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A MOORA-Based Decision Support Framework for Ranking Healthcare Service Performance Using Patient Perception Data

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ABSTRACT

Healthcare service performance evaluation has become an essential aspect in improving service quality and supporting evidence-based decision-making in healthcare institutions. Increasing patient expectations require healthcare providers to assess and enhance their service performance across multiple dimensions continuously. Therefore, a systematic, objective evaluation approach is needed to measure service quality effectively. This study aims to evaluate healthcare service performance using a multi-criteria decision-making approach based on patient perception data. This research employs a quantitative method, collecting data through structured questionnaires administered to 152 respondents. The instrument consists of 25 indicators derived from five service quality dimensions: tangibles, reliability, responsiveness, assurance, and empathy. Data validity and reliability were tested using Pearson correlation and Cronbach's Alpha, confirming that the instrument is valid and reliable. Furthermore, data analysis was conducted using the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method, including the construction of the decision matrix, normalization, optimization, and ranking. The results indicate that the reliability dimension achieved the highest preference value (A1 = 0.059), followed by empathy (A4) and tangibles (A5) (0.057), while responsiveness obtained the lowest value (A2 = 0.052). These findings demonstrate that reliability is the strongest aspect of healthcare service performance, whereas responsiveness requires priority improvement. This study contributes by providing an objective, systematic evaluation framework that integrates patient-perception-based service quality dimensions with the MOORA method to generate measurable performance rankings. The proposed framework offers a practical decision-support tool for healthcare managers in determining priority strategies for service quality improvement.

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1. INTRODUCTION

Healthcare service performance has become a critical concern in modern healthcare management, driven by rising patient expectations and the need to ensure service quality, efficiency, and accountability. Hospitals are required not only to deliver clinical treatment but also to provide high-quality services that meet patient expectations across multiple dimensions such as reliability, responsiveness, assurance, empathy, and tangibles. Consequently, systematic and objective evaluation of healthcare service performance is essential for improving service quality and supporting evidence-based managerial decision-making. In recent years, numerous studies ($\geq$2020) have applied multicriteria decision-making (MCDM) methods to evaluate service performance and support complex decision-making processes in healthcare and related domains. Methods such as Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VIKOR have been widely used due to their ability to handle multiple criteria. However, each method presents certain limitations. AHP relies heavily on pairwise comparisons, which may introduce subjectivity and inconsistency, particularly when dealing with a large number of criteria. TOPSIS provides a clear ranking mechanism based on distance to ideal solutions but is sensitive to normalization techniques and data variability, potentially leading to unstable results. VIKOR emphasizes compromise solutions; however, it involves more complex parameter settings and computational procedures, which may reduce its practical applicability in real-world healthcare evaluation contexts.

Despite the growing interest in healthcare service evaluation, many previous studies still rely on conventional descriptive approaches that primarily measure patient satisfaction levels without producing structured performance rankings or decision-support insights. Such approaches tend to be subjective and limited in their ability to evaluate multiple service criteria simultaneously. As healthcare services involve numerous interrelated factors, a multicriteria evaluation framework is required to provide a more comprehensive and objective assessment. Several multicriteria decision-making (MCDM) methods have been widely applied to support performance evaluation and decision-making processes. Methods such as the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VIKOR have been frequently utilized in service quality assessment and decision support systems. AHP is effective for determining criterion weights through pairwise comparisons, however, it often involves complex consistency calculations and may introduce subjectivity into the judgment process. TOPSIS ranks alternatives based on their distance from the ideal and negative-ideal solutions. Still, it is sensitive to normalization methods and may yield unstable rankings when data variability is high. Meanwhile, VIKOR focuses on compromise solutions and group utility but requires more complex computational procedures and parameter settings.

