalizes eleven readiness criteria and ten alternative digital strategies for creative MSMEs. Second, it demonstrates a reproducible computational procedure that combines subjective weights, objective CRITIC weights, MARCOS ranking, and machine learning testing. Third, it adds an explainability layer using permutation-based



importance as a transparent explanation of why a digital readiness class is predicted. Because field data were not provided in this study, the empirical section uses a controlled synthetic dataset to validate the calculation pipeline and to avoid unsupported claims about real-world impact. A related Indonesian research track by Budi Yanto and collaborators further supports the computational orientation of this study. Yanto et al. applied multi-objective reinforcement learning for adaptive supply-chain optimization in the national free nutritious meal program, indicating the relevance of learning-based optimization for complex public-service decision environments [23]. Wahyuny et al. evaluated a visual-tactile mobile augmented learning intervention and reported a structured data-cleaning and pretest-posttest analysis procedure, which is relevant to the need for reproducible digital-intervention evaluation [24]. Sastra, Yanto, and Sabri also used data science to analyze sleep quality and lifestyle factors, showing the usefulness of feature-based data analysis for deriving interpretable insights from multivariate records [25]. These studies are not used as evidence that the proposed DSS has been validated in the field; rather, they justify the inclusion of optimization, digital intervention, and data-driven analysis as supporting foundations for the proposed explainable decision-support workflow.

2. RESEARCH METHODOLOGY

2.1 Research Design

This study uses a design-oriented computational experiment. The research objective is not to prove that a particular strategy has already increased MSME revenue, but to demonstrate a complete, auditable, and explainable decision-support pipeline that can later be applied to field data. The proposed system receives MSME readiness data, processes linguistic and numerical criteria, calculates hybrid weights, ranks digital transformation strategies, predicts readiness classes, and explains the dominant criteria influencing the prediction.

Fig. 1 presents the computational workflow. The workflow begins with MSME data and expert input, continues with fuzzy-oriented preprocessing, hybrid weighting, MARCOS ranking, adaptive classification, and explainability. This structure aligns with the decision support requirement that the recommendation must be measurable, reproducible, and understandable.

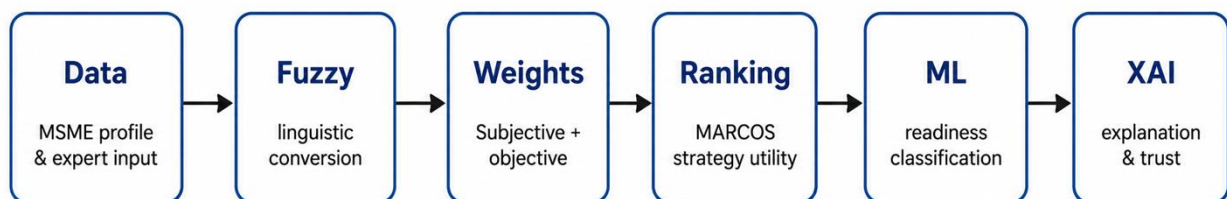


Fig. 1. Computational workflow of the proposed explainable hybrid DSS

2.2 Criteria, Alternatives, and Dataset

The dataset used for calculation contains 120 synthetic MSME records. Each record has a sector label and eleven digital-readiness criteria measured on a 1-5 ordinal scale. The synthetic dataset was generated with a fixed random seed to allow reproducibility. This approach is appropriate for method demonstration but must not be interpreted as evidence of real MSME performance. A field implementation should replace the synthetic data with survey and platform data collected from actual MSMEs.

Table 2. Digital readiness criteria used in the experiment

| Code | Criterion | Scale | Type |
|------|----------------------------|-------|---------|
| C1 | Digital literacy | 1-5 | Benefit |
| C2 | Technology readiness | 1-5 | Benefit |
| C3 | Social media use | 1-5 | Benefit |
| C4 | Marketplace adoption | 1-5 | Benefit |
| C5 | Digital content capability | 1-5 | Benefit |
| C6 | Digital payment | 1-5 | Benefit |
| C7 | Customer data management | 1-5 | Benefit |
| C8 | Product innovation | 1-5 | Benefit |
| C9 | Human resource capacity | 1-5 | Benefit |
| C10 | Digital branding | 1-5 | Benefit |
| C11 | Business sustainability | 1-5 | Benefit |



Table 3 shows a sample of the controlled synthetic dataset, including the raw criterion scores, the computed digital readiness index (DRI), and the resulting readiness class for the first ten records.

