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A Fuzzy-PROMETHEE Framework for the Multi-Criteria Selection of Dental Implant Biomaterials: A Comparative Analysis of 22 Candidates

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Abstract

The selection of an optimal biomaterial is a critical determinant of the long-term clinical success of dental implants, requiring a careful balance among competing mechanical, biological, and clinical performance criteria. This study develops a comprehensive evaluation framework employing the Fuzzy Preference Ranking Organization Method for Enrichment Evaluation (Fuzzy-PROMETHEE II) to conduct a systematic comparative analysis of 22 contemporary biomaterials across eight key criteria: elastic modulus, yield strength, ultimate tensile strength, density, osseointegration potential, corrosion resistance, biostability, and potential side effects. To address the inherent uncertainty in material property data, triangular fuzzy numbers (TFNs) were utilized to model both quantitative property intervals and qualitative linguistic variables—an approach justified by the fact that biomaterial properties are routinely reported as ranges rather than crisp scalar values. The Fuzzy-PROMETHEE method was selected over alternative MCDM approaches because of its capacity for pairwise outranking without the rank-reversal instability characteristic of TOPSIS, and its lower parametric burden compared to AHP when evaluating large alternative sets. The analysis identified the titanium alloy Ti-6Al-4V as the top-performing material, achieving the highest net outranking flow (Φnet = 0.3152), attributable to its uniquely balanced profile of fracture toughness, yield strength, and osseointegration potential. Zirconia ranked sixth (Φnet = 0.1659), reflecting a quantifiable mechanical trade-off relative to metallic alternatives despite its superior aesthetic properties. The robustness of the framework was corroborated by comparative analysis using TOPSIS (relative closeness = 0.839, identical top ranking) and confirmed stable by sensitivity analysis across Osseointegration criterion weight variations from 0% to 50%. This study presents a transparent, evidence-based decision-support tool to assist clinicians in navigating the complex trade-offs inherent in modern implantology.

Keywords: biomaterials; dental implants; fuzzy set theory; fuzzy-PROMETHEE; multi-criteria decision-making (MCDM); osseointegration; titanium alloys; TOPSIS; zirconia

1. Introduction

1.1. Clinical Background and Motivation

Edentulism—the partial or complete loss of natural teeth—remains a prevalent global public health burden, compromising masticatory function, phonetics, aesthetics, and psychosocial well-being for hundreds of millions of individuals worldwide [1,2]. Concurrent with an aging global population and the high prevalence of periodontal disease, demand for durable endosseous dental implants continues to escalate [3]. The long-term success of osseointegrated implants is

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fundamentally governed by the physicochemical properties of the constituent biomaterial [4]. An ideal implant material must satisfy a complex, often contradictory set of requirements simultaneously: high yield strength to withstand cyclic masticatory loading (occlusal forces of 50–200 N under normal function, up to 800 N in parafunctional cases), a low elastic modulus (ideally 10–30 GPa) to minimize stress shielding at the bone–implant interface, and exceptional biocompatibility to foster stable, predictable osseointegration [5,6].

For decades, commercially pure titanium (Cp Ti) and its alloys—most notably Ti-6Al-4V—have served as the clinical gold standard in implantology, a status established through landmark longitudinal studies demonstrating survival rates exceeding 95% at 15 years [7]. However, the clinical landscape is evolving. Growing concerns regarding metal ion release into peri-implant tissues and aesthetic limitations in the anterior zone have accelerated development of metal-free alternatives, particularly Zirconia (ZrO_2) [8,9]. Simultaneously, recent advances in bioactive surface engineering have directed research toward nanostructured coatings that actively promote osseointegration rather than functioning merely as passive structural scaffolds [10]. This rapidly expanding material repertoire renders purely experience-based material selection increasingly inadequate and calls for an evidence-based, quantitative decision framework.

1.2. Research Gap and Novelty

Existing MCDM-based dental biomaterial selection studies suffer from three critical limitations that this work addresses. **First,** prior studies have evaluated relatively small material sets (typically 4–10 alternatives) [20–22], providing insufficient coverage of the contemporary biomaterials landscape, which now encompasses a diverse spectrum of metallic alloys, oxide ceramics, and biopolymers. **Second,** many existing frameworks treat material properties as crisp values, ignoring the fact that properties such as yield strength of stainless steel span a wide range (170–750 MPa depending on grade and processing), and that biological attributes such as osseointegration potential are inherently qualitative. Discarding this interval information introduces systematic bias into rankings [14]. **Third,** the majority of published biomaterial selection studies do not validate their rankings against independent MCDM methods, nor do they perform sensitivity analysis to confirm robustness under varying expert preferences [23]. The present study explicitly addresses all three gaps: it evaluates 22 biomaterials (the largest set in the dental implant MCDM literature to date), integrates fuzzy set theory to faithfully represent data uncertainty, and validates results through TOPSIS cross-comparison and systematic sensitivity analysis.