Compared to these methods, the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method offers a simpler yet robust computational approach. Recent studies highlight that MOORA provides stable ranking results, supports both benefit and cost criteria simultaneously, and requires less computational complexity, making it suitable for practical decision-support systems. Despite these advantages, its application in healthcare service performance evaluation—particularly in studies based on patient perception data—remains limited in the current literature. However, existing literature reveals several important research gaps. First, many studies applying MCDM methods focus on sectors such as education, government programs, or industrial performance evaluation. In contrast, the application of MOORA for evaluating healthcare service performance remains relatively limited. Second, previous research in hospital service evaluation often emphasizes descriptive patient satisfaction analyses without integrating multi-criteria decision-making frameworks capable of producing objective rankings of service performance. Third, studies that integrate patient perception-based service quality dimensions with MOORA-based optimization models are still scarce, particularly in the context of healthcare performance evaluation [1, 2]. This study addresses three gaps in the existing literature. First, although MCDM methods have been widely adopted, the application of MOORA in healthcare service performance evaluation is still relatively underexplored compared to other sectors. Second, many recent studies focus primarily on descriptive analyses of patient satisfaction, without integrating objective ranking mechanisms to support decision-making. Third, there is a lack of integrated frameworks that combine patient-perception-based service quality dimensions (e.g., SERVQUAL) with optimization-based MCDM methods, such as MOORA, to produce structured, actionable performance evaluations [3, 4].

Based on these gaps, this study proposes an integrated MOORA-based framework to evaluate healthcare service performance using patient perception data across five service quality dimensions: tangibles, reliability, responsiveness, assurance, and empathy. The proposed framework aims to transform subjective perceptions into objective performance rankings that can support healthcare managers in identifying priority areas for service improvement.

Accordingly, the research questions of this study are formulated as follows: How can the MOORA method be applied to evaluate healthcare service performance based on patient perception data, How effective is the MOORA-based framework in generating objective and structured performance rankings across multiple service quality dimensions, and Which healthcare service dimensions demonstrate the highest and lowest performance based on the proposed evaluation model.This study contributes to the literature by providing an objective, systematic, and practical evaluation framework that integrates service quality dimensions with the MOORA method, thereby enhancing decision-support capabilities in healthcare service performance assessment.

2. RESEARCH METHOD

This study employs a quantitative research design using a multicriteria decision-making (MCDM) approach to evaluate healthcare service performance based on patient perceptions. The proposed framework integrates service quality measurement with the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method to generate objective performance rankings.

The study population consisted of patients who received healthcare services. A purposive sampling technique was applied with the following criteria: (1) respondents who had direct experience with healthcare services, (2) aged 17 years or older, and (3) willing to participate voluntarily. A total of 152 respondents were included in the analysis. This sample size is considered adequate according to the recommendations of Joseph F. Hair Jr. et al. (2020), who suggest a minimum sample size of 100–150 is sufficient for quantitative analysis involving multivariate techniques, thereby ensuring the reliability and robustness of the results.

Primary data were collected through a structured questionnaire designed to measure patients' perceptions of healthcare service quality. The instrument was developed based on the widely recognized SERVQUAL dimensions, including tangibles, reliability, responsiveness, assurance, and empathy. These five dimensions were operationalized into 22 measurable indicators representing various aspects of healthcare service performance. Each indicator was measured using a four-point Likert scale ranging from strongly disagree (1) to strongly agree (4), allowing respondents to express their level of agreement with each statement [5–7].

Prior to data analysis, the questionnaire instrument was evaluated to ensure its validity and reliability. Construct validity was examined using Pearson product–moment correlation between each item score and the total score. An item was considered valid if its correlation coefficient exceeded the critical value at the 0.05 significance level. Reliability testing was conducted using Cronbach's Alpha to assess the internal consistency of the instrument. The results indicated a Cronbach's Alpha value of 0.70 or higher, demonstrating that the questionnaire items possess acceptable reliability and are suitable for further analysis.

Following the validation process, the collected data were processed using the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method. The analytical procedure involved several stages: construction of the decision matrix, normalization of the criteria values, calculation of the optimization values, and ranking of the alternatives. In this study, the alternatives represent the five healthcare service quality dimensions, while the criteria correspond to the indicators derived from the questionnaire responses [8].

To enhance the objectivity of the evaluation model, this study incorporates a weighting mechanism using the Entropy method. The Entropy weighting approach was selected for its ability to determine objective weights based on data variability, thereby minimizing subjectivity compared to subjective weighting methods such as AHP. The calculated weights were then integrated into the MOORA method to improve the accuracy and discriminative power of the ranking results.

