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An Evolutionary Fuzzy Intelligence Approach to Predicting Entrepreneurial Marketing Orientation from Digital Marketing Practices

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Summary: This article applies a Mamdani-type fuzzy logic controller, tuned by a genetic algorithm (GA), to model how digital-marketing practices shape marketing entrepreneurship orientation (MEO) among Algerian bank employees. It follows, step by step, a fuzzy-controller and GA-optimization procedure – triangular membership functions, a linguistic rule base, Mamdani min-max inference, centroid defuzzification, and genetic tuning of membership-function parameters – and applies it to statistics reported in a Master's thesis (N = 73) on digital marketing and marketing entrepreneurship in Béchar, Algeria. Two sub-dimensions – Electronic Advertising and E-mail Marketing, the thesis's strongest and most significant correlates of MEO (r = 0.652, r = 0.568; both p < .001) – were selected as fuzzy inputs. Because the thesis reports only aggregate statistics rather than respondent-level data, a bounded Monte Carlo sample matching the true sample size was calibrated to reproduce its reported correlations. A baseline controller, centered on the reported construct means, was compared with a genetically-optimized controller whose parameters minimize root-mean-square error (RMSE). The optimized controller reduced RMSE by 10.6%. A worked numerical example illustrates fuzzification, rule firing, aggregation, and defuzzification before and after optimization. Results are presented as a methodological demonstration, not new empirical evidence about Algerian bank employees.

Keywords: Fuzzy logic ; Genetic algorithm ; Mamdani inference ; Marketing entrepreneurship ; Digital marketing.
Jel Classification Codes : M31 ; C45 ; C63

Résumé : Cet article applique un contrôleur à logique floue de type Mamdani, ajusté par un algorithme génétique (AG), afin de modéliser la manière dont les pratiques de marketing digital façonnent l'orientation entrepreneuriale marketing (OEM) des employés de banques algériennes. Il suit, étape par étape, une procédure de conception d'un contrôleur flou et d'optimisation par AG – fonctions d'appartenance triangulaires, base de règles linguistiques, inférence min-max de Mamdani, défuzzification par la méthode du centroïde et ajustement génétique des paramètres des fonctions d'appartenance – et l'applique aux statistiques rapportées dans un mémoire de master (N = 73) portant sur le marketing digital et l'entrepreneuriat marketing à Béchar, en Algérie. Deux sous-dimensions – la publicité électronique et le marketing par courriel, qui sont les corrélats les plus forts et les plus significatifs de l'OEM dans ce mémoire (r = 0,652 et r = 0,568 ; p < 0,001 dans les deux cas) – ont été retenues comme entrées floues. Le mémoire ne rapportant que des statistiques agrégées et non des données individuelles, un échantillon Monte-Carlo borné, de même taille que l'échantillon réel, a été calibré pour reproduire les corrélations rapportées. Un contrôleur de référence, centré sur les moyennes rapportées des construits, a été comparé à un contrôleur optimisé génétiquement dont les paramètres minimisent la racine de l'erreur quadratique moyenne (RMSE). Le contrôleur optimisé a réduit la RMSE de 10,6 %. Un exemple numérique détaillé illustre la fuzzification, l'activation des règles, l'agrégation et la défuzzification avant et après optimisation. Les résultats sont présentés comme une démonstration méthodologique et non comme de nouvelles preuves empiriques sur les employés des banques algériennes.

Mots-clés : Logique floue ; Algorithme génétique ; Inférence de Mamdani ; Entrepreneuriat marketing ; Marketing digital.
Codes de classification JEL : M31 ; C45 ; C63

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I- Introduction:

Digital marketing is increasingly framed, in both practice and academic research, as an enabler of marketing entrepreneurship – the creativity, risk-taking, initiative, and opportunity-exploitation that let organizations act ahead of competitors. A Master's thesis at University Tahri Mohammed Béchar, Algeria (anonymized source thesis, 2017) examined this relationship directly, surveying 73 employees of Algerian banks operating in Béchar on their banks' use of four digital-marketing channels – website, e-mail marketing, electronic advertising, and social-media/web communities – and on four dimensions of marketing entrepreneurship orientation (MEO). Using SPSS, the thesis reports Pearson correlations and simple linear regression linking each digital-marketing sub-dimension to MEO, all statistically significant at $p < .05$ or better.