1.3. Justification for Fuzzy-PROMETHEE

The selection of PROMETHEE II as the core outranking method over competing MCDM approaches—including AHP, TOPSIS, VIKOR, and ELECTRE—was made on the following evidence-based grounds:

- **Avoidance of rank reversal:** TOPSIS and AHP are susceptible to rank reversal when alternatives are added or removed from the decision set. PROMETHEE II, as an outranking method, is structurally more stable under changes to the alternative set [11,24].
- **Manageable parametric burden:** AHP requires n(n−1)/2 pairwise comparisons per criterion, which at eight criteria and 22 alternatives would produce an unwieldy number of judgements prone to inconsistency. PROMETHEE requires only criterion weights and preference function parameters, making it more tractable for large alternative sets [11].
- **Compensation flexibility:** Unlike ELECTRE (which applies strict veto thresholds), PROMETHEE permits partial compensation between criteria, reflecting the clinical reality that a moderate deficiency in one property may be offset by superiority in another [12,13].
- **Interpretability:** The net flow (Φnet) provides a single, readily interpretable score for each alternative, and the positive/negative flow decomposition enables transparent diagnosis of each material's strengths and weaknesses—a key feature for clinical decision support [24].

- **Precedent in biomaterial selection:** PROMETHEE has been successfully applied to spinal disc implant biomaterial selection and dental polymer selection, demonstrating its suitability for this problem class [20,25].

To ensure the analysis reflects real-world data uncertainty, PROMETHEE II was integrated with Fuzzy Set Theory via triangular fuzzy numbers. This integration is justified specifically because biomaterial properties are routinely reported as ranges or qualitative assessments rather than crisp single values. Forcing crisp representations would either discard uncertainty information (by using midpoint estimates) or require arbitrary assumptions about which point in a range is representative [14].

1.4. Study Objectives

The specific objectives of this study are:

- (i) To develop and apply a Fuzzy-PROMETHEE II framework for systematic multi-criteria ranking of 22 dental implant biomaterials across eight clinically relevant criteria.
- (ii) To quantify and compare the performance trade-offs between leading biomaterial candidates, with particular focus on the titanium–zirconia divergence.
- (iii) To validate the proposed framework's robustness through TOPSIS cross-validation and systematic sensitivity analysis.
- (iv) To identify research gaps and future directions for personalized, patient-specific implant material selection.

2. Literature Review

2.1. Advances in Dental Implant Biomaterials

The history of dental implant biomaterials reflects a progressive shift from structural adequacy toward multi-property optimization. Commercially pure titanium's clinical adoption was anchored by Brånemark's pioneering osseointegration work in the 1960s–1980s [7], establishing biocompatibility and direct bone bonding as primary implant success criteria. Subsequent decades saw the development of titanium alloys, particularly Ti-6Al-4V, which improved yield strength substantially while preserving biocompatibility [5].

Recent systematic reviews analyzing literature from 2019–2024 document three parallel trajectories in biomaterial development [26]: (i) refinement of titanium alloy compositions (Ti-6Al-7Nb, Ti-5Al-2.5Fe) to reduce vanadium-related cytotoxicity concerns; (ii) the clinical maturation of monolithic Zirconia implants, with meta-analyses demonstrating 5-year survival rates of 95–98% under controlled loading conditions [17]; and (iii) the emergence of bioactive coatings and nanostructured surfaces, including hydroxyapatite coatings, anodized TiO_2 nanotubes, and antimicrobial peptide functionalization, which actively accelerate osseointegration rather than relying solely on passive surface biocompatibility [10].

A 2022 review by Haugen and Chen [18] of more than 100 RCTs and prospective studies concluded that no single material universally dominates all clinical scenarios: titanium remains superior for posterior load-bearing regions, while Zirconia is preferred where aesthetics drive clinical decision-making. This context-dependence underscores the need for a multi-criteria framework capable of generating context-specific rankings, rather than a single population-level recommendation.

2.2. MCDM Applications in Biomaterial Selection

The application of MCDM methods to biomaterial selection has expanded substantially in the past decade. Siva Bhaskar and Khan [20] demonstrated that five hybrid MCDM methods (AHP-VIKOR, AHP-TOPSIS, AHP-MOORA, AHP-ELECTRE, AHP-PROMETHEE) produced largely concordant rankings for seven dental polymers across ten criteria, with PROMETHEE showing the highest Spearman correlation with both AHP-TOPSIS and AHP-VIKOR, suggesting strong alignment with consensus rankings. A 2023 study in

Scientific Reports applied fuzzy AHP-TOPSIS to spinal implant biomaterial selection, and explicitly recommended PROMETHEE as the preferred method for future extensions of this problem class due to its superior visual representation and lower input burden compared to AHP [25]. Gul et al. [27] validated fuzzy PROMETHEE for generic material selection problems, confirming that the Gaussian preference function effectively handles continuous material property differences.