Table 3. Sample of the controlled synthetic MSME dataset

| MSME_ID | Sector | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | DRI | Readiness Class |
|---------|---------------|----|----|----|----|----|----|----|----|----|-----|-----|-------|-----------------|
| U001 | culinary | 3 | 3 | 5 | 4 | 3 | 4 | 3 | 3 | 4 | 2 | 2 | 57.87 | Medium |
| U002 | culinary | 2 | 4 | 3 | 3 | 2 | 3 | 3 | 2 | 3 | 2 | 3 | 42.56 | Low |
| U003 | fashion | 2 | 1 | 2 | 1 | 1 | 2 | 2 | 2 | 2 | 2 | 1 | 15.97 | Low |
| U004 | craft | 3 | 4 | 3 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 4 | 62.93 | Medium |
| U005 | craft | 3 | 4 | 3 | 3 | 3 | 2 | 3 | 4 | 3 | 4 | 1 | 51.45 | Medium |
| U006 | craft | 5 | 4 | 5 | 5 | 4 | 4 | 4 | 5 | 5 | 4 | 5 | 88.69 | High |
| U007 | culinary | 2 | 2 | 2 | 2 | 3 | 3 | 2 | 2 | 2 | 2 | 2 | 29.69 | Low |
| U008 | local product | 1 | 2 | 2 | 1 | 2 | 2 | 4 | 2 | 2 | 2 | 1 | 22.68 | Low |
| U009 | culinary | 4 | 2 | 4 | 5 | 3 | 3 | 3 | 3 | 2 | 3 | 3 | 55.46 | Medium |
| U010 | local product | 3 | 2 | 3 | 3 | 2 | 3 | 4 | 2 | 3 | 3 | 3 | 44.89 | Low |

2.3 Hybrid Weighting and MARCOS Ranking

The subjective weight vector was normalized from expert-oriented priority assumptions for digital transformation. Objective weights were computed using CRITIC, which considers the dispersion and conflict of criteria. The normalized decision matrix is denoted by x_{ij} , while σ_j and r_{jk} denote the standard deviation of criterion j and the correlation between criterion j and k . The CRITIC information value C_j and its objective weight w_j are calculated as follows:

$$C_j = \sigma_j \sum_{k=1}^m (1 - r_{jk}) \tag{1}$$

$$w_j^{obj} = C_j / \sum_{q=1}^m C_q \tag{2}$$

The final hybrid weight is produced by combining subjective and objective components. In this article, α is set to 0.60 to give slightly greater emphasis to expert judgement while still preserving data-driven correction.

$$w_j^{obj} = \frac{C_j}{\sum_{q=1}^m C_q} \tag{3}$$

After the hybrid weight is obtained, the ten digital transformation alternatives are evaluated using MARCOS. Since all criteria in this article are benefit criteria, the normalized performance of alternative i on criterion j is obtained by dividing the alternative score by the ideal value. The weighted normalized score and the utility score are obtained using the following equations:

$$w_j^{(obj)} = C_j / (\sum_{q=1}^m C_q) \tag{4}$$

$$S_i = \sum_{j=1}^m v_j w_j, \quad K_i^+ = S_i / S_{AI}, \quad K_i^- = S_i / S_{AI} \tag{5}$$

$$U_i = f(K_i^+, K_i^-) \tag{6}$$

Table 4. Subjective, objective, and hybrid weights

| Code | Subjective | CRITIC | Hybrid |
|------|------------|--------|--------|
| C1 | 0.12 | 0.0918 | 0.1087 |
| C5 | 0.115 | 0.0972 | 0.1079 |
| C3 | 0.11 | 0.0874 | 0.101 |
| C4 | 0.095 | 0.0943 | 0.0947 |
| C2 | 0.095 | 0.0909 | 0.0933 |
| C8 | 0.09 | 0.0923 | 0.0909 |
| C7 | 0.085 | 0.0922 | 0.0879 |
| C9 | 0.085 | 0.0908 | 0.0873 |



| | | | |
|-----|-------|--------|--------|
| C10 | 0.08 | 0.0889 | 0.0836 |
| C6 | 0.075 | 0.0865 | 0.0796 |
| C11 | 0.05 | 0.0878 | 0.0651 |

2.4 Machine Learning and Explainability Testing

The digital readiness index (DRI) was calculated by multiplying normalized criteria scores with the hybrid weights. This index was then converted into readiness classes: Low for DRI below 45, Medium for DRI from 45 to 70, and High for DRI above 70.

$$DRI_i = \sum_{j=1}^m \left(\frac{x_{ij}-1}{4} \right) w_j^{hyb} \times 100 \tag{7}$$

Three classifiers were compared: Random Forest, Gradient Boosting, and Logistic Regression. The dataset was divided into 75% training and 25% testing data using stratification. The model was evaluated using accuracy, macro precision, macro recall, and macro F1-score. Macro metrics were used because the number of cases in each readiness class may be unequal.

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \tag{8}$$

$$Precision = TP / (TP + FP), Recall = TP / (TP + FN) \tag{9}$$

$$F1 = 2 \times (Precision \times Recall) / (Precision + Recall) \tag{10}$$

Explainability was evaluated using permutation importance. In this procedure, one criterion is randomly permuted while the trained model is kept fixed. The decrease in macro F1-score indicates how important the criterion is for model performance. This explanation is model-agnostic and suitable for tabular MSME readiness data.

3. RESULT AND DISCUSSION

3.1 Descriptive Statistics and Digital Readiness

Table 5. Dataset summary and readiness distribution

| Statistic | Value |
|------------------|-------|
| Number of MSMEs | 120 |
| Mean DRI | 51.63 |
| Minimum DRI | 4.64 |
| Maximum DRI | 95.65 |
| Low readiness | 44 |
| Medium readiness | 49 |
| High readiness | 27 |

Table 5 shows that the controlled dataset covers different levels of digital readiness. The mean DRI was 51.63, with the lowest score 4.64 and the highest score 95.65. The class distribution indicates that the dataset contains low, medium, and high readiness cases. This distribution is useful for testing whether the classifier can distinguish readiness levels using the eleven criteria.