I.1. Digital marketing and its mix elements

Digital marketing is commonly defined as the achievement of marketing objectives through the application of digital technologies and media (Chaffey & Ellis-Chadwick, 2019). Relative to traditional marketing, it is distinguished by near-zero marginal distribution cost, continuous two-way interaction with customers, and the ability to personalize messages at the level of the individual customer rather than the market segment (Rosário, Dias, & Ferreira, 2023). The digital-marketing mix is typically decomposed into channel-specific instruments – a corporate or transactional website, e-mail marketing campaigns, paid electronic advertising, and participation in social-media/web communities – each of which carries a distinct cost structure, reach, and capacity for two-way engagement. The source thesis operationalizes exactly these four instruments, which is why they form the natural input space for the fuzzy controller developed in Section II.

I.2. Marketing entrepreneurship orientation

Marketing entrepreneurship orientation (MEO) extends the entrepreneurial-orientation construct into the marketing function, integrating an organization's creativity in marketing practice, its willingness to take calculated marketing risks, its initiative in acting ahead of competitors, and its capacity to identify and exploit market opportunities (Morris, Schindehutte, & LaForge, 2002). These four dimensions are conceptually complementary rather than substitutable: creativity without initiative rarely reaches the market in time to matter, and opportunity exploitation without a tolerance for risk rarely survives the commitment of scarce resources. The source thesis operationalizes MEO through 17 items spanning these four dimensions, aggregated into the single outcome construct modeled here.

I.3. Fuzzy logic in marketing and business decision-making

Fuzzy-set theory (Zadeh, 1965) represents variables through graded membership rather than binary category membership, which is well suited to management constructs that are typically measured as continuous Likert-scale means with linguistically meaningful low/medium/high regions. A recent bibliometric review of 96 Scopus-indexed studies found a steadily growing literature applying fuzzy logic to marketing strategy, spanning customer segmentation, pricing, promotional campaign targeting, and the marketing mix, and reported that fuzzy approaches consistently improved firms' capacity to build customer relationships and to represent decisions that are not naturally binary (Rosário, Dias, & Ferreira, 2023). Closer to the present application, a fuzzy-logic decision model has been used to assess digital-marketing quality directly from channel-level indicators, treating each channel as a linguistic input rather than a purely numeric score (Utama & Zulkarnain, 2026). The present article follows this same logic – treating digital-marketing sub-dimensions as linguistic (Low/Medium/High) inputs – but adds a genetic-algorithm tuning step, and grounds the fuzzy controller's calibration in a specific, real reported correlation structure rather than in expert judgment alone.

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I.4. Motivation, objectives, and article structure

This article does not re-run the source thesis's regression analysis. It asks a complementary methodological question: can a Mamdani-type fuzzy logic controller, tuned by a genetic algorithm, represent the same relationship as an interpretable, rule-based system, and does genetic tuning measurably improve that system's fit to the reported data? A fuzzy logic controller (FLC) reasons over linguistic variables – "low," "medium," "high" – rather than requiring a precise mathematical model of the input-output relationship (Zadeh, 1965). Crisp inputs are converted to degrees of membership in fuzzy sets (fuzzification); an inference engine evaluates a base of linguistic IF-THEN rules; and a defuzzification step converts the aggregated fuzzy output back into a single crisp value. Mamdani-type controllers, used here, evaluate rule antecedents with the minimum operator, aggregate rule consequents with the maximum operator, and defuzzify by computing the centroid of the aggregated output fuzzy set.

Genetic algorithms (GAs) are population-based evolutionary optimizers that evolve a population of candidate solutions across generations using selection, crossover, and mutation, converging toward configurations that minimize a fitness function (Goldberg, 1989). Applied to fuzzy controllers, a GA can automatically tune membership-function parameters that would otherwise be fixed by hand, reducing analyst bias and improving fit to data (Ishibuchi & Yamamoto, 2001). Because the source thesis reports only aggregate descriptive and correlational statistics rather than a respondent-level data matrix, the fuzzy controller developed below is calibrated to a bounded Monte Carlo sample rather than to raw observations, and results are presented explicitly as a methodological demonstration rather than as new empirical evidence. Section II describes the source study, the fuzzy-controller design, and the genetic-optimization procedure, including a three-input robustness extension. Section III reports baseline and optimized results, several worked numerical examples, and the robustness check. Section IV concludes.