The data analysis procedure consists of four main stages: (1) construction of the decision matrix based on respondents' perception scores, (2) normalization of the matrix, (3) calculation of optimization values using the MOORA method with Entropy-based weights, and (4) ranking of service quality dimensions based on the obtained preference values. All criteria were treated as benefit attributes, as higher scores indicate better service performance.

All criteria were treated as benefit attributes since higher perception scores indicate better service performance. Equal weighting was applied to all criteria, assuming that each service indicator contributes proportionally to the overall evaluation of healthcare service quality. This assumption is commonly adopted in MOORA-based performance evaluation studies when no prior empirical evidence or expert judgment is available to assign differentiated weights among criteria.

All statistical analyses were conducted using IBM SPSS Statistics for validity and reliability testing, while Microsoft Excel was used for entropy weighting and MOORA calculations. The study adhered to ethical research standards involving human participants. Participation in the survey was voluntary, and all respondents were informed of the study's purpose before completing the questionnaire. Respondents' identities and personal information were kept confidential and used solely for academic research purposes. Ethical approval for this research was obtained from the institutional research ethics committee prior to data collection.

2.1. Likert Scale

The Likert scale is a widely used research instrument for assessing individuals' attitudes, opinions, and perceptions toward a particular subject. This scale requires respondents to indicate their level of agreement or disagreement with a series of statements by selecting one option from a predefined set of response categories provided in a questionnaire. In this study, a four-point Likert scale is applied to capture respondents' perceptions, ranging from strongly disagree to strongly agree. The use of four response categories is intended to eliminate neutral responses and encourage more definitive answers from respondents. The measurement instrument consists of both positive and negative statements to ensure a balanced assessment of perceptions. For positive statements, higher scores indicate more favorable perceptions,

a score of 1 indicates the lowest level of satisfaction, and 4 the highest. Conversely, for negative statements, the scoring is reversed so that higher scores indicate less favorable perceptions. This scoring approach ensures consistency in data interpretation, where higher overall values consistently represent better perceived service quality.

2.2. Service Quality

Quality is an empirically derived approach that service organizations can use to enhance service performance. This approach involves the development of a systematic understanding of service needs as perceived by customers or the public, thereby enabling organizations to align service delivery with user expectations [9, 10].

2.3. Decision Support System

A Decision Support System (DSS) is a computer-based system designed to assist decision-making by using available data and analytical models to solve specific problems. In general, a DSS represents an advanced development of computerized Management Information Systems and is specifically designed to facilitate direct user interaction. This interactive characteristic enables effective integration of various decision-making components, including procedures, policies, analytical results, managerial experience, and insights, thereby supporting the generation of more optimal decisions [11–13]. Previous research has demonstrated the effectiveness of multicriteria decision-making approaches within decision support systems. For instance [14], in their study entitled Implementation of the MOORA Method in Determining the Eligibility of Beneficiaries of the Family Hope Program (PKH), they successfully applied the MOORA method to generate a ranking of prospective beneficiaries. The results indicated that the MOORA method is suitable as a decision-support tool for determining PKH eligibility at the village and sub-district levels. These findings highlight the potential of MOORA as a reliable and practical method for supporting complex decision-making processes involving multiple evaluation criteria [3, 15–17].

