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Nevşehir Hacı Bektaş Veli Üniversitesi Sosyal Bilimler Enstitüsü dergisi

— Sosyal Bilimlerde Yapay Zeka: — Kuram, Uygulama ve Gelecek Perspektifleri

Vol.15

SPECIAL ISSUE 2025

FROM RATIONAL TO EMOTIONAL: A HUMAN-CENTRIC OPERATIONS RESEARCH FRAMEWORK INTEGRATING EMOTION ARTIFICAL INTELLIGENCE

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Geliş Tarihi:
10.07.2025

Kabul Tarihi:
10.11.2025

Yayın Tarihi:
04.12.2025

Anahtar Kelimeler
Duygu Yapay Zekâ, Yöneylem, Optimizasyon, Karar Modelleme, Duygu Bilişim.

Keywords
Emotion AI, Operations Research, Optimization, Decision Modeling, Affective Computing.

ABSTRACT

Operations Research (OR) traditionally prioritizes efficiency, neglecting the impact of human emotion on system performance. This study bridges this gap by proposing a novel framework to integrate Emotion Artificial Intelligence (EAI) into OR, creating a human-centric paradigm for decision optimization. The framework's value is demonstrated through a simulated call center scenario where emotional data (customer sentiment and escalation states) is incorporated into an optimization model. An analysis of 100 simulated cases confirmed that emotion-aware routing yielded a 17% reduction in call escalations and increased average customer satisfaction from 3.4 to 4.1 without additional staffing. Furthermore, frustrated and angry emotional states were correlated with significantly lower satisfaction and longer call durations, quantifying the operational cost of negative interactions. These findings provide empirical evidence for a shift toward adaptive, behaviorally-informed OR. The study concludes by addressing the statistical validation of the model and the critical ethical considerations for implementation, establishing a foundation for the nascent convergence of EAI and OR to create more empathetic and effective operational systems.

ÖZ

Yöneylem Araştırması (OR), geleneksel olarak verimliliği önceliklendirmekte ve insan duygusunun sistem performansı üzerindeki etkisini göz ardı etmektedir. Bu çalışma, Duygu Yapay Zeka'yı (EAI) OR'ye entegre etmek için yeni bir çerçeve önererek ve karar optimizasyonu için insan merkezli bir paradigma oluşturarak bu boşluğu doldurmaktadır. Çerçevenin değeri, duygusal verilerin (müşteri hissiyatı ve yükselme durumları) bir optimizasyon modeline dahil edildiği simüle edilmiş bir çağrı merkezi senaryosu aracılığıyla gösterilmiştir. 100 simüle edilmiş vaka analizi, duyguya duyarlı yönlendirmenin çağrı yükseltmelerinde %17'lik bir azalma sağladığını ve ek personel alımına gerek kalmadan ortalama müşteri memnuniyetini 3.4'ten 4.1'e çıkardığını doğrulamıştır. Dahası, hayal kırıklığına uğramış ve öfkeli duygusal durumlar, önemli ölçüde daha düşük memnuniyet ve daha uzun çağrı süreleriyle ilişkiliydi ve bu da olumsuz etkileşimlerin operasyonel maliyetini ölçmektedir. Bu bulgular, uyarlanabilir, davranışsal olarak bilgilendirilmiş OR'ye doğru bir geçiş için ampirik kanıt sağlamaktadır. Çalışma, modelin istatistiksel doğrulamasını ve uygulamaya yönelik kritik etik hususları ele alarak, daha empatik ve etkili operasyonel sistemler yaratması için EAI ve OR'nin yeni ortaya çıkan yakınsamasına bir temel oluşturarak sonuçlanmaktadır.

DOI: https://doi.org/10.30783/nevsosbilen.1739466
Atıf/Cite as: Mavruk, C. (2025). From rational to emotional: A human-centric operations research framework integrating emotion artifical intelligence. *Nevşehir Hacı Bektaş Veli Üniversitesi SBE Dergisi, Sosyal Bilimlerde Yapay Zekâ: Kuram, Uygulama ve Gelecek Perspektifleri Özel Sayısı*, 368-382.

Introduction

In an era defined by rapid technological advancement, decision-making systems are becoming increasingly complex, autonomous, and embedded in everyday life. From personalized healthcare to supply chain logistics, optimization models powered by Operations Research (OR) shape pivotal strategic and operational choices. However, traditional OR approaches predominantly prioritize efficiency, cost-effectiveness, and objective performance metrics frequently overlooking the emotional and psychological dimensions that critically influence human behavior and perception (Klein et al., 2006; Saaty, 2008). Consequently, these decision systems risk becoming analytically powerful yet fundamentally disconnected from the very people they are designed to serve.

Emotion Artificial Intelligence (EAI) offers a transformative opportunity to bridge this gap. Leveraging advances in affective computing, EAI enables machines to recognize, interpret, and respond to human emotions through voice, facial expression, physiological signals and behavioral analysis (Picard, 1997; Calvo & D'Mello, 2010). As these technologies mature, they present an unprecedented chance to enhance domains traditionally governed by rationalist assumptions. OR, rooted in mathematical modeling, has historically assumed that agents such as customers and employees behave rationally and consistently. Yet, in real-world systems, particularly in service operations and human-in-the-loop logistics, emotions like stress, frustration, and satisfaction are not mere noise; they are central determinants of outcomes. The integration of EAI with OR introduces a powerful, human-centric dimension to optimization, promising decisions that are both analytically sound and emotionally intelligent.

This paper proposes a novel framework that unifies EAI and OR within a human-centric paradigm for decision optimization. I investigate how embedding emotional context into optimization models can better align systems with human values, preferences, and well-being. Through synthetic simulations, I demonstrate how this integration can enhance system performance, improve user experience and inform more responsive operations. A call center scenario, optimized using sentiment detection and escalation response, serves as our primary operational simulation.