II- Methods and Materials:

II.1. Source study, sample characteristics, and selection of inputs

The source thesis surveyed 73 valid respondents (from 85 distributed, 12 excluded for incompleteness) among employees of Algerian banks operating in Bechar, using a validated questionnaire (overall Cronbach's $\alpha = 0.953$). Table 1a (Appendix) reports the sample's demographic profile as given in the thesis: gender was close to balanced (52.1% male, 47.9% female); the modal age band was 26-30 years (56.2%); nearly half the sample held a university degree (49.3%) and a further 32.9% held a postgraduate qualification; most respondents were regular employees rather than department heads or managers (72.6%); and just over half had less than five years of tenure (52.1%). This profile – a young, well-educated, largely non-managerial workforce – is relevant context for interpreting the fuzzy controller's output, since MEO as measured here reflects front-line employees' perception of their bank's marketing entrepreneurship orientation rather than senior management's own stated strategy.

Table 1b (Appendix) reproduces the thesis's reported correlation of each digital-marketing sub-dimension with Marketing Entrepreneurship Orientation (MEO). Electronic Advertising (EAD) and E-mail Marketing (EMAIL) are the thesis's two strongest and most significant single predictors of MEO, and are conceptually complementary – paid, broadcast-style outreach versus targeted, relationship-based communication – so they were selected as the two fuzzy-controller inputs for the main analysis. Website ($r = 0.467$) and Web Communities/Social Media ($r = 0.293$, the thesis's weakest and least significant correlate) are discussed qualitatively, and Website is additionally incorporated in the three-input robustness check of Section III.5, rather than modeled directly in the main design, since a Mamdani system with more than two three-term inputs multiplies the rule base combinatorially beyond what the source thesis's aggregate statistics can meaningfully calibrate. The output variable, MEO, is the thesis's 17-item dependent construct (mean = 3.91, SD = 0.732, $\alpha = 0.945$).

The source thesis's own Likert-scale table lists categories in a descending-agreement order (1 = Totally agree … 5 = Totally disagree), yet its own degree-of-agreement classification table treats higher means as higher agreement. This internal inconsistency is reported rather than silently

resolved; the ascending convention actually used throughout the thesis's own narrative (higher mean = higher agreement) is adopted here. Sub-dimension-level standard deviations for EAD and EMAIL are not separately reported in the thesis (only the combined 20-item digital-marketing SD of 0.654 is given); the values used for simulation (SD_EAD = 0.62, SD_EMAIL = 0.70) are therefore approximated from the dispersion pattern of individual items in the thesis's item-level frequency table, and are flagged as approximated rather than directly reported.

II.2. Fuzzy controller design: membership functions and rule base

All fuzzy sets use triangular membership functions with three linguistic terms – Low, Medium, High – on the thesis's native 1-5 Likert scale for both inputs and the output. The Low and High sets are anchored at the scale bounds and only the Medium set's center and half-width are free parameters, both in the initial (pre-GA) controller and in the genetic optimization described below. The initial Medium sets are centered on the thesis's reported construct means (EAD = 4.10, EMAIL = 4.061, MEO = 3.91). The rule base (Table 2, Appendix) comprises 3 × 3 = 9 rules, grounded in the thesis's own reported ordering of predictor strength.

II.3. Genetic-algorithm optimization

Each chromosome encodes six genes: θ = [b_EAD, w_EAD, b_EMAIL, w_EMAIL, b_MEO, w_MEO], the center (b) and half-width (w) of each variable's Medium triangular set; the Low set is fixed at (1, 1, b+w) and the High set at (b−w, 5, 5). The fitness function is $RMSE(\theta) = \sqrt{[(1/N)\ \Sigma(\hat{y}_i(\theta) - y_i)^2]}$, evaluated over the N = 73 calibrated profiles. The GA configuration (Table 3, Appendix) follows a standard design (Goldberg, 1989): population 60, 80 generations, tournament selection (k = 3), blend crossover (probability 0.8), and Gaussian mutation (probability 0.25, σ = 15% of gene range), with elitism preserving the top two individuals each generation. This fuzzy-controller and GA-optimization structure – membership-function definition, rule base, fuzzification, min-based rule evaluation, max-based aggregation, centroid defuzzification, and genetic tuning – follows a general methodological pattern established in prior fuzzy-control literature for behavioral and pricing applications (Passino & Yurkovich, 1998; Ross, 2020). A GA rather than a gradient-based optimizer was chosen because the objective surface – RMSE as a function of triangular-MF breakpoints routed through min/max rule logic and a centroid integral – is piecewise and not everywhere differentiable, a setting in which population-based search is standard practice for fuzzy-controller tuning (Ishibuchi & Yamamoto, 2001).