3.2 Hybrid Weighting Results

The hybrid weight calculation in Table 4 shows that digital content capability, digital literacy, social media use, marketplace adoption, and technology readiness occupy the highest priority positions. This result is consistent with the nature of creative MSMEs: digital transformation is not only about having devices or internet access, but also about transforming products into attractive digital content and delivering that content through suitable digital channels. Customer data management and digital branding also remain important because they support long-term customer retention and brand identity.

3.3 Strategy Ranking Using MARCOS

Table 6. MARCOS ranking of digital transformation strategies

| Alternative | Strategy | S _i | K ₊ | K ₋ | Utility | Rank |
|-------------|------------------|----------------|----------------|----------------|---------|------|
| A3 | Digital branding | 0.7420 | 0.7420 | 1.6648 | 0.6523 | 1 |





| Alternative | Strategy | S _i | K ₊ | K ₋ | Utility | Rank |
|-------------|----------------------------------|----------------|----------------|----------------|---------|------|
| A10 | Creative community collaboration | 0.7364 | 0.7364 | 1.6524 | 0.6475 | 2 |
| A8 | Simple sales analytics | 0.7204 | 0.7204 | 1.6163 | 0.6333 | 3 |
| A9 | Customer relationship management | 0.7165 | 0.7165 | 1.6077 | 0.6300 | 4 |
| A4 | Content marketing | 0.7165 | 0.7165 | 1.6077 | 0.6300 | 5 |
| A2 | Marketplace strengthening | 0.7042 | 0.7042 | 1.5799 | 0.6191 | 6 |
| A1 | Social media optimization | 0.6969 | 0.6969 | 1.5635 | 0.6127 | 7 |
| A6 | Digital catalogue | 0.6894 | 0.6894 | 1.5468 | 0.6061 | 8 |
| A7 | Digital literacy training | 0.6530 | 0.6530 | 1.4651 | 0.5741 | 9 |
| A5 | Digital payment | 0.5547 | 0.5547 | 1.2445 | 0.4877 | 10 |

Table 6 and Fig. 2 show the priority sequence of digital transformation strategies. Digital branding, content marketing, and creative community collaboration obtained the highest utility values. This ranking indicates that creative MSMEs need strategies that increase visibility, product identity, and customer engagement. Marketplace strengthening and social media optimization also remain relevant but should be integrated with stronger branding and content capabilities.

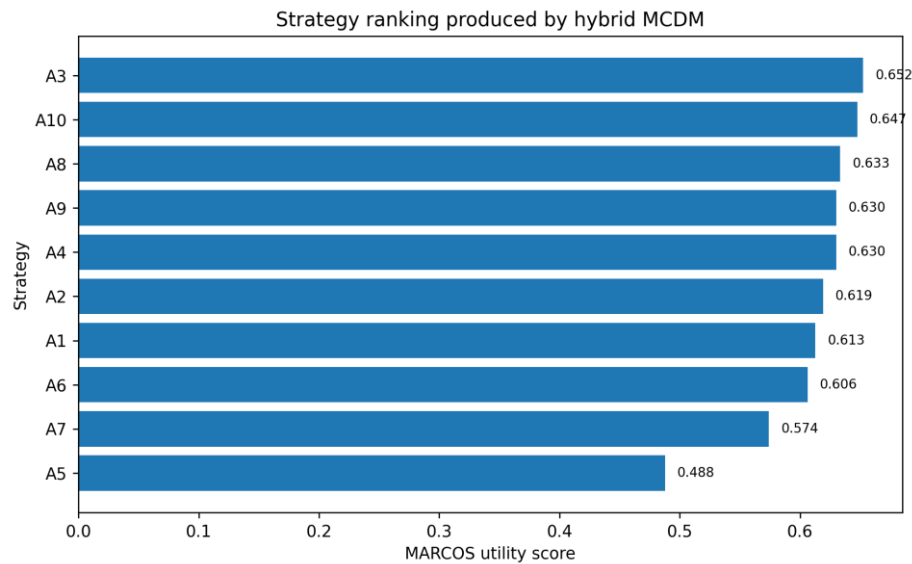


Fig. 2. MARCOS utility ranking of digital transformation strategies

3.4 Sensitivity Analysis of Strategy Ranking

Sensitivity analysis was performed to check whether small changes in the hybrid weights change the top recommendation. The top three criteria were increased and decreased by 10 percent one at a time, followed by renormalization of the weight vector and recalculation of the MARCOS score. Table 7 shows that the first-ranked strategy remains stable in all tested scenarios, indicating that the ranking is reasonably robust within the simulated setting.