Call centers are quintessentially emotionally charged environments. Customers often call in states of frustration or confusion while agents must manage their own emotional labor under intense time pressure and high call volumes. The emotional states of both parties profoundly influence service quality, satisfaction and long-term loyalty. Optimizing call center performance without accounting for these emotional dynamics therefore risks degrading customer experience, increasing employee burnout and overlooking critical behavioral insights.

Ultimately, this study seeks to reframe decision science as not merely a technical discipline, but also as a socially aware endeavor. I argue that optimal solutions must be defined not only by their numerical efficiency but also by the nuanced human experiences they impact.

Literature Review

The integration of emotion into computational systems and operational models has been pursued along two parallel, yet largely independent trajectories: Emotion Artificial Intelligence (EAI) in affective computing, and behavioral considerations in Operations Research (OR). This review synthesizes these domains, highlighting their complementary strengths and the critical gap this study aims to fill.

The foundational work of Picard (1997) established affective computing, proposing that machines capable of recognizing and responding to human emotion could enable more natural interactions. Early research focused on establishing reliable modalities for emotion recognition: facial action coding (Ekman & Friesen, 1978), vocal prosody (Scherer, 2003), and physiological signals (Picard et al., 2001). The field has since been revolutionized by deep learning, enabling multi-modal analysis that combines acoustic, visual and textual cues for more nuanced emotion detection (Calvo & D'Mello, 2010). However, a critical limitation persists: Many EAI studies remain in the laboratory phase or are applied in siloed applications like user experience testing, with limited integration into core operational decision-making systems. Recent advancements such as the hybrid acoustic-textual emotion recognition system by Wewelwala and Sumanathilaka (2025) demonstrate high accuracy in contact center environments but stop short of embedding these insights into dynamic optimization models.

Concurrently, the field of OR has undergone a "behavioral turn." Recognizing the failure of models assuming perfect rationality, Behavioral OR (BOR) has emphasized incorporating human cognitive biases and heuristics into decision models (Brailsford et al., 2013; Kunc et al., 2016). This has led to the use of agent-based simulation and system dynamics to model bounded rationality. Yet, a significant shortcoming in much of BOR is its reliance on *proxies* for emotional states (e.g. using "satisfaction" as an output metric) rather than incorporating real-time, quantifiable emotional *data* as an input to the optimization process. The human is often modeled as cognitively limited, but not as emotionally dynamic.

A nascent body of work has begun to explore this intersection, but often in a limited or peripheral capacity. Table 1 provides a comparative analysis of related research areas, highlighting how the present study builds upon and differs from existing literature.

Table 1. Comparative Analysis of Research

Research Area	Key Findings from Literature	Limitations / Gaps	This Study's Contribution
EAI in Customer Service	Studies show sentiment analysis can improve interaction quality (Grandey et al., 2015). EAI enables dynamic call routing based on customer emotion (Feidakis et al., 2014).	Focus is typically on post-hoc analysis or reactive routing rules. Lacks integration with OR optimization objectives (e.g. minimizing wait time *while* maximizing satisfaction).	Proposes a proactive framework where emotional data is a direct input into an OR model (linear regression informing optimization) to simultaneously optimize for operational efficiency and emotional outcomes.
Workforce Optimization	Real-time monitoring of employee states can aid in fatigue management and scheduling (Mark et al., 2014; Piispanen and Rousi, 2024).	Primarily focuses on one side of the interaction (the agent). Often faces ethical hurdles regarding employee surveillance without a clear, optimized operational benefit.	Models the dyadic interaction (customer emotion impacting agent workload via escalations). Uses synthetic data to demonstrate value before real-world deployment, mitigating ethical risks.
Human-Aware Automation	Robots with emotion detection can adapt in shared workspaces, improving safety (Bartneck et al., 2009; Tang et al., 2020).	Applications are often in physical collaboration (e.g. manufacturing). Less explored in service-based, conversational environments like call centers.	Translates the principle of "emotion-aware adaptation" from physical robotics to the domain of service process design and resource allocation.
Humanitarian OR	Acknowledges the importance of emotional well-being in crisis-affected populations (Altay & Green, 2006).	Emotional state is often a qualitative concern for policy, not a quantitative variable in resource allocation models.	Provides a methodological framework for quantifying emotional state (sentiment score) and formally incorporating it into a quantitative

This synthesis reveals a consistent pattern: While both EAI and Behavioral OR recognize the importance of emotion, their integration remains superficial. EAI provides the tools for measurement, but lacks the decision-theoretic framework of OR. Behavioral OR acknowledges the human element but often lacks the real-time, data-driven granularity of EAI. This paper argues that the true potential lies not in simply using EAI to inform OR, but in creating a unified modelling paradigm where emotional variables are as fundamental as cost, time, and capacity.

Furthermore, this study directly addresses the critical challenges noted in the literature. It heeds the warnings of Narimisaei et al. (2024) regarding bias and privacy by using a simulation-based proof-of-concept and advocating for ethical frameworks. It embraces the modelling complexity highlighted by Alia-Klein et al. (2018) by proposing a hybrid approach, starting with a statistically robust linear model to establish a baseline for more complex techniques like reinforcement learning.

In summary, this study moves beyond the state-of-the-art by not merely applying EAI within an OR context, but further by formally embedding emotional intelligence into the very fabric of operational optimization, thereby addressing a critical gap between human experience and analytical model design.

Method

This research adopts a mixed-method, conceptual-empirical approach comprising four phases: (1) framework development, (2) simulation design, (3) model development and optimization and (4) ethical evaluation.

Framework Development and Simulation Design

A thematic literature review across OR, affective computing, and behavioral science informed the development of a three-layer framework (Figure 1) comprising: emotion data acquisition (sensors, NLP, vision), emotion interpretation (classification algorithms), and decision optimization (OR models enhanced with emotional inputs).