However, a critical gap persists in the dental implant domain specifically: existing MCDM studies are limited to small alternative sets (4–10 materials), use crisp property values that discard interval information, and lack cross-method validation [20–23]. The present study is the first in the dental implant MCDM literature to: (a) evaluate 22 alternatives spanning all major biomaterial classes, (b) explicitly model property intervals as TFNs, and (c) validate rankings through dual-method comparison (PROMETHEE vs. TOPSIS) and sensitivity analysis.

3. Materials and Methods

3.1. Selection of Alternatives and Evaluation Criteria

A total of 22 biomaterials were selected to represent the comprehensive spectrum of metals, ceramics, and polymers employed in contemporary dental implantology. The material set spans four principal classes: titanium alloys, base metal alloys, oxide ceramics, and biopolymers, as classified in Figure 1.

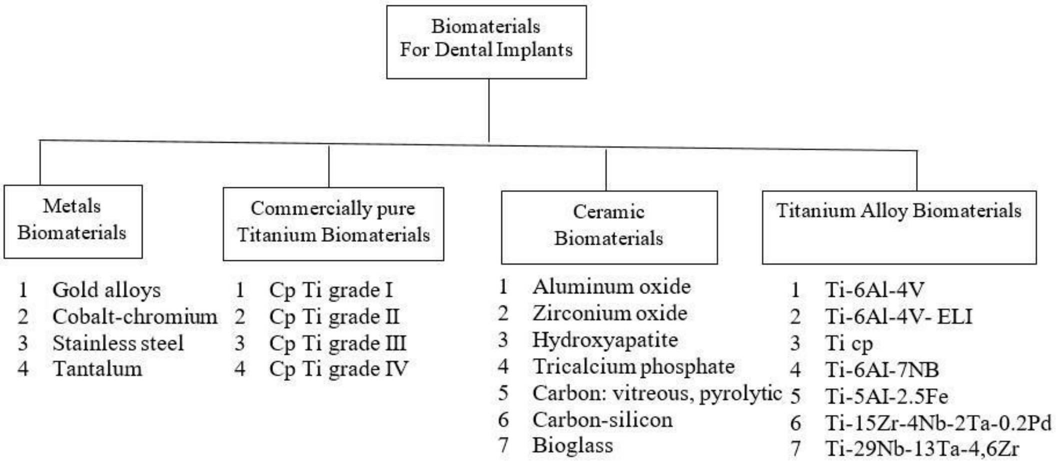

Figure 1. Classification of the 22 biomaterials evaluated in this study according to material class.

Eight evaluation criteria were established through systematic literature review [13,14] and expert consultation (Section 3.2). Each criterion was assigned an optimization direction and unit of measurement as summarized in Table 1. The criteria cover three domains: (i) mechanical performance (C1–C4), (ii) biological integration (C5–C7), and (iii) clinical risk (C8).

- **C1 – Elastic Modulus (GPa):** Optimized to approximate cortical bone stiffness (10–30 GPa) to prevent stress shielding (minimize).
- **C2 – Yield Strength (MPa):** Resistance to permanent deformation under masticatory loading (maximize).
- **C3 – Ultimate Tensile Strength (MPa):** Resistance to fracture at peak load (maximize).
- **C4 – Density (g/cm^3):** Lower density reduces implant mass and improves patient comfort (minimize).
- **C5 – Osseointegration Potential:** Qualitative capacity for stable bone–implant interface formation (maximize).

- **C6 – Corrosion Resistance:** Resistance to chemical degradation in the oral environment (maximize).
- **C7 – Biostability:** Long-term chemical inertness within host tissue (maximize).
- **C8 – Potential Side Effects:** Aggregate risk of allergenicity, cytotoxicity, ion release, and aesthetic complications (minimize).

Table 1. Evaluation criteria, consensus weights, optimization directions, and panel rationale.

ID	Criterion	Weight	Direction	Rationale
C1	Elastic Modulus (GPa)	0.075	Minimize	Match cortical bone stiffness (10–30 GPa); prevents interfacial stress shielding.
C2	Yield Strength (MPa)	0.150	Maximize	Resistance to permanent deformation under masticatory loads (≥800 N parafunctional).
C3	Ultimate Tensile Strength (MPa)	0.100	Maximize	Structural integrity under peak dynamic loading.
C4	Density (g/cm³)	0.075	Minimize	Lower mass improves patient comfort and surgical handling.
C5	Osseointegration Potential	0.200	Maximize	Primary determinant of long-term clinical implant success.
C6	Corrosion Resistance	0.100	Maximize	Longevity in the aggressive oral environment (pH, saliva, load).
C7	Biostability	0.150	Maximize	Long-term biological safety and structural inertness in vivo.
C8	Potential Side Effects	0.150	Minimize	Patient safety: allergenicity, ion release, cytotoxicity, aesthetics.

