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Developing an Artificial Intelligence–Based Organizational Behavior Model in Iranian Sports Federations: A Mixed-Methods Approach Based on Psychological Capital Theory and Data Mining

ABSTRACT

The present study aimed to develop and validate an artificial intelligence–based organizational behavior model in three selected Iranian sports federations, drawing on psychological capital theory and its four dimensions of hope, self-efficacy, resilience, and optimism. The study employed a sequential exploratory mixed-methods design (QUAL → QUAN). In the qualitative phase, semi-structured interviews were conducted with 18 experts selected through purposive snowball sampling until theoretical saturation was achieved, and the data were analyzed using open, axial, and selective coding. In the quantitative phase, data were collected from 174 employees selected through proportionate stratified random sampling using standardized psychological capital and organizational behavior questionnaires and were analyzed using decision tree, random forest, artificial neural network, support vector machine, K-Means, and Apriori algorithms. The qualitative analysis yielded 82 open codes, 21 subcategories, and six main categories. Cluster analysis identified three behavioral profiles: “Hopeful Resilients” (38%), “Optimistic Self-Efficacious Employees” (42%), and “Employees at Risk of Deviant Behavior” (20%). The Apriori algorithm generated 28 rules with a minimum confidence of 0.70; the strongest rule indicated that the combination of low self-efficacy and low hope was associated with a high level of deviant behavior with a probability of 88%. The artificial neural network achieved the best predictive performance, with an accuracy of 88.6% and an AUC of 0.905 on the test set. Significant differences were observed among the three federations in self-efficacy, hope, organizational commitment, organizational trust, job satisfaction, and organizational citizenship behavior. The final model consists of three operational components—“if–then” rules, standardized behavioral profiles, and a prediction algorithm—and can serve as a decision-support tool for human resource management in sports federations, particularly for the early identification of employees at risk.

Keywords: organizational behavior, psychological capital, artificial intelligence, data mining, sports federations

Introduction

Organizational behavior represents one of the central fields of management because it provides a systematic framework for understanding how individual, group, and organizational factors shape employees’ attitudes, decisions, interactions, and performance within formal work systems. In contemporary organizations, employee behavior can no longer be interpreted solely through static job descriptions or conventional administrative indicators, because organizational outcomes increasingly depend on dynamic psychological, social, technological, and contextual processes. Organizational behavior therefore encompasses a broad spectrum of phenomena, including organizational commitment, trust, job satisfaction, organizational citizenship behavior, motivation, interpersonal interaction, and counterproductive or deviant workplace behavior, all of which can substantially influence organizational effectiveness and long-term sustainability [1]. Among these outcomes,

positive behaviors such as commitment and citizenship behavior facilitate cooperation, discretionary effort, knowledge sharing, and organizational adaptability, whereas deviant workplace behaviors may undermine productivity, interpersonal trust, organizational climate, and the efficient use of resources. Deviant workplace behavior has been conceptualized as voluntary conduct that violates significant organizational norms and threatens the well-being of the organization, its members, or both, making its early identification an important managerial concern [2]. This concern is particularly salient in sports organizations and federations, which typically operate under conditions of intense performance pressure, stakeholder scrutiny, constrained resources, frequent managerial changes, public accountability, and the need for rapid coordination between administrative and technical units. Such conditions create an environment in which employee attitudes and behavioral responses can have consequences extending beyond internal management to athlete support, competition preparation, national representation, and the broader institutional legitimacy of sport organizations. Accordingly, the management of organizational behavior in sports federations requires analytical approaches that can capture not only observable behaviors but also the psychological resources that predispose employees toward adaptive or maladaptive behavioral patterns.