2.4. Moora Method (Multi-Objective Optimization on the Basis of Ratio Analysis)

The implementation process of the MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) method represents one of the approaches within multicriteria decision-making (MCDM) techniques [18]. The application of this method requires a systematic sequence of steps to ensure a structured and objective decision-making process based on the developed model [5, 19]. The Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method is a multicriteria decision-making (MCDM) approach widely used to support objective, structured decision-making processes. This method evaluates multiple alternatives against a set of predefined criteria using a systematic computational procedure. The implementation of the MOORA method begins with constructing a decision matrix that presents the performance values of each alternative for each evaluation criterion. In this matrix, the rows correspond to the alternatives, while the columns represent the criteria used in the assessment. After constructing the decision matrix, a normalization process is performed to transform the data to a comparable scale. This step is essential to eliminate differences in measurement units and ensure that each criterion contributes proportionally to the analysis. The normalization process is performed by dividing each element in the matrix by the square root of the sum of squares of all elements in the corresponding criterion, yielding a normalized matrix that reflects relative performance values. After normalization, the optimization process is conducted to obtain the preference value for each alternative. This process involves aggregating the normalized values by summing the criteria categorized as benefit attributes and, if applicable, subtracting the criteria classified as cost attributes. In this study, all criteria are treated as benefit attributes, with higher values indicating better performance. When weighting is applied, each normalized value is multiplied by its corresponding criterion weight before aggregation, thereby reflecting each criterion's relative importance. The final step in the MOORA method is the ranking of alternatives based on their calculated preference values. These values indicate the overall performance of each alternative across all considered criteria. The alternative with the highest preference value is identified as the most optimal option, while the alternative with the lowest value represents the least favorable performance. This ranking mechanism enables decision-makers to determine priority areas objectively and supports data-driven decision-making in complex evaluation scenarios [20].

The Yi value may be either positive or negative, depending on the maximum and minimum values present in the decision matrix [21]. The Yi value is subsequently used to determine each alternative's final ranking. Accordingly, the alternative with the highest Yi value is considered the most optimal choice, whereas the alternative with the lowest Yi value is regarded as the least favorable option [4]. It is important always to provide sufficient information to allow other researchers to adopt or replicate your methodology. This information is particularly important when a new method is developed or an innovative use of an existing method is adopted. Last, please avoid making a subsection in Method. This study employed a quantitative research design using a multi-criteria decision-making (MCDM) approach to evaluate healthcare service performance based on patients' perceptions. The evaluation framework integrates service quality measurement with the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method to generate objective performance rankings [22–24, 22, 25].

The research population consisted of patients who received healthcare services. A purposive sampling technique was applied with the following inclusion criteria: (1) respondents who had experienced healthcare services, (2) respondents aged 17 years or older, and (3) willingness to participate by completing the questionnaire. A total of 152 valid responses were collected and used for the analysis [8, 26, 27]. Data were obtained through a structured questionnaire developed based on the five dimensions of service quality: tangibles, reliability, responsiveness, assurance, and empathy. These dimensions were represented by 25 service indicators, measured on a four-point Likert scale from strongly disagree to strongly agree. Prior to the main analysis, the instrument was tested for validity and reliability to ensure the quality of the collected data.

Construct validity was evaluated using Pearson product–moment correlation between each item score and the total score. An item was considered valid if its correlation coefficient exceeded the critical value at the 0.05 significance level. Reliability testing was conducted using Cronbach's Alpha to assess the questionnaire's internal consistency. The reliability test results indicated a Cronbach's Alpha value of 0.70 or higher, confirming that the measurement instrument has acceptable reliability and internal consistency for further analysis.

All service indicators were treated as benefit criteria in the MOORA model. Equal weighting was applied to each criterion, assuming that each service quality indicator contributes proportionally to the overall perception of healthcare service performance. This approach is commonly adopted in multicriteria decision-making studies when no prior empirical evidence or expert consensus is available to justify differential weighting among criteria. The analysis process consisted of several stages. First, the decision matrix was constructed based on the average scores of each service indicator. Second, normalization was performed to standardize the matrix values and eliminate differences in measurement scales. Third, the optimization process aggregated normalized values to obtain the MOORA preference value (Yi) for each alternative. Finally, alternatives were ranked according to their optimization values, where the highest value indicates the best-performing service dimension [28].

All statistical analyses and MOORA calculations were conducted using Microsoft Excel and IBM SPSS Statistics software. SPSS was used to perform validity and reliability testing, while Excel was utilized to construct the decision matrix, perform normalization, calculate MOORA preference values, and generate the final ranking results. This study adhered to ethical research standards involving human participants. Participation was voluntary, and respondents provided informed consent prior to completing the questionnaire. All collected data were anonymized and used solely for research purposes. Ethical approval for this study was obtained from the institutional research ethics committee of Universitas Methodist Indonesia prior to data collection.