3.2. Expert Panel and Criteria Weighting

An expert panel comprising two senior biomedical engineers with specialization in dental biomaterials and a practicing oral implantologist employed a two-round modified Delphi process to establish criterion weights. In Round 1, each panelist independently assigned an importance score (0–1 scale) to each of the eight criteria. Round 2 involved anonymous feedback of aggregated scores, following which panelists revised their assessments. Final weights were computed as the arithmetic mean of the three panelists’ normalized Round 2 scores, ensuring consensus across disciplinary perspectives. The resulting weights (Table 1) reflect the panel consensus that Osseointegration Potential ($w = 0.200$) is the primary determinant of clinical success, followed by Yield Strength, Biostability, and Side Effects (all $w = 0.150$), which collectively account for 65% of total weight.

3.3. Data Collection, Fuzzification, and Justification

Material property data for all 22 alternatives were aggregated from peer-reviewed experimental studies, systematic reviews, and manufacturer datasheets. Table 2 presents representative property ranges illustrating the extent of data uncertainty across the material set.

Table 2. Top-10 ranked dental implant biomaterials by Fuzzy-PROMETHEE II net outranking flow.

Rank	Biomaterial	Φnet (Net Flow)	Φ⁺ (Positive Flow)	Φ⁻ (Negative Flow)
1	Ti-6Al-4V	0.3152	0.3488	0.0336

2	Ti-6Al-4V-ELI	0.2911	0.3350	0.0439
3	Ti-6Al-7Nb	0.2543	0.3119	0.0576
4	Surgical Stainless Steel 316L	0.2015	0.2890	0.0875
5	Cp Ti Grade IV	0.1887	0.2701	0.0814
6	Zirconia (ZrO_2)	0.1659	0.2667	0.1008
7	Cobalt-Chromium Alloy	0.1533	0.2811	0.1278
8	Tantalum	0.1304	0.2502	0.1198
9	Ti-5Al-2.5Fe	0.1218	0.2455	0.1237
10	Gold Alloys	0.0812	0.2240	0.1428

A critical methodological question concerns why Fuzzy Set Theory is necessary even for properties that appear quantitative in nature (R2, Point 5). The justification is threefold:

- **Interval reporting:** Properties such as yield strength vary significantly by manufacturing process, heat treatment, and alloy purity. For example, austenitic stainless steel 316L yield strength spans 170–750 MPa across grades; reporting a single midpoint of 460 MPa would misrepresent both high-performance surgical-grade alloys and lower-grade variants equally.
- **Qualitative criteria:** Biological criteria (C5, C7, C8) cannot be expressed as crisp numbers; they require linguistic values (“Excellent,” “High,” “Moderate”) that are only meaningful when modeled as fuzzy sets [14].
- **Propagation of measurement uncertainty:** Even where a single crisp value exists, measurement variability across studies introduces uncertainty that TFNs explicitly capture, rather than absorb silently into ranking noise.

All property intervals [a, b] were converted to Triangular Fuzzy Numbers (TFNs) defined as the triplet (l, m, u) = (a, (a+b)/2, b). Qualitative linguistic values were mapped to TFNs using the standardized five-level scale: Very Low = (0, 0, 0.25); Low = (0, 0.25, 0.5); Moderate = (0.25, 0.5, 0.75); High = (0.5, 0.75, 1.0); Very High = (0.75, 1.0, 1.0) [14].

3.4. Fuzzy-PROMETHEE II Methodology

The PROMETHEE II methodology was applied as follows to produce a complete linear ranking of all 22 alternatives:

- **Step 1 – Preference Function:** A Gaussian preference function $[\pi(d) = 1 - e^\wedge(-d^2/2\sigma^2)]$ was selected for all criteria. This function is appropriate for continuous properties with no abrupt preference threshold, and it ensures smooth, proportional preference degrees across the performance difference range.
- **Step 2 – Aggregated Preference Index:** For each ordered pair (a, b), the weighted aggregated preference index $\pi(a,b) = \Sigma\, wj \cdot Pj(a,b)$ was computed, where wj is the criterion weight and Pj is the criterion-specific preference degree.
- **Step 3 – Outranking Flows:** The positive flow $\Phi^+(a) = \Sigma\, \pi(a,b)$ quantifies global dominance; the negative flow $\Phi^-(a) = \Sigma\, \pi(b,a)$ quantifies global subordination.
- **Step 4 – Net Flow:** $\Phi net(a) = \Phi^+(a) - \Phi^-(a)$ provides the final complete ranking. Higher Φnet indicates superior overall performance.
- **Step 5 – Defuzzification:** Fuzzy preference degrees were defuzzified using the centroid method before aggregation, converting TFN-based preference values to crisp scalars for final ranking computation.