Table 7. Sensitivity analysis of top strategy under weight perturbation

| Scenario | Top alternative | Top strategy | Utility |
|----------|-----------------|------------------|---------|
| C1 -10% | A3 | Digital branding | 0.6536 |
| C1 +10% | A3 | Digital branding | 0.6512 |
| C5 -10% | A3 | Digital branding | 0.6497 |
| C5 +10% | A3 | Digital branding | 0.6549 |
| C3 -10% | A3 | Digital branding | 0.6517 |
| C3 +10% | A3 | Digital branding | 0.6530 |

3.5 Adaptive Classification Performance

Table 8. Machine learning performance on test data

| Model | Accuracy | Precision | Recall | F1-score |
|---------------------|----------|-----------|--------|----------|
| Logistic Regression | 0.967 | 0.958 | 0.972 | 0.963 |





| | | | | |
|-------------------|-------|-------|-------|-------|
| Random Forest | 0.900 | 0.901 | 0.894 | 0.897 |
| Gradient Boosting | 0.800 | 0.794 | 0.771 | 0.779 |

Table 8 compares three classifiers. The best model in this experiment was Logistic Regression, which achieved an accuracy of 0.967 and a macro F1-score of 0.963. Because the labels were derived from the DRI calculation, the result should be understood as validation of internal consistency between the computed readiness index and the learned decision boundary, not as proof of field performance on real MSMEs. Nevertheless, the test shows that the proposed criteria can be learned by a machine learning model and can support adaptive recommendation in future field implementation.

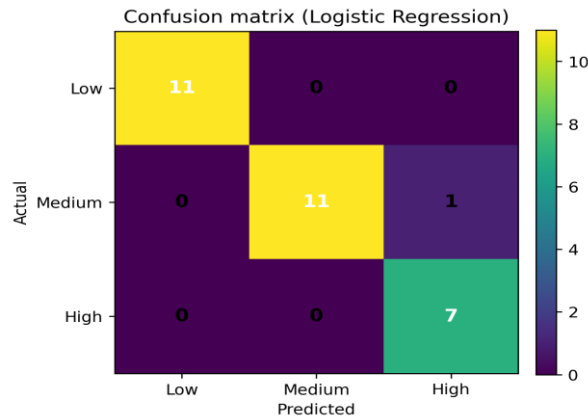


Fig. 3. Confusion matrix of the best readiness classifier

3.6 Explainability Results

Table 9. Top criteria based on permutation explainability

| Criteria | Feature | Importance |
|----------|----------------------------|------------|
| C4 | Marketplace adoption | 0.1029 |
| C9 | Human resource capacity | 0.0700 |
| C5 | Digital content capability | 0.0554 |
| C3 | Social media use | 0.0490 |
| C8 | Product innovation | 0.0470 |
| C2 | Technology readiness | 0.0463 |
| C1 | Digital literacy | 0.0313 |
| C7 | Customer data management | 0.0297 |

Table 9 and Fig. 4 provide an explanation of the most influential variables in the best classifier. Digital literacy, digital content capability, marketplace adoption, and social media use appeared among the influential predictors. This explanation is meaningful because these variables directly represent the operational ability of MSMEs to use digital tools and communicate product value online. In a real decision-support dashboard, the explanation can be translated into simple recommendations, such as strengthening content production when the content criterion contributes negatively to the readiness prediction.

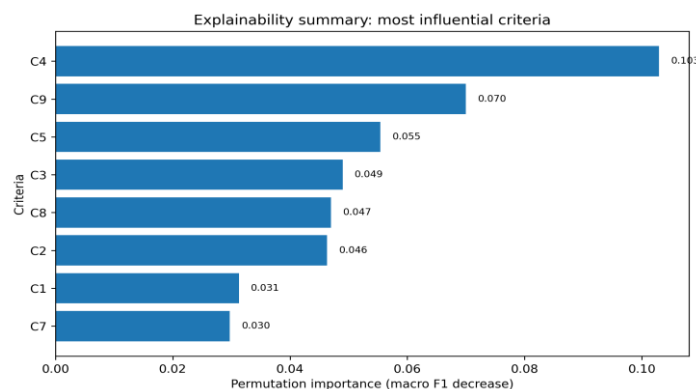


Fig. 4. Permutation-based explainability summary



3.7 Proposed System Architecture

The computational results are embedded in a layered DSS architecture. Fig. 5 shows the proposed architecture. The data layer stores MSME profiles, criteria, expert inputs, and historical records. The decision intelligence layer performs weighting and ranking. The adaptive learning layer predicts readiness classes from accumulated data. The explainability layer translates model behavior into reasons, while the dashboard layer presents ranked strategies and follow-up actions to MSME mentors and owners.

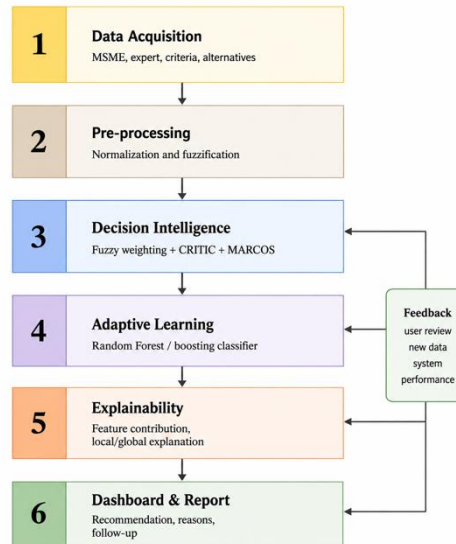


Fig. 5. Layered architecture of the explainable hybrid DSS

3.9 Detailed Manual Calculation and Reproducibility

This subsection provides a detailed manual calculation to make the proposed computational workflow auditable. The calculation uses the first synthetic MSME record (U001) and the first-ranked strategy (A3: Digital branding). The values are used only for method demonstration because the dataset is controlled and synthetic, not field data.