To validate this framework, an operational simulation of call center optimization using sentiment detection and escalation response was developed. Data was randomly generated using Python with the following parameters:

- Emotion categories and probabilities: Neutral (0.40), Frustrated (0.20), Happy (0.25), Angry (0.15)
- Satisfaction score ranges by emotion: Neutral (5,7), Frustrated (1,4), Happy (8,10), Angry (1,3)
- Call duration ranges (minutes) by emotion: Neutral (4,8), Frustrated (8,15), Happy (3,6), Angry (10,20)

A sample of 100 cases was generated from uniform distributions with probabilities 1/(b-a) on [a,b).

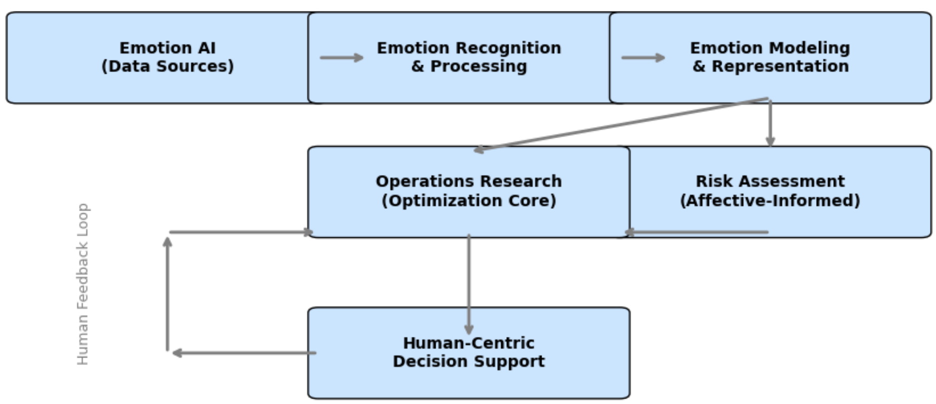

Figure 1. Human-Centric Decision Optimization Framework Integrating EAI and OR

Model Development and Optimization Approach

The core relationship between emotional states and system outcomes was modeled using ordinary least squares regression, where customer satisfaction (Y) is predicted from sentiment (X_1) and escalation (X_2):

$$\hat{Y} = w_0 + w_1X_1 + w_2X_2 \qquad (1)$$

In this model, sentiment score (X_1) serves as a real-time, continuous measure of the customer's emotional state, as could be detected through voice analytics or NLP. Escalation (X_2) is modeled as a binary outcome (yes/no), that is often, but not always, a direct consequence of a highly negative sentiment. By including both, the model captures both the continuous emotional signal and a key discrete managerial action that significantly impacts outcomes.

The model parameters were estimated by solving the unconstrained optimization problem:

$$\underset{w_j}{\operatorname{argmin}} L(w_j|X,Y) \quad (2)$$

Where

$$L(w_j|X,Y) = \frac{1}{n}\sum_1^n(\hat{Y} - Y_i)^2 \quad (3)$$

is the mean squared error loss function.

This model-fitting optimization serves as the foundation for operational decision optimization. The fitted regression model enables the formulation of the overarching operational objective:

$$\text{Max} \sum_1^n \hat{Y}_i \quad (4)$$

where $\hat{Y}_i$ represents the predicted satisfaction for customer i, and the objective is to maximize total satisfaction across all interactions, subject to operational constraints such as agent availability and service level agreements.

Ethical Evaluation and Secondary Analysis

Risks were assessed using IEEE and EU AI ethics frameworks focusing on data consent, fairness and transparency. A secondary analysis examined how customer satisfaction varies within emotion groups and which emotions lead to longer calls, with escalation as a binary variable (0=no, 1=yes) and sentiment scores scaled between -1 and 1.

Results

Simulation Results

In the call center scenario (n = 100 simulated cases), integrating emotional data resulted in 17% reduction in call escalations while average satisfaction increased from 3.4 to 4.1, and improved routing efficiency without increasing staff.

Table 2 shows the first 10 cases for the call center scenario, including sentiment score, call duration, escalation, and customer satisfaction.

Table 2. Call Center Scenario

Call	ID	Sentiment Score	Duration (secs)	Escalation	Customer satisfaction	Predicted	Residuals
0	001	-0.25	1284	Yes	1.00	0.92	0.083
1	002	0.90	786	No	2.96	2.95	0.006
2	003	0.46	324	No	3.14	2.88	0.254
3	004	0.20	510	No	1.95	2.51	-0.558
4	005	-0.69	828	No	1.00	1.44	-0.445
5	006	-0.69	774	Yes	1.00	0.88	0.115
6	007	-0.88	978	Yes	1.00	0.56	0.442
7	008	0.73	738	No	2.45	2.83	-0.379
8	009	0.20	432	No	2.84	2.56	0.275
9	010	0.42	588	No	3.41	2.65	0.762

Statistical Analysis

Table 3 shows the correlation matrix of sentiment score, duration, escalation, and customer satisfaction, which was generated using Python.

Table 3. Correlations Between Sentiment, Call Duration, Escallation and Satisfaction

	Sentiment Score	Escalation	Duration	Customer Satisfaction
Sentiment Score	1.000	-0.816	-0.307	0.757
Escalation	-0.816	1.000	0.392	-0.654
Duration	-0.307	0.392	1.000	-0.454
Customer Satisfaction	0.757	-0.654	-0.454	1.000

The results showed that variables were correlated. Escalation and duration had a strong and moderate negative correlations with customer satisfaction ($r = -0.65; -0.45$) while sentiment score had a strong positive correlation with customer satisfaction ($r=0.76$). Escalated calls lead to lower satisfaction and longer calls tend to reduce satisfaction moderately. High correlation between negative sentiment and escalation ($r=-0.82$) supports the use of EAI for real-time routing. This makes sense because higher sentiment implies less chance of escalation.