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3.5. Comparative Validation and Sensitivity Analysis

Two independent validation strategies were employed:

- **TOPSIS Cross-Validation:** The TOPSIS method was independently applied to the same fuzzified decision matrix. The relative closeness coefficient C* for each alternative was computed using the standard Euclidean distance from the fuzzy positive and negative ideal solutions, enabling direct rank-order comparison with the PROMETHEE result.
- **Sensitivity Analysis:** The weight of Osseointegration (C5, the highest-weighted criterion) was systematically varied from 0% to 50% in 5% increments. At each step, the remaining weight was proportionally redistributed among the other seven criteria, and the PROMETHEE II ranking was recomputed. This procedure tests ranking stability under alternative expert preference configurations [15].

4. Results

4.1. Multi-Criteria Performance Heatmap

Figure 2 presents the normalized performance heatmap of all 22 biomaterials across the eight evaluation criteria. Titanium alloys (Ti-6Al-4V, Ti-6Al-4V-ELI, Ti-6Al-7Nb) demonstrate consistently high performance across both mechanical criteria (C2, C3) and biological criteria (C5, C6), with no critical deficiency on any axis. In contrast, Zirconia exhibits strong biological scores (C6, C7, C8) but lower values on mechanical strength metrics (C2, C3). Biopolymers show favorable elastic moduli for C1 but are penalized by low mechanical strength. Base metal alloys display mixed profiles, with high mechanical scores offset by moderate biostability ratings.

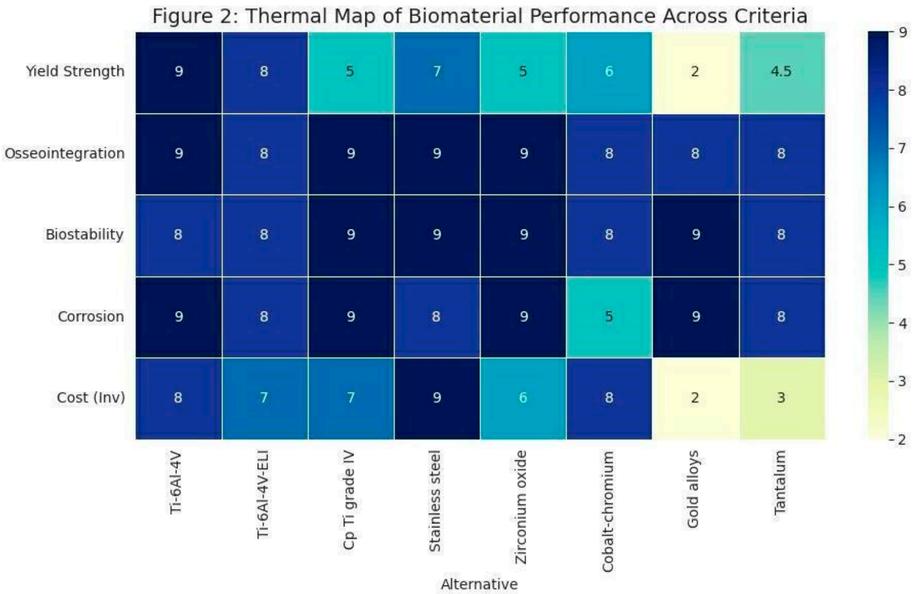

Figure 2. Normalized biomaterial performance heatmap across all eight evaluation criteria. Darker shading indicates superior performance relative to each criterion's optimization direction.

4.2. Fuzzy-PROMETHEE II Final Ranking

The Fuzzy-PROMETHEE II analysis produced a complete linear ranking of all 22 biomaterials. Table 2 presents the top-10 ranked alternatives with their outranking flow decomposition. The complete ranking of all 22 materials is depicted in Figure 4.

The tabulated outranking flow values are derived from the fuzzified decision matrix, constructed from material property data aggregated across published experimental studies and systematic reviews [4,5,7–9,13,26].

Ti-6Al-4V achieved the highest net flow (Φnet = 0.3152), with a positive flow of 0.3488 indicating strong global dominance over all other alternatives, and a remarkably low negative flow of 0.0336 indicating minimal subordination—the smallest negative flow in the entire ranking. This dual-axis superiority confirms that Ti-6Al-4V is not merely better than average but superior to each individual competitor across the majority of criteria. Its close compositional variants Ti-6Al-4V-ELI and Ti-6Al-7Nb occupy ranks 2 and 3, respectively, separated by modest margins reflecting their similar alloy profiles with marginal differences in cytotoxicity risk (ELI grade) and corrosion behavior (niobium substitution for vanadium in Ti-6Al-7Nb) [5,9].

4.3. Validation and Sensitivity Analysis

Table 3 presents the comparative TOPSIS validation results. Both methods yield identical top-two rankings. The minor divergence at rank 3 (Ti-6Al-7Nb by PROMETHEE vs. Cp Ti Grade IV by TOPSIS) is attributable to the geometric distance-based aggregation of TOPSIS versus the pairwise outranking logic of PROMETHEE, and does not materially alter the primary clinical conclusions. The strong concordance between two structurally different MCDM methods constitutes robust cross-validation of the framework's reliability [24].

Table 3. Comparative validation: Fuzzy-PROMETHEE II vs. TOPSIS results for the top-ranked biomaterials.