3.9.1 Manual Verification of Hybrid Weighting

The hybrid weight combines expert-oriented subjective weights and CRITIC objective weights. In this experiment, alpha is set to 0.60, meaning that 60% of the final weight comes from subjective priority and 40% comes from the objective CRITIC structure. For example, the hybrid weight for C1 is calculated as follows:

$$w_{(C1)}^{(hyb)} = (0.60 \times 0.1200) + (0.40 \times 0.0918) = 0.0720 + 0.0367 = 0.1087.$$

The same calculation is applied to all criteria. Table 10 verifies the hybrid weight computation used in the article.

Table 10. Manual verification of hybrid weight calculation

| Code | Criterion | Subjective | CRITIC | Hybrid formula | Hybrid |
|------|----------------------------|------------|--------|---|--------|
| C1 | Digital literacy | 0.1200 | 0.0918 | $(0.60 \times 0.1200) + (0.40 \times 0.0918)$ | 0.1087 |
| C2 | Technology readiness | 0.0950 | 0.0909 | $(0.60 \times 0.0950) + (0.40 \times 0.0909)$ | 0.0933 |
| C3 | Social media use | 0.1100 | 0.0874 | $(0.60 \times 0.1100) + (0.40 \times 0.0874)$ | 0.1010 |
| C4 | Marketplace adoption | 0.0950 | 0.0943 | $(0.60 \times 0.0950) + (0.40 \times 0.0943)$ | 0.0947 |
| C5 | Digital content capability | 0.1150 | 0.0972 | $(0.60 \times 0.1150) + (0.40 \times 0.0972)$ | 0.1079 |
| C6 | Digital payment | 0.0750 | 0.0865 | $(0.60 \times 0.0750) + (0.40 \times 0.0865)$ | 0.0796 |
| C7 | Customer data management | 0.0850 | 0.0922 | $(0.60 \times 0.0850) + (0.40 \times 0.0922)$ | 0.0879 |
| C8 | Product innovation | 0.0900 | 0.0923 | $(0.60 \times 0.0900) + (0.40 \times 0.0923)$ | 0.0909 |
| C9 | Human resource capacity | 0.0850 | 0.0908 | $(0.60 \times 0.0850) + (0.40 \times 0.0908)$ | 0.0873 |



| | | | | | |
|-----|-------------------------|--------|--------|---|--------|
| C10 | Digital branding | 0.0800 | 0.0889 | $(0.60 \times 0.0800) + (0.40 \times 0.0889)$ | 0.0836 |
| C11 | Business sustainability | 0.0500 | 0.0878 | $(0.60 \times 0.0500) + (0.40 \times 0.0878)$ | 0.0651 |

3.9.2 Manual Calculation of Digital Readiness Index for U001

The digital readiness index (DRI) is calculated by normalizing each raw score from the 1-5 scale into a 0-1 range, multiplying the normalized value by the hybrid weight, and multiplying the result by 100. For a benefit criterion, the normalized value is computed as $(x_{ij} - 1) / 4$. For U001, C1 has a raw score of 3; therefore, the normalized value is $(3 - 1) / 4 = 0.50$. Its DRI contribution is $0.50 \times 0.1087 \times 100 = 5.44$.

For C3, the raw score is 5; therefore, the normalized value is $(5 - 1) / 4 = 1.00$. Its DRI contribution is $1.00 \times 0.1010 \times 100 = 10.10$. Table 11 shows the complete calculation for all criteria in U001.

Table 11. Detailed manual DRI calculation for MSME U001

| Code | Raw | Normalized | Hybrid | Contribution formula | DRI contribution |
|------|-----|------------------|--------|---------------------------------|------------------|
| C1 | 3 | $(3-1)/4 = 0.50$ | 0.1087 | $0.50 \times 0.1087 \times 100$ | 5.44 |
| C2 | 3 | $(3-1)/4 = 0.50$ | 0.0933 | $0.50 \times 0.0933 \times 100$ | 4.67 |
| C3 | 5 | $(5-1)/4 = 1.00$ | 0.1010 | $1.00 \times 0.1010 \times 100$ | 10.10 |
| C4 | 4 | $(4-1)/4 = 0.75$ | 0.0947 | $0.75 \times 0.0947 \times 100$ | 7.10 |
| C5 | 3 | $(3-1)/4 = 0.50$ | 0.1079 | $0.50 \times 0.1079 \times 100$ | 5.39 |
| C6 | 4 | $(4-1)/4 = 0.75$ | 0.0796 | $0.75 \times 0.0796 \times 100$ | 5.97 |
| C7 | 3 | $(3-1)/4 = 0.50$ | 0.0879 | $0.50 \times 0.0879 \times 100$ | 4.39 |
| C8 | 3 | $(3-1)/4 = 0.50$ | 0.0909 | $0.50 \times 0.0909 \times 100$ | 4.55 |
| C9 | 4 | $(4-1)/4 = 0.75$ | 0.0873 | $0.75 \times 0.0873 \times 100$ | 6.55 |
| C10 | 2 | $(2-1)/4 = 0.25$ | 0.0836 | $0.25 \times 0.0836 \times 100$ | 2.09 |
| C11 | 2 | $(2-1)/4 = 0.25$ | 0.0651 | $0.25 \times 0.0651 \times 100$ | 1.63 |

The total DRI for U001 is obtained by summing all criterion contributions:

$$DRI_{U001} = 5.44 + 4.67 + 10.10 + 7.10 + 5.39 + 5.97 + 4.39 + 4.55 + 6.55 + 2.09 + 1.63 = 57.88 \approx 57.87.$$

Because the DRI value is between 45 and 70, U001 is classified as Medium readiness. This calculation verifies that the readiness class in the sample dataset is traceable from the raw criterion scores and the hybrid weights.