The emergence of positive organizational behavior shifted attention from employees' deficiencies and dysfunctions toward measurable, developable, and performance-relevant psychological capacities. Positive psychology similarly emphasized the scientific investigation of strengths, optimal functioning, and psychological resources rather than an exclusive focus on pathology and dysfunction [3]. Within this intellectual movement, positive organizational behavior was introduced as the study and application of positively oriented human resource strengths and psychological capacities that can be measured, developed, and effectively managed for performance improvement [4]. One of the most influential developments arising from this perspective is psychological capital, which extends the traditional organizational emphasis on economic, human, and social capital by focusing on the positive psychological state of employees as a strategic organizational resource [5]. Psychological capital is commonly conceptualized through four interrelated dimensions: self-efficacy, hope, resilience, and optimism, frequently represented by the acronym HERO. Unlike relatively stable personality traits, these dimensions are considered state-like and therefore potentially susceptible to development through targeted organizational interventions [6]. Self-efficacy reflects an individual's confidence in mobilizing motivation, cognitive resources, and courses of action required to successfully execute a specific task; Bandura's social cognitive theory established self-efficacy as a central determinant of effort, persistence, coping, and behavioral choice [7]. Hope involves both agency, or goal-directed determination, and pathways, or the perceived capacity to generate alternative routes toward desired goals [8]. Optimism refers to generalized positive expectations regarding future outcomes and to explanatory patterns through which individuals interpret favorable and unfavorable events, with learned optimism suggesting that adaptive explanatory styles can be developed rather than being entirely fixed [9]. Resilience refers to the capacity to adapt, recover, and continue functioning effectively under conditions of adversity, disruption, stress, or significant challenge; importantly, resilience has been described not as a rare exceptional quality but as an adaptive process grounded in ordinary psychological resources [10]. These dimensions can also be understood within a broader resource framework in which individuals seek to acquire, preserve, and protect valued psychological and social resources, while resource loss or insufficiency increases vulnerability to stress and maladaptive responses [11].

Empirical evidence has consistently demonstrated that psychological capital is associated with important employee attitudes, behaviors, and performance outcomes. Psychological capital can provide employees with cognitive and emotional resources that enable them to maintain goal-directed behavior, interpret occupational challenges more constructively, recover from setbacks, and sustain confidence in their ability to influence work outcomes. Consequently, employees with stronger psychological capital are expected to exhibit higher levels of job satisfaction, organizational commitment, constructive extra-role behavior, and adaptive performance while showing lower levels of undesirable occupational attitudes and behaviors. Meta-analytic evidence confirms that psychological capital is positively associated with desirable employee attitudes, desirable organizational behaviors, and performance, while being negatively related to undesirable employee attitudes and behaviors [12]. The multidimensional character of psychological capital is particularly important because organizational behaviors rarely originate from one isolated psychological characteristic. For example, high self-efficacy may encourage initiative, but without hope an employee may lack the ability to generate alternative pathways when obstacles emerge; similarly, optimism without resilience may be insufficient when individuals encounter repeated organizational setbacks. Psychological capital is therefore theoretically valuable not only because each component can independently contribute to positive outcomes, but also because the combined psychological resource may generate a synergistic effect greater than its separate components [6]. From a measurement perspective, the distinctiveness of psychological constructs must also be empirically established to ensure that conceptually different variables are not merely statistical reflections of the same underlying factor. Contemporary validity assessment therefore emphasizes rigorous examination of discriminant validity, including approaches such as the heterotrait–monotrait ratio of correlations, particularly when multiple related psychological constructs are incorporated into explanatory or predictive models [13]. These theoretical and methodological considerations make psychological capital an appropriate foundation for examining employee behavioral patterns in sports federations, where staff must operate under uncertainty, competitive pressure, institutional constraints, and changing managerial priorities.

At the same time, the rapid development of artificial intelligence and data-driven management has transformed the analytical possibilities available to organizational researchers and human resource managers. Traditional organizational behavior research has predominantly relied on descriptive statistics, correlational analyses, regression models, and structural equation modeling. Although these methods remain valuable for testing theory and estimating linear relationships, they may be less capable of identifying nonlinear interactions, complex combinations of predictors, latent behavioral profiles, or decision rules embedded within multidimensional employee data. Artificial intelligence and machine-learning techniques can complement conventional inferential methods by detecting patterns that may be difficult to identify through traditional modeling alone. A growing body of organizational research has therefore examined artificial intelligence not merely as a technical innovation but as an organizational phenomenon that influences decision-making, job design, human resource practices, employee experiences, accountability, and the distribution of managerial authority [14]. Algorithms such as decision trees, random forests, artificial neural networks, support vector machines, clustering procedures, and association-rule mining can be particularly valuable in organizational behavior because they support both prediction and pattern discovery. Decision trees can produce interpretable classification structures; random forests can improve predictive stability and estimate feature importance; neural networks can model complex nonlinear relationships; support vector machines can classify observations in high-dimensional spaces; K-Means clustering can identify naturally occurring employee profiles; and

association-rule methods such as Apriori can reveal combinations of conditions linked to specific behavioral outcomes. In sport management, data-driven approaches have already been applied to managerial decision-making, and machine-learning methods such as decision trees have been used to predict contingency decision-making styles among sports managers [15]. These developments suggest that artificial intelligence may provide a useful analytical bridge between psychological theory and operational human resource decision support.