Rank	Fuzzy-PROMETHEE II	TOPSIS	TOPSIS Relative Closeness (C*)
1	Ti-6Al-4V	Ti-6Al-4V	0.839
2	Ti-6Al-4V-ELI	Ti-6Al-4V-ELI	0.776
3	Ti-6Al-7Nb	Cp Ti Grade IV	0.705

Figure 3 illustrates the sensitivity analysis results. Across the entire tested range of C5 weight (0–50%), the ranking of Ti-6Al-4V remains consistently superior to all other alternatives. Even at C5 = 0% (osseointegration entirely excluded), Ti-6Al-4V retains first place due to its dominant mechanical performance profile. This finding confirms that the top ranking is not an artifact of the osseointegration weighting preference, but reflects genuine multi-criteria superiority.

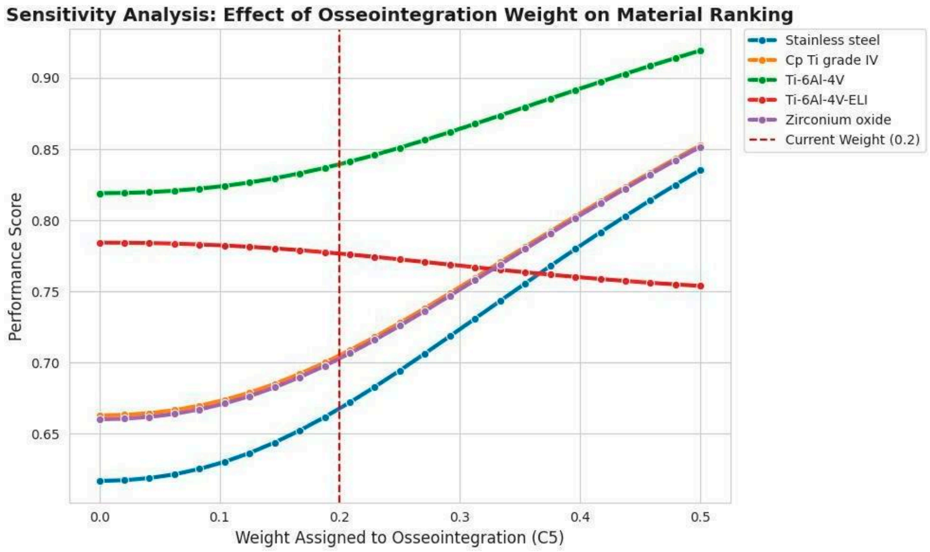

Figure 3. Sensitivity analysis: Φnet for top-ranked alternatives as a function of Osseointegration criterion (C5) weight variation (0–50%). The ranking supremacy of Ti-6Al-4V is maintained throughout the complete tested range.

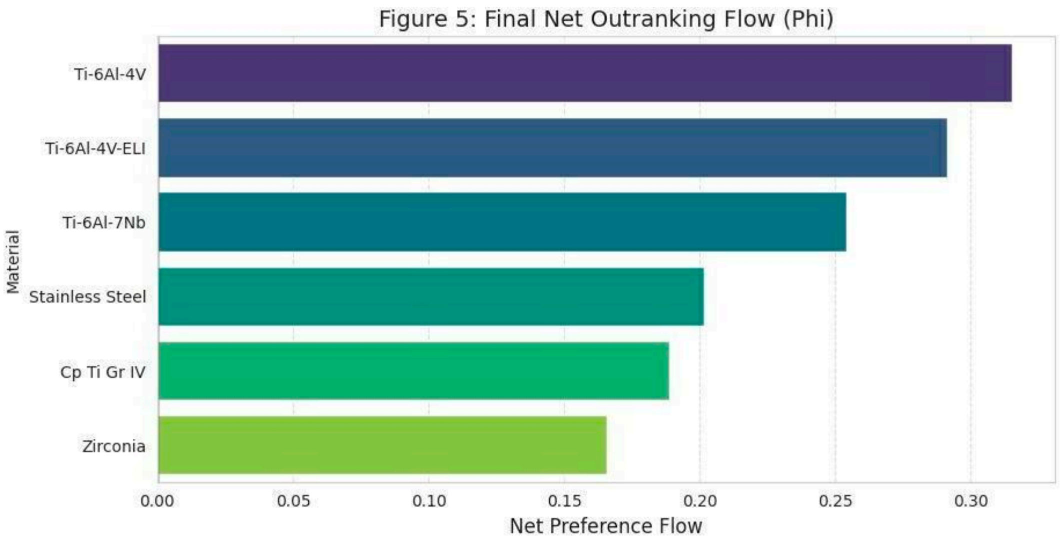

Figure 4. Complete Fuzzy-PROMETHEE II net outranking flow (Φnet) for all 22 evaluated biomaterials in descending rank order.