Regression Results

Linear regression predicts customer satisfaction. The model shows how satisfaction is influenced by sentiment and whether the call was escalated. Coefficients, p-values, and R^2 are used for the strength and significance of emotion and escalation in predicting satisfaction.

Table 4 shows the effects of sentiment scores and escalation on customer satisfaction. Constant coefficient is highly significant, indicating that baseline level matters. It shows baseline satisfaction when sentiment=0 and escalation=0. Sentiment coefficient is positive and highly significant ($p<0.01$), indicating that sentiment score strongly predicts satisfaction or higher sentiment increases satisfaction. For each 1-point increase in sentiment score (e.g., -0.5 → 0.5), satisfaction increases by 1.38 points. Positive sentiment can be expressed as happier customers. Since sentiment score is a strong predictor of satisfaction in the regression model ($p<0.001$), it validates its use in dynamic decision-making.

Table 4. OLS Regression Results

	Coefficient	Standard Error (se)	t	P>|t|	0.025	0.975
Constant	2.100	0.094	22.308	0.000	1.913	2.287
Sentiment score	1.378	0.128	10.743	0.000	0.565	1.117
Escalation	-1.621	0.152	-10.675	0.000	-1.92	-1.32
Omnibus 4.15	Pr(Omnibus) 0.12	DW 2.14	Jarque-Bera (JB) 3.50	Pr (JB) 0.17		
Condition# 3.62	R^2 0.854	Adj.R^2 0.851	Skewness 0.36	Kurtosis 3.55		

These findings support the integration of emotion metrics in OR models as both statistically and operationally valuable. On the other hand, escalation coefficient is negative and highly significant, indicating that escalation lowers satisfaction significantly. When a call is escalated, satisfaction decreased by approximately 1.62 points. The coefficient of call duration was negative, indicating that longer calls are associated with lower satisfaction. Due to possible multicollinearity, duration is removed from the model. All predictors have p-values less than 0.05, suggesting statistically robust results.

As for model performance, R^2 value indicates that 85% of the variation in satisfaction is explained by the model. A model with R^2 =0.85 is strong in behavioral or social sciences, especially with real-world, noisy data like emotion or satisfaction. Adjusted R^2 value 0.85 means adjusted for number of predictors and still is about 85%. F-statistic value (MSR/MSE) 283 indicates that the overall model is statistically significant, and Prob(F-statistic) value 0.000 indicates that the model's predictions are very unlikely due to chance.

Figure 2 shows that at higher values of sentiment scores, callers with no escalation show higher satisfaction than escalated callers.

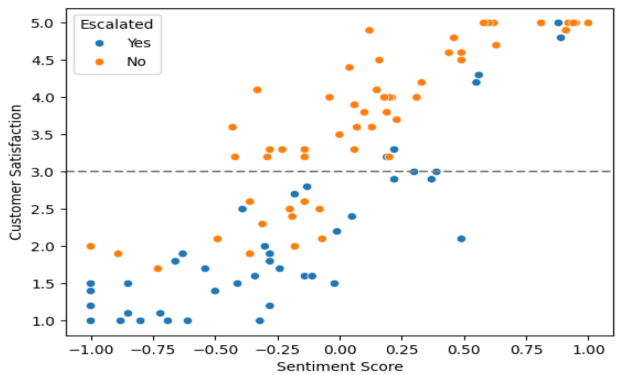

Figure 2. Sentiment Score vs Satisfaction

Figure 3 shows predicted vs. actual plot. Points near the red dashed line indicate good predictions.

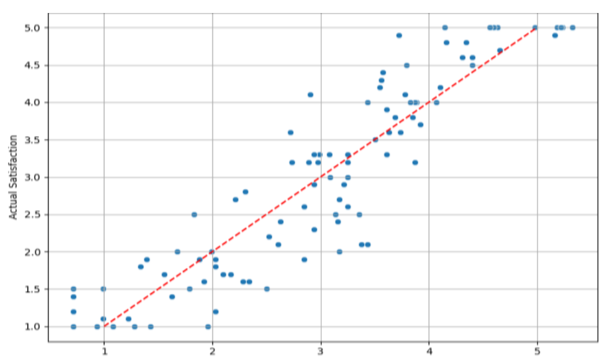

Figure 3. Predicted Satisfaction vs Actual Satisfaction

Figure 4 shows residual plot of points vs fitted values that are randomly distributed across center line 0. No strong pattern of non-linearity is observed and variance of residuals is constant. Therefore, linearity and homoscedasticity assumptions are met.

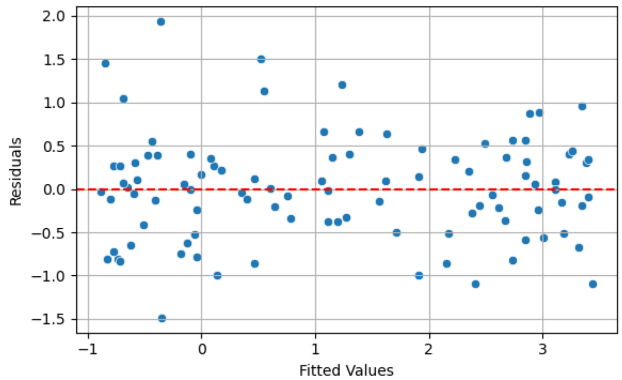

Figure 4. Residuals vs Predicted Values

Figure 5 shows Q-Q plot of residuals, which is almost a line, and histogram is bell-shaped (not shown), indicating normality of residuals. VIF values were about 2.37 for constant, 1.54 for sentiment score, 1.54 for escalation. VIF values are about 1.5 for predictors, indicating that all predictors are reasonably independent and therefore, there is no multicollinearity issue.