The increasing use of artificial intelligence in organizational settings, however, should not be interpreted as a purely technological substitution for managerial judgment. Its value depends on how technological tools are integrated with human capacities, organizational structures, and ethical safeguards. The future of AI-enabled work raises important concerns regarding transparency, accountability, fairness, autonomy, surveillance, human dignity, and the possible displacement of human judgment by algorithmic systems [16]. These issues are highly relevant to human resource management because employee-related algorithms may influence evaluation, development, promotion, intervention, or risk identification. A technically accurate prediction may still be managerially problematic if employees do not understand how it was produced, if the data are culturally inappropriate, or if algorithmic classifications are treated as deterministic labels rather than probabilistic decision-support indicators. For this reason, AI-based organizational behavior systems should be human-centered, interpretable, context-sensitive, and designed to augment rather than replace managerial judgment. Recent arguments have also suggested that artificial intelligence can contribute to the development of psychological capital in learning organizations by providing individualized feedback, adaptive learning opportunities, and data-informed support for employee growth [17]. This perspective is especially important because it reframes AI from being solely a mechanism for monitoring or predicting employee behavior to being a possible instrument for strengthening positive psychological resources. In parallel, the broader field of positive sport organizations has increasingly emphasized the importance of constructive organizational environments, psychological strengths, positive leadership, and sustainable human functioning in sport institutions [18]. Integrating these perspectives implies that the most useful AI-based organizational behavior model for sports federations would not simply classify employees according to behavioral risk but would connect prediction to actionable strategies for psychological development and supportive human resource management.

Sports organizations are particularly suitable contexts for data-driven organizational behavior research because they are becoming increasingly dependent on analytics while simultaneously facing distinctive managerial and cultural constraints. Advanced analytics have already become embedded in many aspects of professional sport, including performance monitoring, recruitment, tactical analysis, injury prevention, commercial planning, and strategic decision-making. Evidence from professional football clubs and national federations indicates that data analytics is increasingly institutionalized, although substantial differences remain in analytical infrastructure, staffing, operational integration, and the capacity to transform data into managerial action [19]. The administrative side of sports federations is likewise undergoing digital transformation, creating opportunities to use data not only for competitive and technical purposes but also for human capital and organizational management. Recent evidence from sport-sector research indicates that artificial intelligence and information technology can influence human capital through organizational structures, demonstrating that technological adoption and organizational design are closely interconnected rather than independent processes [20]. Research focused specifically on sports federations has similarly shown the importance of AI methods for improving administrative performance, highlighting their potential to strengthen decision quality, efficiency, responsiveness, and managerial

effectiveness [21]. Nevertheless, the organizational adoption of AI in sports federations may be constrained by fragmented databases, insufficient technical infrastructure, limited analytical expertise, resistance to technological change, weak integration between information systems and human resource units, and uncertainty regarding the interpretability of algorithmic outputs. These limitations are likely to be particularly consequential in environments where administrative practices and organizational cultures differ from those in which many existing AI tools have been developed. Therefore, an effective model for sports federations must combine computational performance with contextual validity and organizational interpretability.