3.9.3 Manual MARCOS Calculation for A3 Digital Branding

The MARCOS calculation for the first-ranked alternative, A3 Digital branding, begins by comparing each A3 score with the ideal value of the corresponding criterion. Because all criteria are benefit criteria, the normalized value is x_{ij} divided by the ideal value. The normalized value is then multiplied by the hybrid weight.

For C1, the A3 score is 3 and the ideal value is 5, so the normalized value is $3 / 5 = 0.600$. The weighted value is $0.600 \times 0.1087 = 0.0652$. For C5, the A3 score is 5 and the ideal value is 5, so the normalized value is 1.000 and the weighted value is $1.000 \times 0.1079 = 0.1079$.

Table 12. Detailed MARCOS calculation components for A3 Digital branding

| Code | A3 score | Ideal | Normalized | Weighted formula | Weighted value |
|------|----------|-------|---------------|-----------------------|----------------|
| C1 | 3 | 5 | $3/5 = 0.600$ | 0.600×0.1087 | 0.0652 |
| C2 | 3 | 4 | $3/4 = 0.750$ | 0.750×0.0933 | 0.0700 |
| C3 | 4 | 5 | $4/5 = 0.800$ | 0.800×0.1010 | 0.0808 |
| C4 | 3 | 5 | $3/5 = 0.600$ | 0.600×0.0947 | 0.0568 |
| C5 | 5 | 5 | $5/5 = 1.000$ | 1.000×0.1079 | 0.1079 |
| C6 | 3 | 5 | $3/5 = 0.600$ | 0.600×0.0796 | 0.0478 |
| C7 | 3 | 5 | $3/5 = 0.600$ | 0.600×0.0879 | 0.0527 |
| C8 | 4 | 5 | $4/5 = 0.800$ | 0.800×0.0909 | 0.0727 |
| C9 | 3 | 5 | $3/5 = 0.600$ | 0.600×0.0873 | 0.0524 |
| C10 | 5 | 5 | $5/5 = 1.000$ | 1.000×0.0836 | 0.0836 |
| C11 | 4 | 5 | $4/5 = 0.800$ | 0.800×0.0651 | 0.0521 |

The sum of the weighted values forms the MARCOS score for A3:

$$S_{A3} = 0.0652 + 0.0700 + 0.0808 + 0.0568 + 0.1079 + 0.0478 + 0.0527 + 0.0727 + 0.0524 + 0.0836 + 0.0521 = 0.7420.$$

The ideal score is $S_{AI} = 1.0000$ because each criterion reaches its ideal value after normalization. The anti-ideal score is $S_{AAI} = 0.4457$, obtained from the minimum value of each criterion divided by the corresponding ideal value and multiplied by the hybrid weight. Therefore:

$$K_{(A3)}^+ = S_{A3} / S_{AI} = 0.7420 / 1.0000 = 0.7420.$$

$$K_{A3}^- = S_{A3} / S_{AAI} = 0.7420 / 0.4457 = 1.6648.$$



The utility function is calculated using the MARCOS compromise formulation. First, the auxiliary functions are computed as follows:

$$f(K_A 3^+) = K_A 3^- / (K_A 3^+ + K_A 3^-) = 1.6648 / (0.7420 + 1.6648) = 0.6917.$$

$$f(K_A 3^-) = K_A 3^+ / (K_A 3^+ + K_A 3^-) = 0.7420 / (0.7420 + 1.6648) = 0.3083.$$

$$U_{(A3)} = (K_{(A3)}^+ + K_{(A3)}^-) / \left(1 + \left(1 - f(K_{(A3)}^+) \right) / f(K_{(A3)}^+) + \left(1 - f(K_{(A3)}^-) \right) / f(K_{(A3)}^-) \right) = 0.6523.$$

Thus, A3 obtains $S_i = 0.7420$ and utility = 0.6523. This value is the highest utility in the MARCOS ranking, so A3 Digital branding is ranked first.

3.9.4 Manual Calculation of Classification Metrics

The best classifier is evaluated using a test set of 30 MSME records. The confusion matrix is summarized in Table 13. Rows represent actual classes and columns represent predicted classes.