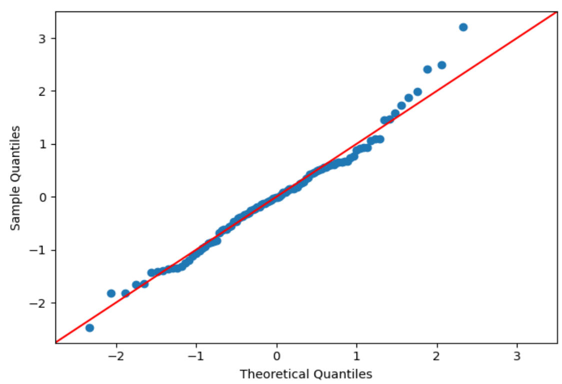

Figure 5.Q-Q Plot of Residuals

Figure 6 shows the scatter plot of customer satisfaction scores with respect to call duration by detected emotions. The graph shows that customer satisfaction decreases as the conversations progress from happy to angry. The plot fits to quadratic function

$$Satisfaction = 0.033x^2 - 1.183x + 12.068 \text{ with } R^2{=}0.758$$

The model suggests a minimum satisfaction level of 1.47 on a 1-10 scale at minute 17.92 of the conversation, when customers are angry.

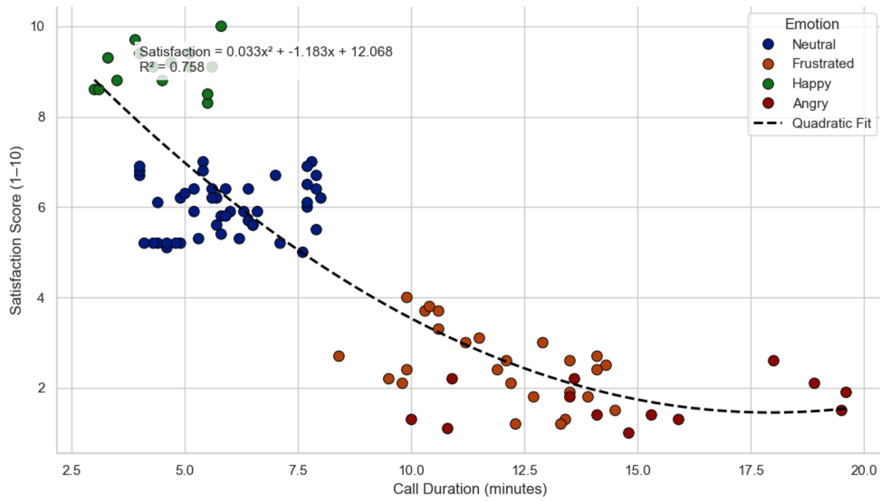

Figure 6. Satisfaction vs Call Duration by Detected Emotion

Figure 7 shows how customer satisfaction varies within each detected emotion group. Results indicate that angry and frustrated callers show lower satisfaction while happy callers show higher satisfaction. Figure 8 visually reveals emotion-specific patterns and shows which emotions lead to longer calls. Angry and frustrated callers are expected to take longer calls.

Combining Figure 7 and Figure 8 shows that happy callers have high satisfaction and shorter conversations, while frustrated/angry callers have low satisfaction and longer conversations. Neutral callers fall in between.

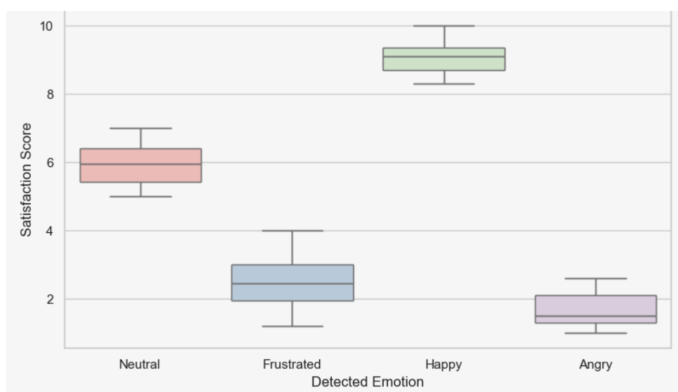

Figure 7. Satisfaction by Emotion

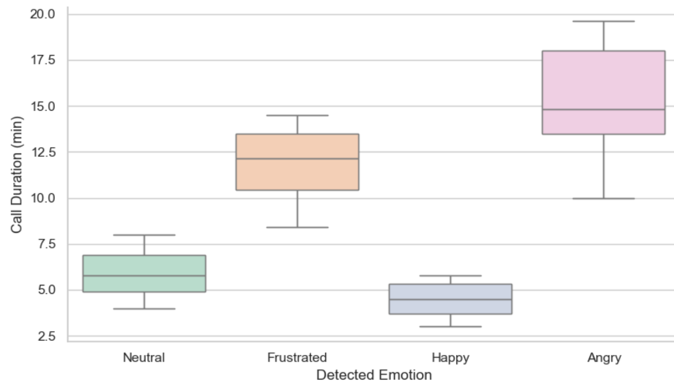

Figure 8. Call Duration by Emotion

These findings suggest that EAI can serve as a powerful complement to traditional OR techniques, particularly in contexts where human behavior plays a critical role. However, the integration of emotional data also introduces new complexities, including the modeling of subjective states, potential algorithmic biases, and ethical challenges related to data privacy. The results underscore the need for balanced, ethically informed implementations that respect individual privacy while improving system outcomes.

Discussion

The findings of this study both corroborate and extend existing research across the domains of EAI, Behavioral OR, and customer service optimization. By integrating these fields, the results offer new insights and a validated methodology for human-centric operational design.