3. RESULT AND ANALYSIS

3.1. Result

This study employs a descriptive, quantitative research design and a multicriteria decision-making (MCDM) approach. The Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method is employed to analyze and determine the level of healthcare service performance based on patients' perceptions. A quantitative approach is selected because the research data are expressed numerically and analyzed using mathematical and statistical techniques. The study population consisted of patients who had received healthcare services at a public healthcare institution. A purposive sampling technique was employed with the following inclusion criteria: (1) patients or patients' family members who had experienced healthcare services, (2) respondents aged 17 years or older, and (3) respondents who were willing to participate in the study by completing the research questionnaire. A total of 152 respondents were included in the final dataset to ensure sufficient data reliability for the MOORA-based analysis.

The study utilizes both primary and secondary data. Primary data were collected through structured questionnaires, while secondary data were obtained from relevant institutional documents and literature. Following data collection, data processing and analysis were conducted in accordance with the MOORA methodology. The research variables and indicators presented in Table 1 are described narratively to enhance clarity and methodological transparency. This study adopts the SERVQUAL framework as a theoretical foundation to measure healthcare service quality from the patients' perspective, which has been widely validated in healthcare performance evaluation studies. Specifically, five core dimensions are utilized: tangibles, reliability, responsiveness, assurance, and empathy, each operationalized into observable, measurable indicators to ensure construct validity.

The tangibles dimension represents the physical aspects of healthcare services that directly influence patients' first impressions and perceived service quality. This dimension is measured through indicators such as the cleanliness and maintenance of hospital buildings, the availability of comfortable waiting areas, the completeness of medical equipment and facilities, the clarity of directional signage, and the adequacy and modernity of medical equipment. These indicators reflect the extent to which healthcare institutions provide a supportive physical environment for service delivery.

The reliability dimension captures healthcare providers' ability to deliver services accurately, consistently, and dependably. It includes indicators related to the accuracy and timeliness of service delivery, the willingness of medical staff to assist patients when problems occur, the clarity of explanations regarding treatment procedures and medication instructions, the provision of relevant pre-service information, and the ability to communicate medical procedures effectively. This dimension is critical, as reliability is often identified as a primary determinant of patient trust and satisfaction in healthcare settings.

The responsiveness dimension reflects healthcare personnel's willingness and promptness in addressing patient needs and concerns. The indicators include staff readiness to receive and respond to complaints, promptness of nurses in providing assistance, courteous and professional service delivery, efficiency and accuracy of medical procedures, and effectiveness of waiting time management. This dimension is particularly important in dynamic healthcare environments where timely response significantly affects patient perceptions.

The assurance dimension concerns the competence, professionalism, and credibility of healthcare providers in delivering safe, trustworthy services. It is measured through indicators such as physicians' knowledge and diagnostic competence, the availability of necessary medical resources, the ability to instill a sense of safety and confidence in patients, the accuracy of medical record management, and the demonstration of polite and professional behavior by hospital staff. This dimension emphasizes the importance of perceived safety and professional integrity in healthcare delivery.

Finally, the empathy dimension represents the extent to which healthcare providers offer individualized attention and emotional support to patients. This includes allocating sufficient consultation time, understanding and accommodating patient needs and preferences, demonstrating genuine care and concern, actively listening to patient complaints, and providing friendly, respectful services. Empathy plays a significant role in enhancing patient experience and strengthening the patient–provider relationship.

In total, these 25 indicators form a comprehensive measurement framework that captures multiple aspects of healthcare service quality based on patient perceptions. All indicators are treated as benefit criteria in the MOORA model, where higher scores indicate better service performance. This operationalization ensures that subjective patient perceptions can be systematically transformed into quantitative inputs for multicriteria decision-making analysis, thereby improving the objectivity and robustness of healthcare service performance evaluation.

3.2. Discussion

This study involved 152 respondents who had received healthcare services at a healthcare institution. All respondents met the research criteria and completed a 25-item questionnaire based on five service quality dimensions: reliability, responsiveness, assurance, empathy, and tangibles.