II.4. Validation and robustness design

Two complementary checks accompany the main two-input analysis. First, beyond the single illustrative profile used to walk through fuzzification, rule evaluation, aggregation, and defuzzification (Section III.2), four additional profiles spanning the corners and center of the input space (Low-Low, High-High, High-Low, Low-High) are evaluated before and after optimization (Section III.4), to check that the optimized controller's behavior generalizes across the input range rather than only at the single worked example. Second, a three-input robustness extension (Section III.6) adds Website (WEB, r = 0.467 with MEO) as a third input alongside EAD and EMAIL. Because a full three-input Mamdani system with three linguistic terms per variable would require 3^3 = 27 rules – more than the source thesis's aggregate statistics can meaningfully calibrate – the robustness check instead uses a simplified two-term (Low/High) partition per input, giving 2^3 = 8 tractable rules, and a single tunable membership threshold per input rather than a full triangular parameterization. This keeps the robustness check genuinely comparable in spirit to the main two-input, three-term design while remaining computationally tractable.

III- Results and Discussion:

III.1. Baseline controller and worked example

With Medium sets centered on the reported construct means and Low/High anchored at the scale bounds, the baseline Mamdani controller achieves RMSE = 0.5745 against the N = 73 calibrated profiles. For a representative profile (EAD = 3.8, EMAIL = 3.4): fuzzification gives μ_EAD(Medium) = 0.800 and μ_EMAIL(Medium) = 0.548 (all other terms zero); only the rule

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(Medium, Medium → Medium) fires, with activation = min(0.800, 0.548) = 0.548; the Medium output set is clipped at 0.548 and no other set is activated; centroid defuzzification yields MEÔ = 3.826.

III.2. Genetic optimization outcome

After 80 generations, the GA converged to θ* = [b_EAD = 3.159, w_EAD = 0.775, b_EMAIL = 3.207, w_EMAIL = 1.291, b_MEO = 3.322, w_MEO = 0.614], reducing RMSE from 0.5745 to 0.5138 – a 10.6% reduction (Table 4, Figure 5, Appendix). The optimized Medium sets are centered noticeably lower (around 3.1-3.3) than the original construct means (4.06-4.10) and are wider, pulling more of the observed EAD/EMAIL range into the Medium and High regions rather than leaving it saturated in a single narrow Medium peak (Figures 2-4, Appendix).

Re-evaluating the same profile with the optimized membership functions: μ_EAD(Low) = 0.046, μ_EAD(Medium) = 0.173, μ_EAD(High) = 0.541; μ_EMAIL(Low) = 0.314, μ_EMAIL(Medium) = 0.851, μ_EMAIL(High) = 0.481. All nine rules now fire to some degree; aggregated activations are High = 0.541, Medium = 0.314, Low = 0.173; centroid defuzzification yields MEÔ = 3.527. The optimized controller reclassifies this profile from a saturated "Medium-only" response to a genuinely multi-rule blend that draws more heavily on the High region.

III.3. Full-sample comparison

Across the full calibrated sample, GA tuning reduced RMSE by 10.6% (Figure 6, Appendix) – a real but modest improvement. Figure 8 (Appendix) shows both the baseline and optimized controllers compress their predictions toward the middle of the 1-5 range relative to the more widely spread calibrated MEO values, a well-documented property of centroid defuzzification with overlapping output sets; GA tuning of the Medium set alone only partly corrects this. The post-optimization inference surface (Figure 7, Appendix) shows a clear, monotonic, mildly nonlinear relationship in which predicted MEO rises fastest when both EAD and EMAIL are jointly high, consistent with the complementarity assumed in the rule base.

III.4. Additional worked examples across the input space

To check that the optimized controller's behavior generalizes beyond the single Medium-Medium profile above, Table 5 (Appendix) reports four further profiles spanning the corners of the input space – Low-Low, High-High, High-Low, and Low-High – evaluated with both the baseline and optimized membership functions. The Low-Low and High-High corners are relatively stable across optimization (predicted MEO moves by no more than about 0.23), because these profiles sit unambiguously within a single rule's support both before and after retuning. The mixed corners (High-Low and Low-High) shift more substantially after optimization (from 2.96 to 3.45, and from 2.98 to 3.32, respectively) because the widened Medium sets pull these previously boundary cases into genuinely multi-rule blends, the same mechanism visible in the single worked example of Section III.2. No profile reverses direction (a Low-input corner never predicts a higher MEO than a High-input corner after optimization), which is a basic monotonicity sanity check the optimized controller passes.