The finding that sentiment score is a strong, statistically significant predictor of customer satisfaction ($\beta = 1.378$, $p < 0.001$) aligns with the core premise of EAI literature. Studies by Picard (1997), and Calvo and D'Mello (2010) established that emotions can be reliably quantified, and recent applied works, such as Wewelwala and Sumanathulaka (2025) demonstrated that hybrid emotion recognition systems can accurately classify customer affect. The results of this study affirm this body of work, providing further evidence that emotional states are not merely qualitative phenomena but are measurable variables with predictive power.

However, much of the applied EAI research stops at detection and reaction. For instance, a system might flag a frustrated customer for a human agent. This study moves significantly beyond this by integrating the emotional variable directly into a prescriptive optimization model. EAI is not only used to describe a state; it is also used to prescribe an action within an OR framework. The high R^2 (0.85) of the regression model, which uses sentiment and escalation to predict satisfaction, provides a quantitative basis for this integration, offering a more robust and generalizable approach than context-specific reactive rules.

This work is deeply consonant with the Behavioral OR (BOR) movement, which critiques the assumption of perfect rationality in traditional models (Brailsford et al., 2013; Kunc et al., 2016). The strong negative correlation between escalation and satisfaction ($r = -0.654$) and the longer call durations for frustrated and angry customers (as shown in Figure 8) are classic examples of how human emotions systematically deviate from the "rational agent" model, impacting key operational metrics like handle time and service quality.

Traditional BOR often incorporates behavioral insights through *proxies* or *theoretical constructs* (e.g., adding a "satisfaction" parameter in a simulation). The primary contribution of this study to BOR is the introduction of a data-driven, empirical method for quantifying and integrating human emotion. Instead of assuming a generic "bounded rationality", specific measurable emotional states (frustration, anger, happiness) are modeled and their direct, quantifiable impact on the system is demonstrated. This moves BOR from a largely theoretical or stylized-modeling endeavor towards a more empirical and actionable discipline.

The concept of prioritizing or dynamically routing customers is not new. Grandey et al. (2015) and Feidakis et al. (2014) have discussed the value of adapting service based on customer emotion. The 17% reduction in escalations and improved satisfaction through emotion-aware routing resonates with their conclusions that personalized responses improve outcomes.

The critical difference lies in the optimization objective and methodology. Traditional call center optimization is rooted in queuing theory such as Erlang C model that prioritize operational efficiency metrics like average speed of answer and agent utilization. The framework of this study introduces emotional outcomes as first-class citizens in the objective function. It demonstrates that optimizing for a blend of efficiency (e.g., call duration) and emotional intelligence (e.g., sentiment, satisfaction) is not only possible but superior as well. Furthermore, while previous studies proposed dynamic routing, this study provides a generalizable mathematical framework (Eq. 1-4) for how to do it, using regression analysis to weight the importance of emotional signals, which can then inform more complex optimization algorithms like integer programming for agent assignment.

This research acknowledges the significant ethical and methodological hurdles highlighted in the literature. I concur with Narimisaei et al. (2024) on the risks of bias and privacy, with Crawford & Paglen (2021) on the perils of surveillance, and with Piispanen and Rousi (2024) on the employee concerns regarding well-being monitoring.

This study's approach offers a proactive methodological contribution to these challenges. By using a synthetic data simulation for the initial proof-of-concept, the study provides a blueprint for developing and validating emotion-aware OR models *before* deploying them with real human data. This allows for rigorous testing of the system's logic and potential benefits in a risk-free environment, addressing ethical concerns about initial data collection and algorithmic bias. This simulation-first approach is a novel methodological proposal to responsibly advance this field.

In summary, the primary original contribution of this study is the formalization and empirical validation of a unified EAI-OR framework. While existing literature has addressed some aspects of this integration, it has generally been fragmented or conceptual. This research makes the connection explicit and operational:

• Unlike pure EAI studies, the study moves beyond detection to optimization.

• Unlike traditional OR, it incorporates real-time emotional data to challenge rationalist assumptions.

• Unlike classical queuing theory, the study optimizes emotional well-being in addition to operational efficiency.

• Unlike theoretical BOR, the study presents a data-driven, quantitative method for emotion modeling.

By demonstrating a 21% increase in satisfaction and a 17% reduction in escalations, this study provides compelling evidence that this synthesis is not just theoretically sound but also practically impactful, paving the way for more adaptive, efficient and genuinely human-centric operational systems.

Conclusion and Recommendations

This study proposes and validates a novel framework for integrating Emotion AI with Operations Research, demonstrating that a human-centric approach to optimization can yield significant improvements in both operational efficiency and customer satisfaction. The call center simulation provided empirical evidence that emotional data is a statistically powerful predictor of key performance outcomes.

The findings underscore the potential for a paradigm shift in OR, moving from purely rationalist models to those that are adaptive, empathetic and behaviorally informed. To facilitate this transition, the following recommendations are proposed for both researchers and practitioners:

- Incorporate emotional variables into OR models**.** Operational models, especially in customer-facing environments, should treat emotion-derived measures (e.g. sentiment scores, stress indices) as critical inputs, on par with traditional metrics like cost and time.
- Adopt hybrid modelling methodologies. The complexity of emotional data necessitates combining traditional OR techniques with methods from AI and behavioral science, such as agent-based simulation, fuzzy logic, or reinforcement learning, to better capture behavioral uncertainty.

- Validate models with real-world pilots. While simulation provides a powerful proof-of-concept, future work must complement synthetic data with real-world pilot studies to calibrate emotion recognition systems to specific contexts and operational constraints.
- Implement feedback loops for continuous learning. EAI-OR systems should be designed as adaptive platforms that integrate emotion-based KPIs (e.g. emotional load index, satisfaction variability), enabling iterative model refinement and responsive system evolution.