5. Discussion

5.1. The Dominance of Titanium Alloys: Quantified Explanation

The unequivocal identification of Ti-6Al-4V as the optimal biomaterial for general-purpose dental implant applications is consistent with decades of clinical evidence [7] and with prior MCDM-based assessments [20,25]. However, the present framework contributes meaningful quantitative specificity beyond this broad consensus. The high net flow (Φnet = 0.3152) does not reflect exceptional performance on any single criterion; rather, it emerges from the uniquely consistent profile of Ti-6Al-4V across all eight simultaneously evaluated dimensions. Its yield strength (880–950 MPa), superior to most metallic and all ceramic alternatives, combined with a well-documented osseointegration track record and exceptional corrosion resistance in vivo [5,7], produces a multi-criteria profile that no other tested material replicates.

Comparison with Siva Bhaskar and Khan [20], who found PROMETHEE concordant with TOPSIS and VIKOR for dental polymer selection, supports the generalizability of these findings and the methodological reliability of PROMETHEE in this problem class. The Scientific Reports study on spinal implants [25] similarly identified Ti-6Al-4V as the dominant material when evaluated against ceramic and polymer competitors, despite using a different MCDM method (fuzzy AHP-TOPSIS) and a different criterion set, reinforcing cross-study robustness.

Within the titanium family, the model discriminates meaningfully: Ti-6Al-4V-ELI (Extra-Low Interstitial) ranks second, reflecting marginally superior biocompatibility for patients with known sensitivity to trace contaminants; Ti-6Al-7Nb ranks third, benefiting from niobium substitution for vanadium, which reduces cytotoxic ion release risk [9]. These fine-grained distinctions are clinically actionable and would not emerge from cruder ranking methods.

5.2. The Titanium–Zirconia Trade-Off: Clinical Implications

The sixth-place ranking of Zirconia (Φnet = 0.1659) is one of the most clinically significant findings of this study, and merits careful interpretation. As illustrated in Figure 5, Zirconia's radar profile exhibits strong scores on biological criteria (C6, C7, C8)—reflecting its chemical inertness, absence of metallic ion release, and superior gingival aesthetics—but incurs substantial penalties on mechanical criteria C2 and C3 relative to titanium alloys, reflecting its lower fracture toughness and brittle failure mode under tensile loading [16].

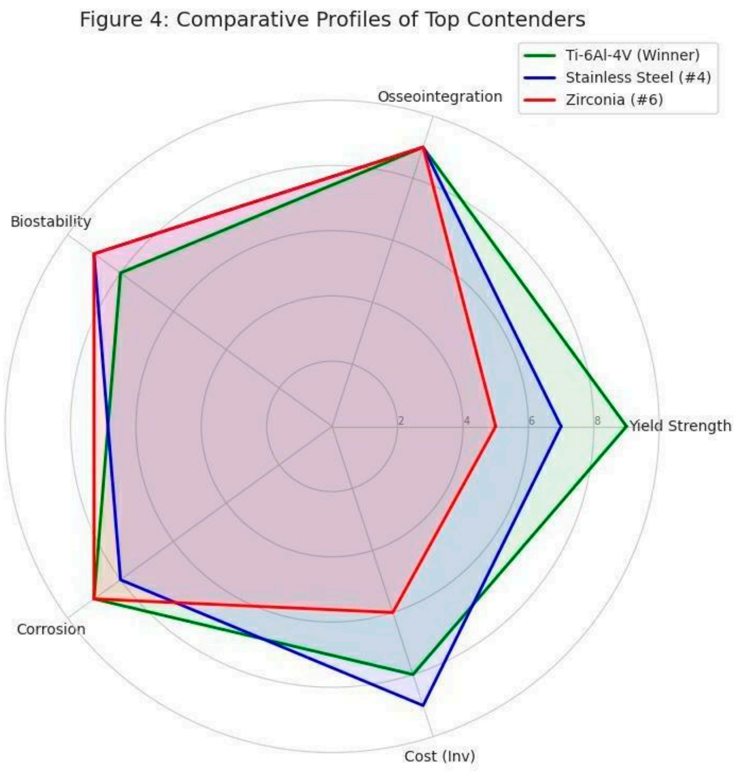

Figure 5. Radar chart comparing normalized multi-criteria performance profiles of Ti-6Al-4V, Surgical Stainless Steel 316L, and Zirconia. The polygon area of Ti-6Al-4V substantially exceeds that of Zirconia on mechanical axes (C2, C3) while remaining competitive on biological axes.

This quantified trade-off aligns with, and extends, recent clinical meta-analyses. Morena et al. [17] found titanium implants demonstrated significantly higher survival rates and less marginal bone loss at 12 months compared to zirconia counterparts ($p < 0.05$) in load-bearing conditions. Haugen and Chen [18] similarly concluded that titanium is preferred for posterior implants, while Zirconia is clinically suitable for aesthetically driven anterior placements. The present framework provides the quantitative basis for this clinical distinction: the Φnet gap between Ti-6Al-4V (0.3152) and Zirconia (0.1659) represents a 90% net flow differential, quantifying the magnitude of the mechanical penalty that clinicians implicitly accept when selecting Zirconia for aesthetic reasons.