Table 13. Confusion matrix used for manual metric calculation

| Class | Predicted Low | Predicted Medium | Predicted High | Total |
|---------------|---------------|------------------|----------------|-------|
| Actual Low | 11 | 0 | 0 | 11 |
| Actual Medium | 0 | 11 | 1 | 12 |
| Actual High | 0 | 0 | 7 | 7 |
| Column total | 11 | 11 | 8 | 30 |

The number of correct predictions is the sum of the diagonal values: $11 + 11 + 7 = 29$. The total number of test cases is 30. Therefore, the accuracy is:

$$\text{Accuracy} = 29 / 30 = 0.9667.$$

The class-wise precision, recall, and F1-score are computed as follows. For the Low class, TP = 11, FP = 0, and FN = 0, so Precision = $11 / (11 + 0) = 1.0000$, Recall = $11 / (11 + 0) = 1.0000$, and F1 = 1.0000. For the Medium class, TP = 11, FP = 0, and FN = 1, so Precision = $11 / (11 + 0) = 1.0000$, Recall = $11 / (11 + 1) = 0.9167$, and F1 = 0.9565. For the High class, TP = 7, FP = 1, and FN = 0, so Precision = $7 / (7 + 1) = 0.8750$, Recall = $7 / (7 + 0) = 1.0000$, and F1 = 0.9333.

Table 14. Manual calculation of class-wise and macro-average metrics

| Class | TP | FP | FN | Precision | Recall | F1-score |
|---------------|----|----|----|-----------|--------|----------|
| Low | 11 | 0 | 0 | 1.0000 | 1.0000 | 1.0000 |
| Medium | 11 | 0 | 1 | 1.0000 | 0.9167 | 0.9565 |
| High | 7 | 1 | 0 | 0.8750 | 1.0000 | 0.9333 |
| Macro average | - | - | - | 0.9583 | 0.9722 | 0.9633 |

The macro-average metrics are obtained by averaging the three class-wise values: Macro Precision = $(1.0000 + 1.0000 + 0.8750) / 3 = 0.9583$; Macro Recall = $(1.0000 + 0.9167 + 1.0000) / 3 = 0.9722$; and Macro F1-score = $(1.0000 + 0.9565 + 0.9333) / 3 = 0.9633$. These values are consistent with the machine learning performance table.

The manual calculation confirms that every major output in this article--hybrid weight, readiness index, MARCOS utility, and classification performance--can be reproduced from the input values without hidden operations.

3.8 Discussion and Research Implications

The experiment demonstrates that a digital transformation DSS for creative MSMEs should not be limited to a single MCDM ranking method. Expert judgement is necessary because mentors understand the practical constraints of MSMEs, while objective weights are useful to capture variability and conflict in the data. The hybrid weight approach therefore provides a more balanced decision basis than a purely subjective or purely data-driven approach.

The MARCOS ranking also provides practical insight. Strategies that emphasize branding and content were ranked higher than purely transactional strategies. This does not mean that digital payment or marketplace adoption is unimportant; rather, the result indicates that for creative MSMEs, transaction channels must be supported by product identity and content strength. This finding is consistent with the logic that creative-economy products compete through differentiation, visual quality, and customer engagement. The machine learning component adds adaptivity. Once real data are collected from MSMEs over time, the system can learn which readiness patterns are associated with certain recommendations or performance outcomes. The explainability component is essential because MSME owners and mentors need to know the reason behind a recommendation. A recommendation without explanation may be treated as a black-box output and may not be trusted.



There are limitations. The dataset in this article is simulated and controlled, so it cannot represent the entire population of Indonesian MSMEs. The weights and alternative scores were used for methodological demonstration and should be refined through expert validation and field surveys. Future research should use actual MSME data, include longitudinal performance indicators such as sales growth and customer engagement, and evaluate the dashboard through user acceptance and usability studies.

3.9 Manual Calculation Example and Reproducibility

To make the calculation transparent, this subsection shows one complete example from the first MSME record in the synthetic dataset. The record is not a real business entity; it is used only to demonstrate how the values in the method are converted into a readiness index. Table 10 reports the raw scores, normalized scores, hybrid weights, and DRI contribution for each criterion. The sum of all contributions produces the readiness score of the MSME case.

Table 10. Manual DRI calculation example for one MSME record

| Criterion | Raw score | Normalized | Hybrid weight | DRI contribution |
|-----------|-----------|------------|---------------|------------------|
| C1 | 3 | 0.50 | 0.1087 | 5.44 |
| C2 | 3 | 0.50 | 0.0933 | 4.67 |
| C3 | 5 | 1.00 | 0.1010 | 10.10 |
| C4 | 4 | 0.75 | 0.0947 | 7.10 |
| C5 | 3 | 0.50 | 0.1079 | 5.39 |
| C6 | 4 | 0.75 | 0.0796 | 5.97 |
| C7 | 3 | 0.50 | 0.0879 | 4.39 |
| C8 | 3 | 0.50 | 0.0909 | 4.55 |
| C9 | 4 | 0.75 | 0.0873 | 6.55 |
| C10 | 2 | 0.25 | 0.0836 | 2.09 |
| C11 | 2 | 0.25 | 0.0651 | 1.63 |

For the selected case, the calculated DRI is 57.87. The computation follows Equation (7), in which a raw criterion score of 1 becomes 0.00, a score of 3 becomes 0.50, and a score of 5 becomes 1.00 after normalization. This example is included to ensure that readers can reproduce the readiness calculation without relying on hidden spreadsheet operations.

Table 11 shows the MARCOS calculation for the first-ranked strategy, digital branding (A3). Each alternative score is compared with the ideal value of each criterion. The normalized value is then multiplied by the hybrid weight to produce the weighted value. The sum of weighted values forms S_i , which is then used to calculate the utility score. This step explains how the final ranking in Table 6 is produced.