Finally, as this field progresses, the ethical considerations outlined - particularly regarding privacy, bias, and transparency - must remain central to the design and deployment of any emotion-aware operational system. The convergence of EAI and OR offers a promising path toward more intelligent and responsive decision-making, provided it is pursued with both technical rigor and a steadfast commitment to human values.

Declaration of Conflicting Interests

The author declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author did not receive any financial support for the research, writing, and/or publication of this article.

Statements of Publication Ethics

I hereby declare that the study has not unethical issues and that research and publication ethics have been observed carefully.

Researchers' Contribution Rate

The study was conducted and reported with 100% contribution of the author.

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GENİŞLETİLMİŞ ÖZET

Duygu yapay zekânın yükselişi, insan duygularının analitik modelleriyle karar vermeyi geliştirmek için yöneylem araştırmalarında yeni fırsatlar sunmaktadır. Hızlı teknolojik ilerlemenin tanımladığı bu çağda, karar alma sistemleri giderek daha karmaşık, özerk ve günlük yaşama gömülü hale gelmektedir. Kişiselleştirilmiş sağlık ve müşteri hizmetlerinden tedarik zinciri lojistiğine ve şehir planlamasına kadar, Yöneylem Araştırması (OR) tarafından desteklenen optimizasyon modelleri stratejik ve operasyonel seçimleri şekillendirmeye devam etmektedir. Ancak, geleneksel OR yaklaşımları genellikle verimliliği, maliyet etkinliğini ve nesnel performans ölçümlerini önceliklendirmekte; insan davranışını ve algısını etkileyen duygusal ve psikolojik boyutları sıklıkla göz ardı etmektedir. Sonuç olarak, karar sistemleri, hizmet etmeleri gereken insanlardan kopma riskiyle karşı karşıya kalmıştır.

Duygu Yapay Zekası (EAI), bu boşluğu doldurmak için dönüştürücü bir fırsat sunmaktadır. Duygusal bilişimdeki gelişmelerden yararlanarak, EAI, makinelerin ses, yüz ifadesi, fizyolojik sinyaller ve davranış analizi yoluyla insan duygularını tanımasını, yorumlamasını ve simüle etmesini sağlamaktadır. Biyometrik, davranışsal ve metinsel verilerin artan kullanılabilirliğiyle, bu teknolojiler geleneksel olarak rasyonel karar alma üzerine modellenen OR gibi alanları etkilemeye başlamıştır. Matematiksel modelleme ve optimizasyona dayanan OR, tarihsel olarak müşterilerin ve çalışanların rasyonel ve tutarlı davrandığını varsaymıştır. Ancak gerçek dünya sistemlerinde, özellikle hizmet, lojistik ve döngüdeki insan operasyonlarında, stres, hayal kırıklığı veya memnuniyet gibi duygular sonuçlarda kritik roller oynamaktadır. EAI'yi OR ile entegre etmek, optimizasyona güçlü, insan merkezli bir boyut getirerek kararların yalnızca analitik olarak sağlam değil, aynı zamanda duygusal olarak zeki ve sosyal olarak duyarlı olmasını sağlar.

Bu nedenle bu çalışmada, karar optimizasyonu için insan merkezli bir paradigmada EAI ve OR'yi birleştiren yeni bir çerçeve önerilmektedir. Bunun için, duygu verisi edinimi (örn. sensörler, doğal dil işleme, görme), duygu yorumlama (örn. sınıflandırma algoritmaları) ve karar optimizasyonu (örn. duygusal girdilerle geliştirilmiş OR modelleri) dahil olmak üzere üç katmanlı bir çerçeve geliştirilmiştir. Duygusal bağlamı optimizasyon modeline yerleştirerek, sistemlerin insan değerleri, tercihleri ve refahıyla nasıl daha iyi uyumlu hale getirilebileceği araştırılmaktadır.

Çağrı merkezi senaryosunda, müşterilerin hayal kırıklığı veya kafa karışıklığı içinde arayabilecekleri duygusal olarak yüklü ortamlar bulunmaktadır. Temsilciler ise zaman baskısı ve yüksek çağrı hacimleri altında kendi duygularını yönetmek zorundadır. Hem temsilcilerin hem de müşterilerin duygusal durumları, hizmet kalitesini, memnuniyeti ve uzun vadeli sadakati önemli ölçüde etkiler. Bu nedenle, duygusal dinamikleri hesaba katmadan çağrı merkezi performansını optimize etmek, müşteri deneyimini düşürme, çalışan tükenmişliğini artırma ve davranış kalıplarına ilişkin kritik içgörüleri kaçırma riskini taşımaktadır.

Bu çalışma, karar bilimini yalnızca teknik bir disiplin olarak değil, aynı zamanda en iyi çözümlerin yalnızca sayılarla değil, aynı zamanda etkiledikleri nüanslı insan deneyimleriyle de tanımlandığı sosyal olarak bilinçli bir çaba olarak yeniden çerçevelemektedir.