Importantly, the framework is not prescriptive: by adjusting criterion weights toward C6–C8 (biological/aesthetic criteria) and reducing weights on C2–C3 (mechanical criteria), a rational clinician could obtain a justifiably different ranking for anterior aesthetic indications. This flexibility is precisely the value of a transparent, weight-adjustable decision-support tool over a fixed, population-level recommendation.

5.3. The Stainless Steel Paradox and Model Limitations

Surgical Stainless Steel 316L ranked fourth (Φnet = 0.2015), outperforming Zirconia. This outcome reflects its exceptionally high tensile strength (up to 950 MPa), which drives strong performance on C2 and C3. Its lower biostability score (C7) captures the established risks of fibrous tissue encapsulation and progressive Cr-Ni-Mo ion release under long-term implantation [18]. This discrepancy—high mechanical ranking, lower clinical adoption for permanent implants—highlights a structural limitation inherent to all MCDM models: the model optimizes within the defined criterion set and weighting scheme. Phenomena such as time-dependent ion accumulation, peri-implant tissue reactions, and patient-specific immune responses cannot be fully captured by the static, literature-derived property scores used here.

This limitation contextualizes the growing interest in nanostructured “smart” biomaterials that combine the mechanical superiority of metallic matrices with actively bioactive surface chemistry

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[10]. Future material candidates emerging from this research direction—including titanium-zirconium binary alloys (Ti-Zr), 3D-printed porous titanium scaffolds, and hydroxyapatite-functionalized Ti surfaces—represent natural expansions for future iterations of this framework as their clinical evidence bases mature.

5.4. Comparison with Prior MCDM Studies

The findings of this study can be placed in the context of existing MCDM-based implant studies. In spinal disc implant selection, a 2023 fuzzy AHP-TOPSIS study [25] similarly ranked Ti-6Al-4V first among six biomaterials, with CoCr alloy and PEEK in intermediate positions—consistent with CoCr's 7th-place ranking and polymers' lower positions in the present analysis. In the dental polymer domain [20], PROMETHEE consistently produced the highest Spearman rank correlation with the AHP-TOPSIS consensus, providing methodological precedent for our PROMETHEE-TOPSIS cross-validation. The novel contribution of the present study relative to these prior works is the scale (22 vs. 4–10 alternatives), the explicit TFN-based uncertainty modeling, and the systematic sensitivity analysis.

6. Conclusions

This study successfully developed, applied, and validated a Fuzzy-PROMETHEE II framework for the systematic multi-criteria selection of dental implant biomaterials, evaluating 22 candidates across eight clinically derived criteria. Three principal, evidence-anchored conclusions emerge:

- **Ti-6Al-4V is the optimal biomaterial for general-purpose dental implant applications** (Φnet = 0.3152). This conclusion is cross-validated by TOPSIS (C^* = 0.839, identical top ranking) and confirmed stable by sensitivity analysis across C5 weight variations of 0–50%. Its dominance reflects balanced multi-criteria superiority rather than exceptional performance on any single dimension.
- **Material selection is inherently context-dependent.** The quantified Φnet gap between Ti-6Al-4V and Zirconia (0.3152 vs. 0.1659) provides a measurable basis for the clinically recognized anterior–posterior selection dichotomy: Zirconia's mechanical penalty is acceptable in aesthetic, low-load anterior regions, while titanium alloys are unambiguously superior for load-bearing posterior applications.
- **Future work should transition toward patient-specific decision support.** Immediate priorities include: (i) expanding the material set to include emerging candidates (Ti-Zr alloys, 3D-printed porous titanium, HA-functionalized surfaces); (ii) integrating patient-specific parameters (bone density, systemic health, parafunctional habits) as dynamic criterion weights via Bayesian updating; (iii) incorporating time-dependent property degradation curves to model long-term implant performance; and (iv) prospectively validating the framework's recommendations against longitudinal clinical implant survival data to close the loop between computational selection and clinical outcome.

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Data Availability: All data supporting the findings of this study are included within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

Ethical Approval: Not applicable. This study is a computational analysis of existing material property data and does not involve human participants, animal subjects, or identifiable personal data.

Limitations: Three limitations of this study warrant acknowledgment. First, material property values are drawn from literature-reported data, which varies by manufacturer, alloy grade, processing route, and testing standard; this variability is modeled via TFNs but cannot be entirely eliminated. Second, extrinsic factors that influence clinical material selection—including implant cost, manufacturing complexity, surgeon familiarity, and regulatory approval status—were intentionally excluded to focus on intrinsic material properties; clinical decisions should integrate these factors alongside the framework's rankings. Third, the expert panel comprised three members; future work should expand and stratify panel composition across specializations (periodontology, prosthodontics, materials science) to assess the sensitivity of weight assignments to expert background.

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