Table 11. MARCOS calculation components for digital branding (A3)

| Criterion | A3 score | Ideal | Normalized | Weighted value |
|-----------|----------|-------|------------|----------------|
| C1 | 3 | 5 | 0.600 | 0.0652 |
| C2 | 3 | 4 | 0.750 | 0.0700 |
| C3 | 4 | 5 | 0.800 | 0.0808 |
| C4 | 3 | 5 | 0.600 | 0.0568 |
| C5 | 5 | 5 | 1.000 | 0.1079 |
| C6 | 3 | 5 | 0.600 | 0.0478 |
| C7 | 3 | 5 | 0.600 | 0.0527 |
| C8 | 4 | 5 | 0.800 | 0.0727 |
| C9 | 3 | 5 | 0.600 | 0.0524 |
| C10 | 5 | 5 | 1.000 | 0.0836 |
| C11 | 4 | 5 | 0.800 | 0.0521 |

3.10 Algorithmic Procedure

The proposed article can be implemented using a simple and reproducible algorithm. The procedure starts by collecting the MSME readiness matrix and expert weight assumptions. The criteria matrix is normalized, objective weights are calculated with CRITIC, and the final weights are obtained by combining subjective and objective components. Strategy alternatives are ranked with MARCOS, while the readiness class is learned using a classifier. The final output consists of ranked strategies, readiness class, and explanation of influential criteria.

Table 12. Algorithmic procedure of the proposed DSS





| Step | Procedure |
|------|---|
| 1 | Input MSME profile matrix X, alternative matrix A, and subjective weight vector w_{sub} . |
| 2 | Normalize each criterion because all readiness variables are benefit criteria. |
| 3 | Calculate CRITIC objective weights from standard deviation and inter-criterion correlation. |
| 4 | Combine subjective and objective weights using $\alpha = 0.60$. |
| 5 | Calculate DRI for each MSME and assign Low, Medium, or High readiness class. |
| 6 | Calculate MARCOS utility for each transformation strategy. |
| 7 | Train machine learning models and evaluate accuracy, precision, recall, and F1-score. |
| 8 | Apply permutation importance to explain the influence of each criterion. |
| 9 | Generate ranked strategies and explanation for the decision dashboard. |

This algorithmic formulation is useful for future replication because every output can be traced from the input matrix to the final recommendation. The calculation does not depend on subjective interpretation after the data have been entered. Expert judgement appears only in the subjective weight component, while the objective weight, ranking, prediction, and explanation are computed automatically. This is important for decision support in MSME mentoring because recommendations must be consistent across different users and different mentoring sessions.

3.11 Threats to Validity

Several threats to validity must be considered when interpreting the findings. Construct validity is limited by the selected eleven criteria; although the criteria are grounded in digital-readiness literature and prior MSME digitalization studies, other variables such as access to finance, local market competition, logistics capability, and regulatory support may also affect digital transformation success. Internal validity is limited because the readiness labels were derived from the same criteria used for model training. Therefore, the classifier performance reflects computational consistency rather than independent causal evidence. External validity is also limited because the dataset is synthetic and should be replaced with real MSME data before policy-level conclusions are made.

Despite these limitations, the experimental design remains useful for article-level method validation. It demonstrates that the DSS workflow can be executed from raw criteria values to final recommendations, that the calculations can be audited, and that the model output can be explained using feature importance. The main value of the article is therefore methodological: it provides a structured and reproducible starting point for future field-based implementation in creative MSME mentoring programs.

Table 13. Threats to validity and mitigation plan

| Validity aspect | Potential threat | Mitigation plan |
|-------------------------|--|--|
| Construct validity | Criteria may not capture every MSME condition. | Add expert validation and additional contextual variables. |
| Internal validity | Readiness class is derived from the same input criteria. | Use independent outcome labels in future field data. |
| External validity | Synthetic data do not represent all Indonesian MSMEs. | Collect multi-region MSME survey data. |
| Conclusion validity | Performance metrics are sensitive to class distribution. | Apply cross-validation and report class-wise metrics. |
| Implementation validity | Dashboard usability was not tested with real users. | Conduct SUS, UAT, and mentor interviews. |

4. CONCLUSION

This paper presented an explainable hybrid decision support approach for digital transformation strategy selection in creative MSMEs. The proposed approach integrates hybrid weighting, MARCOS ranking, adaptive machine learning, and explainability in a single computational workflow. A controlled synthetic dataset of 120 MSMEs was used to demonstrate the calculations, including readiness scoring, objective CRITIC weighting, hybrid weighting, strategy ranking, classification testing, and feature-based explanation. The results showed that digital content capability, digital literacy, social media use, marketplace adoption, and technology readiness were dominant criteria in the hybrid weighting process. The MARCOS calculation ranked digital branding, content marketing, and creative community collaboration as the highest priority strategies. The best classifier achieved strong internal predictive performance on the simulated test



set, while permutation explainability identified criteria that influenced readiness prediction. The study contributes a transparent and reproducible framework for developing DSS-based MSME digitalization research. However, the results should be interpreted as method validation using simulated data, not as a field impact claim. Future work should implement the system using real MSME datasets, conduct expert validation, and evaluate usability in mentoring programs.

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