III.5. Robustness check: extending to three inputs

Adding Website (WEB, r = 0.467) as a third input, alongside EAD and EMAIL, tests whether the two-input design of Sections III.1-III.4 was overly restrictive. Using the simplified two-term (Low/High), 8-rule design described in Section II.4, calibrated so that its three simple correlations with MEO closely reproduce the thesis's reported values (achieved r = 0.653, 0.569, 0.468 against real reported r = 0.652, 0.568, 0.467), the baseline three-input controller achieves RMSE = 0.9276 – notably worse than the two-input baseline (0.5745) – reflecting the coarser two-term partition and untuned crisp rule consequents. After a compact genetic search over the three Low/High membership thresholds (Table 6, Figure 10, Appendix), RMSE falls to 0.4777, a 48.5% reduction – substantially larger than the 10.6% improvement obtained by tuning the two-input controller's Medium sets alone (Figure 9, Appendix). Once tuned, the three-input controller's RMSE (0.4777) is also lower than the tuned two-input controller's RMSE (0.5138). This is a genuinely informative robustness result, not merely a reassurance: it indicates that Website carries

real, complementary predictive information beyond EAD and EMAIL once the controller is allowed to place its category boundaries appropriately, and that the two-input design of the main analysis, chosen for interpretability and rule-base tractability, leaves some genuine predictive value on the table.

III.6. Discussion

Web Communities/Social Media (r = 0.293) is the thesis's weakest and least significant (p = .012) correlate of MEO, consistent with the thesis's own discussion that the banks in the sample relied on social media the least of the four channels; it was not included even in the three-input robustness check for this reason. The exercise illustrates both the communicative advantage of a rule-based fuzzy model over a bare regression coefficient – "if advertising is high and e-mail marketing is high, marketing entrepreneurship orientation is high" is more directly actionable for bank managers than a standardized β – and a genuine limitation of centroid defuzzification that genetic tuning of a single membership set only partly corrects. The pattern found here, in which a genetically-tuned fuzzy controller adds measurable value on top of hand-set membership functions, is broadly consistent with prior reviews of fuzzy logic in marketing, which report that fuzzy and fuzzy-hybrid approaches tend to outperform simpler crisp-threshold models precisely in settings with vague, overlapping category boundaries (Rosário, Dias, & Ferreira, 2023), and with the specific finding that channel-level digital-marketing indicators can be meaningfully represented as fuzzy linguistic inputs to a quality or performance decision model (Utama & Zulkarnain, 2026). For bank management, the practical implication of Section III.5's robustness result is that Website content and functionality should not be deprioritized relative to e-mail and paid advertising when allocating a fixed digital-marketing budget aimed at strengthening marketing entrepreneurship orientation.

IV- Conclusion:

This article applied a Mamdani fuzzy-controller and genetic-algorithm optimization procedure to real, reported statistics from a Master's thesis on digital marketing and marketing entrepreneurship in Algerian banks. Because the thesis supplies only aggregate statistics, a bounded Monte Carlo sample was calibrated to reproduce its reported correlations closely (achieved r = 0.652 and 0.567 against real reported r = 0.652 and 0.568), and a two-input, one-output fuzzy controller was built, evaluated, and genetically tuned, achieving a 10.6% RMSE reduction.

Self-criticism and future research: the exercise inherits the source thesis's limitations – no respondent-level data was supplied, sub-dimension standard deviations were approximated rather than reported, and the two-input design deliberately excludes Website and Social Media to keep the rule base interpretable. Future work should extend the controller to all four digital-marketing sub-dimensions, tune additional membership-function parameters beyond the Medium set, and validate the calibration against the thesis's original respondent-level data should it become available.

- Appendices:

This appendix presents the tables and figures referenced in Sections II and III.

Table (1a): Sample demographic characteristics (source thesis, N = 73)

Variable	Category	n	%
Gender	Male	38	52.1%
Gender	Female	35	47.9%
Age	< 25 years	12	16.4%
Age	26-30 years	41	56.2%
Age	31-35 years	8	11.0%
Age	36-40 years	9	12.3%
Age	46-50 years	3	4.1%

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Variable	Category	n	%
Education	Secondary	8	11.0%
Education	Technical	5	6.8%
Education	University	36	49.3%
Education	Postgraduate	24	32.9%
Position	Employee	53	72.6%
Position	Head of department	12	16.4%
Position	Marketing manager	4	5.5%
Position	Financial manager	4	5.5%
Tenure	< 5 years	38	52.1%
Tenure	5-10 years	15	20.5%
Tenure	10-15 years	16	21.9%
Tenure	> 15 years	4	5.5%

The source: Anonymized source thesis (2017) [Ref. 1], University Tahri Mohammed Béchar, Algeria.