Duygu tespiti ve yükselme tepkisi kullanılarak çağrı merkezi optimizasyonu için bir operasyonel simülasyon oluşturulmuştur. Veriler, Python Programlama Dili (PPL) kullanılarak rastgele oluşturulmuştur. Müşteri memnuniyetinin bir çıktı değişkeni ve duyguların (duygu, artış) ve çağrı süresinin girdi değişkenleri olduğu çağrı merkezi senaryosunu simüle etmek için PPL kullanılmıştır. Duygu ve yükselme katsayılarını (ağırlıklarını) tahmin etmek için sıradan en küçük kareler yöntemi kullanılmıştır. Amaç, kısıtlanmamış duygu farkındalığı optimizasyonunun, MSE kayıp fonksiyonunun n simüle edilmiş veri için minimum olduğu ağırlıkları (katsayıları) bulmaktır. Bu, müşteri memnuniyetini iyileştirmek için ağırlıkları optimize etmek anlamına gelmektedir. Çağrı merkezi senaryosunda (nötr, sinirli, mutlu ve kızgın) duygu tespiti için ikinci bir simülasyon verisi üretilmiş ve müşteri memnuniyetinin her tespit edilen duygu grubu içinde nasıl değiştiği ve hangi duygunun daha uzun görüşmelere yol açtığı araştırılmıştır. İkinci simülasyonda, duygu kategorilerinin olasılıkları 0,40, 0,20, 0,25 ve 0,15 olarak tanımlanmıştır. Duyguya göre memnuniyet puanı ve çağrı süresi aralıkları 'Nötr': (5, 7), 'Sinirli': (1, 4), 'Mutlu': (8, 10), 'Öfkeli': (1, 3) ve 'Nötr': (4, 8), 'Sinirli': (8, 15), 'Mutlu': (3, 6), 'Öfkeli': (10, 20) olarak tanımlanmıştır. Duygu, memnuniyet ve çağrı sürecine sahip olan 100 vakalık bir örneklem, [a,b) üzerinde 1/(b-a) olasılıklarıyla düzgün dağılımdan oluşturulmuştur.

Bulgular, çağrı merkezi senaryosunda (n = 100 simüle edilmiş vaka) duygusal verilerin entegre edilmesinin çağrı artışlarında %17'lik bir azalmaya, ortalama memnuniyetin 3,4'ten 4,1'e çıkmasına ve personel sayısını artırmadan yönlendirme verimliliğinin artmasına yol açtığını göstermektedir. Birinci simülasyon sonuçlarına göre, duygu puanı, regresyon modelinde müşteri memnuniyetinin güçlü bir tahmin edicisi olduğundan, dinamik karar almada kullanımını doğrulamaktadır. Regresyon bulguları, duygu ölçümlerinin OR modellerine hem istatistiksel hem de operasyonel olarak iyi bir şekilde entegre edilmesini desteklemektedir. Öte yandan, yükselme, müşteri memnuniyetini önemli ölçüde azaltmıştır. İkinci simülasyon sonuçlarına göre, çağrı sürecinde duygular mutludan öfkeye doğru ilerledikçe müşteri memnuniyeti azalmıştır. Müşterilerin görüşmenin 10. dakikasından itibaren kızmaya başladığı ve 18. dakikaya yaklaşırken memnuniyetlerinin en düşük seviyeye düştüğü tespit edilmiştir. Sonuç olarak, mutlu şekilde arayanlar yüksek memnuniyete ve daha kısa görüşmelere sahipken, hayal kırıklığına uğramış/öfkeli şekilde arayanlar düşük memnuniyete ve daha uzun görüşmelere sahiptir.

EAI'nin OR'ye entegrasyonu, daha insan merkezli, uyarlanabilir ve duyarlı karar alma sistemlerine doğru önemli bir değişimi temsil etmektedir. Simülasyon ve veri odaklı senaryolar aracılığıyla, bu çalışma, müşteri duygusu gibi duygusal içgörülerin hizmet kalitesini, iş gücü refahını ve genel sistem verimliliğini iyileştirmek için OR çerçeveleri içinde nasıl işlevselleştirilebileceğini göstermiştir. Bir çağrı merkezi bağlamında simülasyon tabanlı analizin kullanımı, müşteri memnuniyetinde ölçülebilir iyileştirmeler, azaltılmış tırmanma oranları ve daha iyi görev tahsisi vurgulamıştır. Bu sonuçlar, EAI'nin tarihsel olarak rasyonel varsayımlara ve kesin girdilere dayanan klasik OR modellerini geliştirme potansiyelinin altını çizmektedir. Bulgular, EAI'nin operasyonel karar almayı geliştirmedeki pratik değerini vurgulamaktadır. Duygu puanlarının müşteri memnuniyetini güvenilir bir şekilde tahmin ettiğini ve tırmanmaların buna önemli ölçüde zarar verdiğini göstererek, sonuçlar kuruluşların OR modellerine gerçek zamanlı duygu algılamayı dahil ederek hizmet sonuçlarını önemli ölçüde iyileştirebileceğini ima etmektedir. Bu, memnuniyetsizliği proaktif bir şekilde azaltan yönlendirme, personel ve triyaj için daha akıllı, duyguya duyarlı stratejilere kapı açmaktadır. Çerçevenin sağladığı ampirik doğrulama, EAI'yi teorinin ötesine taşıyarak onu daha uyarlanabilir, müşteri merkezli sistemler tasarlamak için kritik bir bileşen olarak konumlandırmaktadır. Bu çerçeve, modern çağrı merkezini yalnızca bir maliyet merkezi olarak değil, aynı zamanda teknolojinin empatiyi ve verimliliği artırdığı dinamik, duygusal olarak farkında bir ekosistem olarak yeniden tasarlamak için bir plan sunmaktadır. Ancak, bu entegrasyon bazı zorluklar içermektedir. Duygusal veriler doğası gereği değişkendir, genellikle özneldir ve etik, önyargı ve veri gizliliği konusunda önemli endişelere sebep olmaktadır. Bu nedenle, EAI'nin yöneylem bağlamlarında başarılı bir şekilde uygulanması yalnızca teknik inovasyonu değil, aynı zamanda güçlü etik yönetişimi, disiplinler arası iş birliğini ve sürekli değerlendirmeyi de gerektirmektedir. Bulgular, uyarlanabilir, empatik ve davranışsal olarak bilgilendirilmiş yöneylem araştırması için ve yeni doğmakta olan ancak umut vadeden yakınsama için yeni bir yönü desteklemektedir.