The analysis of healthcare service performance was conducted by applying the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method. The alternatives in this study consisted of the five service quality dimensions, while the criteria were the service indicators classified as benefit criteria. All indicators were assumed to have an equal level of importance, and therefore no weighting differences were applied [29–33]. From a methodological perspective, integrating Entropy weighting with the MOORA method enhances the objectivity of the evaluation results. Unlike equal-weighting approaches, the Entropy method assigns weights based on data variability, resulting in a more discriminative and reliable ranking.

The alternatives were defined as A1 (Reliability), A2 (Responsiveness), A3 (Assurance), A4 (Empathy), and A5 (Tangibles). Table 1 presents the average scores for the questionnaire items, based on respondents' perceptions of healthcare service experiences. Table 2 presents the normalization process of the alternatives and criteria that has been conducted. Table 3 presents the preference values. In the preference value calculation process, each criterion value is multiplied by the assigned weight. The findings reveal that Reliability (A1) achieves the highest preference value (0.059), followed by Empathy (A4) and Tangibles (A5) (0.057), Assurance (A3) (0.056), and Responsiveness (A2) (0.052). This indicates that reliability plays a critical role in shaping patients' perceptions of healthcare service performance, particularly with respect to accuracy, consistency, and timeliness of service delivery.

Table 1. Alternatives and Criteria Matrix

	C1	C2	C3	C4	C5
A1 (Reliability)	3.86	3.57	3.91	3.68	**3.61**
A2 (Responsiveness)	3.59	3.27	3.35	3.29	**3.04**
A3 (Assurance)	3.30	3.84	3.74	3.78	**3.02**
A4 (Empathy)	3.39	3.34	3.70	3.78	**3.71**
A5 (Tangibles)	3.93	3.93	3.24	3.92	**3.05**

Table 2. Normalization Table

	C1	C2	C3	C4	C5
A1 (Reliability)	0.06	0.06	0.06	0.05	**0.07**
A2 ((Responsiveness)	0.05	0.05	0.05	0.05	**0.06**
A3 (Assurance)	0.05	0.06	0.06	0.06	**0.06**
A4 (Empathy)	0.05	0.05	0.06	0.06	**0.07**
A5 (Tangibles)	0.06	0.06	0.05	0.06	**0.06**

Table 3. Preference Values

Code	Preference Values
A1 (Reliability)	0.059
A2 ((Responsiveness)	0.052
A3 (Assurance)	0.056
A4 (Empathy)	0.057
A5 (Tangibles)	0.057

4. CONCLUSION

This study demonstrates that the Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) method can be effectively applied to evaluate healthcare service performance using patient perception data. The proposed framework provides an objective evaluation model that produces optimization values and performance rankings across different service quality dimensions. The primary novelty of this study lies in applying the MOORA method to integrate five patient-perceived service quality dimensions into a single quantitative evaluation framework. This approach enables hospital management to systematically identify service dimensions with optimal performance and those requiring priority improvement. Accordingly, the findings of this study contribute not only to the academic development of decision support systems and healthcare service performance evaluation but also to the development of a practical, applicable, and easily implementable performance assessment model. Future research may further enhance this model by incorporating weighted criteria, comparing MOORA with other Multi-Criteria Decision-Making (MCDM) methods, or integrating it into an information technology–based decision support system.

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6. DECLARATIONS

AI USAGE STATEMENT

The author used ChatGPT (OpenAI) as a language assistance tool to improve the clarity, grammar, and readability of the manuscript. The author critically reviewed and revised the generated text to ensure its accuracy, originality, and academic integrity. The author takes full responsibility for the content of this manuscript.

AUTHOR CONTIBUTION

The conceptual design of the study, research methodology, data validation, and interpretation of results were collaboratively developed by Samuel Manurung, Indra M. Sarkis, Mufria J. Purba, Gortap Lumbantoruan and Hans Hendri. All authors contributed to the writing, review, and approval of the final manuscript.

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COMPETING INTEREST

The authors declare no competing interests regarding the publication of this paper.

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