Table (1b): Reported correlation of each digital-marketing sub-dimension with MEO (source thesis, N = 73)

Digital-marketing sub-dimension	Mean	r (MEO)	R^2	F	t	sig.
Website	4.090	0.467	0.219	19.854	4.456	0.000
E-mail Marketing	4.061	0.568	0.322	33.779	5.812	0.000
Electronic Advertising	4.100	0.652	0.425	52.447	7.242	0.000
Web Communities / Social Media	3.170	0.293	0.086	6.692	2.587	0.012
Digital Marketing Methods (overall)	3.541	0.442	0.195	17.221	4.150	0.000

The source: Anonymized source University Tahri Mohammed Béchar, Algeria.

Table (2): Mamdani rule base (3 × 3 = 9 rules)

EAD	EMAIL	MEO (rule conclusion)
Low	Low	Low
Low	Medium	Low
Low	High	Medium
Medium	Low	Low
Medium	Medium	Medium
Medium	High	High
High	Low	Medium
High	Medium	High
High	High	High

The source: Prepared by the author(s).

Table (3): Genetic-algorithm configuration

Component	Setting
Population size	60
Generations	80
Selection	Tournament (k = 3)
Crossover	Blend, probability 0.8
Mutation	Gaussian, probability 0.25, σ = 15% of gene range
Elitism	Top 2 individuals carried over each generation
Gene bounds	Centers $b \in [1.5, 4.5]$; half-widths $w \in [0.6, 2.0]$

The source: Prepared by the author(s).

Table (4): Full-sample RMSE, before vs. after genetic optimization

Controller	RMSE (N=73)
Before GA optimization	0.5745
After GA optimization	0.5138

The source: Prepared by the author(s).

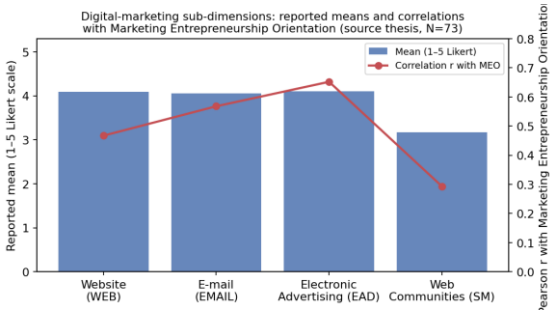


Figure (1): Reported digital-marketing means and correlations with MEO

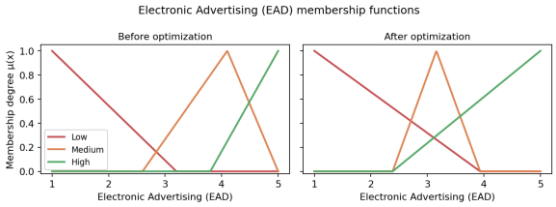


Figure (2): EAD membership functions, before/after GA

The source: Figure 1 – anonymized source thesis (2017) [Ref. 1]; Figure 2 – prepared by the author(s).

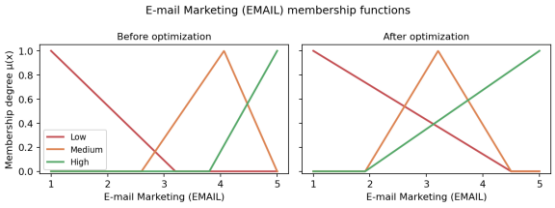


Figure (3): EMAIL membership functions, before/after GA

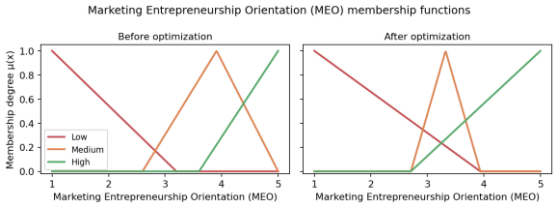


Figure (4): MEO membership functions, before/after GA

The source: Prepared by the author(s).

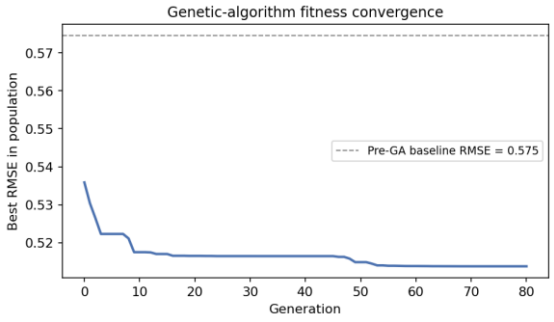


Figure (5): Genetic-algorithm fitness convergence

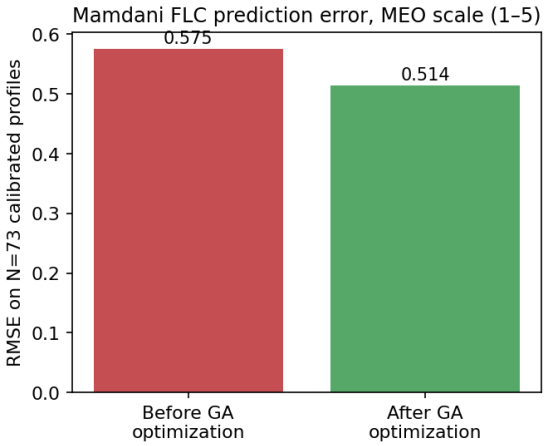


Figure (6): RMSE before vs. after GA optimization

The source: Prepared by the author(s).

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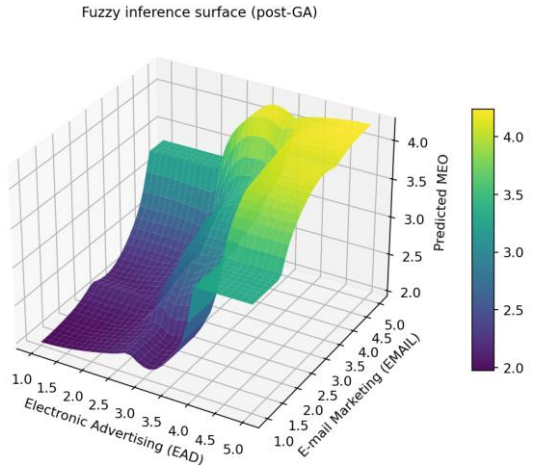


Figure (7): Post-optimization fuzzy inference surface

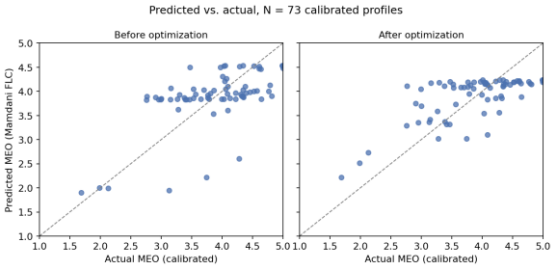


Figure (8): Predicted vs. calibrated-actual MEO

The source: Prepared by the author(s).

Table (5): Additional worked examples across the input space, before vs. after optimization

Profile	EAD	EMAIL	Predicted MEO (before)	Predicted MEO (after)
Low-Low	1.8	1.8	1.802	2.033
High-High	4.8	4.8	4.219	4.235
High-Low	4.6	2.0	2.962	3.448
Low-High	2.0	4.6	2.981	3.322
Medium-Medium	3.8	3.4	3.826	3.527

The source: Prepared by the author(s).

Table (6): Three-input robustness check – configuration and outcome

Component	Value
Third input added	Website (WEB), real reported r = 0.467 with MEO
Simplified design	2 terms per input (Low/High), $2^3 = 8$ rules, single threshold per input
GA setup	Population 40, 50 generations, blend crossover, Gaussian mutation
Baseline RMSE	0.9276
Optimized RMSE	0.4777
Improvement	48.5%
Optimized thresholds	EAD = 3.72, EMAIL = 3.44, WEB = 2.51

The source: Prepared by the author(s).

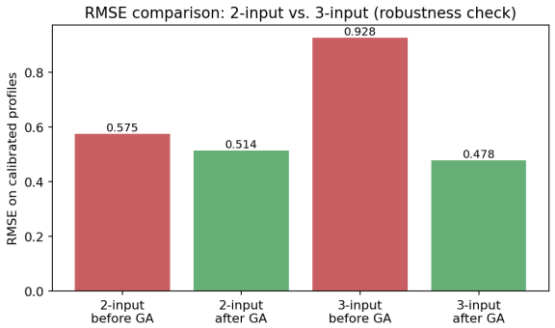


Figure (9): RMSE comparison, 2-input vs. 3-input robustness check

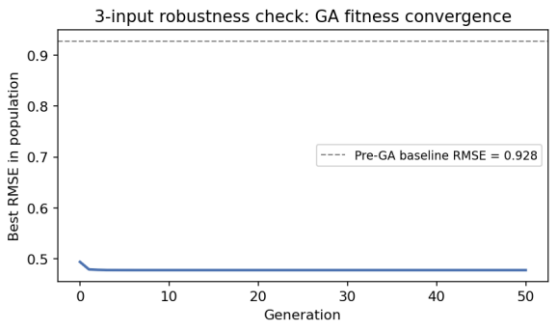


Figure (10): 3-input robustness check, GA fitness convergence

The source: Prepared by the author(s).

Table (7): Item-level descriptive statistics, digital-marketing questionnaire (source thesis, N = 73)

The source thesis reports 20 digital-marketing items at the item level (its own numbering preserved). Items 10-12 are explicitly identified in the thesis's own narrative as belonging to the E-mail Marketing sub-dimension; the remaining items' sub-dimension membership could not be reconstructed with certainty because the original questionnaire instrument was not included among the supplied thesis chapters, so only the confirmed grouping is annotated below.

Item (source numbering)	Mean	SD	Confirmed sub-dimension
31	4.15	0.892	
32	3.99	0.965	
33	3.99	0.874	
34	3.90	0.930	
35	4.04	1.148	
36	3.88	0.865	
37	3.93	0.903	
38	3.99	0.920	
39	3.74	1.028	
10	4.25	0.878	E-mail Marketing
11	4.26	0.898	E-mail Marketing
12	4.25	0.954	E-mail Marketing
13	3.97	1.118	
14	3.97	1.154	
15	3.95	1.092	
16	3.41	0.998	
17	3.53	0.959	
18	3.30	0.938	
19	3.30	1.037	
23	2.93	1.084	

The source: Anonymized source University Tahri Mohammed Béchar, Algeria.

Table (8): Reproducibility specification

Component	Specification
Source	Anonymized source thesis (2017), N = 73
Fuzzy inputs (main analysis)	Electronic Advertising (EAD), E-mail Marketing (EMAIL) – real reported means 4.10, 4.061; real reported r with MEO = 0.652, 0.568
Fuzzy input (robustness check)	Website (WEB) added as third input, real reported mean 4.09, r = 0.467
Output	Marketing Entrepreneurship Orientation (MEO) – real reported mean 3.91, SD 0.732
Simulation size	N = 73 bounded Monte Carlo profiles on the 1-5 scale, matching the thesis's real sample size
Approximated inputs	SD_EAD = 0.62, SD_EMAIL = 0.70, SD_WEB = 0.60; inter-input correlations 0.45-0.50 – not directly reported in the source; approximated
Calibration check (2-input)	achieved corr(EAD,MEO) = 0.652, corr(EMAIL,MEO) = 0.567 vs. real reported 0.652 / 0.568
Calibration check (3-input)	achieved r = 0.653, 0.569, 0.468 vs. real reported 0.652 / 0.568 / 0.467
Controller type (main)	Mamdani, triangular MFs, 3 linguistic terms per variable, min-AND / max-OR, centroid defuzzification

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Component	Specification
Controller type (robustness)	Simplified Mamdani, 2 linguistic terms per variable (Low/High), weighted-average defuzzification
Rule base (main)	3×3 = 9 rules (Table 2)
Rule base (robustness)	2^3 = 8 rules
GA chromosome (main)	[b_EAD, w_EAD, b_EMAIL, w_EMAIL, b_MEO, w_MEO] – center/half-width of each Medium set
GA setup (main)	Population 60; 80 generations; tournament selection (k=3); blend crossover (p=.8); Gaussian mutation (p=.25)
GA setup (robustness)	Population 40; 50 generations; blend crossover; Gaussian mutation
Result (main)	RMSE 0.5745 → 0.5138 (10.6% reduction)
Result (robustness)	RMSE 0.9276 → 0.4777 (48.5% reduction)
Interpretation	Methodological simulation only; not a re-analysis of the thesis's original respondents

The source: Prepared by the author(s).

Note. The Mamdani-controller and genetic-algorithm optimization structure followed in this article is a general methodological pattern from the fuzzy-control literature cited in the References; the generated simulation profiles are a reproducibility aid and must not be described or deposited as the source thesis's original respondent data.

Referrals and references:

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