Despite the parallel growth of psychological capital research and AI-based organizational analytics, important conceptual and empirical gaps remain. First, most studies examining psychological capital have relied on conventional variable-centered statistical models that estimate average relationships between psychological resources and organizational outcomes, whereas considerably less attention has been paid to identifying heterogeneous employee profiles through unsupervised machine-learning techniques. Yet two employees with similar aggregate psychological capital scores may have substantially different configurations of self-efficacy, hope, resilience, and optimism and may therefore exhibit different behavioral patterns. Second, traditional organizational behavior models frequently assume additive or approximately linear effects, whereas real organizational behavior may be shaped by conditional combinations, thresholds, and nonlinear interactions. Association-rule mining and nonlinear prediction algorithms offer opportunities to identify these relationships in a form that can be translated into concrete “if-then” managerial rules. Third, many artificial intelligence studies emphasize predictive accuracy without sufficiently grounding predictor selection and interpretation in established organizational theory. A theoretically informed model based on psychological capital can address this limitation by ensuring that algorithmic prediction remains connected to meaningful, developable psychological constructs. Fourth, existing AI applications in sports management have focused predominantly on competitive performance, athlete-related analytics, and managerial decision-making, whereas AI-based prediction of employee organizational behavior in sports federations remains comparatively underdeveloped. Fifth, models developed in other organizational or national contexts may not automatically reflect the structural, cultural, managerial, and technological characteristics of Iranian sports federations. A context-specific model is therefore needed to connect expert knowledge, psychological theory, empirical employee data, and machine-learning techniques within a coherent analytical framework.

A mixed-methods strategy is particularly appropriate for addressing these limitations because organizational behavior in sports federations contains both context-dependent meanings and empirically measurable patterns. A qualitative phase can identify the organizational conditions, managerial concerns, contextual barriers, and perceived mechanisms that experts consider important, thereby preventing the model from being determined solely by variables imported from the literature. A subsequent quantitative phase can test and operationalize these insights using employee-level data, identify naturally occurring behavioral profiles, extract association rules, rank predictive features, and compare the predictive performance of alternative algorithms. Such integration reflects the broader managerial requirement that organizational models be both theoretically defensible and practically actionable. It also responds to the need to move beyond a dichotomy between human-centered management and data-driven management. Psychological capital provides a human-centered theoretical foundation because it emphasizes strengths that can be measured and developed, while data mining provides a technological mechanism through which complex relationships can be discovered and converted into decision-support outputs. If these

two perspectives are effectively integrated, an AI-based organizational behavior model may enable human resource managers to identify employees who require developmental support, recognize combinations of psychological resources associated with constructive organizational behavior, detect patterns linked to deviant behavior, differentiate employee profiles, and allocate interventions more precisely. At the same time, such a model should remain consistent with the principle that algorithmic recommendations inform rather than replace managerial decision-making and should be interpreted within the specific organizational context in which employees work.

Accordingly, the aim of the present study was to develop and validate an artificial intelligence–based organizational behavior model for selected Iranian sports federations by integrating psychological capital theory, qualitative expert knowledge, and data-mining techniques to identify behavioral profiles, association rules, key predictive factors, and an accurate algorithm for predicting employees' organizational behavior.

Methodology

The present study was applied-developmental in terms of purpose and employed a sequential exploratory mixed-methods design grounded in the pragmatic paradigm. In the qualitative phase, which followed inductive logic, the context-specific dimensions and components of the model were derived from expert knowledge. In the quantitative phase, which followed deductive logic, the extracted model was tested and validated using field data and data-mining algorithms. The study was conducted in three Iranian sports federations—football, volleyball, and athletics—which were coded as F1, F2, and F3 to preserve confidentiality. The federations were selected based on three criteria: willingness to cooperate, structural diversity in terms of team and individual sports and different levels of international activity, and employment of at least 50 staff members. The study period extended from October 2025 to September 2026.

The study population consisted of university professors and specialists in organizational behavior, sport management, psychological capital, and artificial intelligence, as well as experienced senior managers of the federations. Using purposive and snowball sampling, 18 experts were interviewed. Their professional experience ranged from 6 to 25 years and covered sport management, organizational behavior, artificial intelligence and data mining, human resource management, and industrial-organizational psychology. Sampling and interviewing continued until theoretical saturation was reached.

The population consisted of permanent and contractual employees with at least six months of work experience in the three federations, totaling approximately 280 individuals. Proportionate stratified random sampling was employed, with each federation treated as a stratum. Based on Cochran's formula at a 95% confidence level and a 5% margin of error, the required sample size was estimated at approximately 162. Allowing for a 20% attrition or nonresponse rate, 200 questionnaires were distributed. Of these, 174 complete questionnaires were returned, yielding a response rate of 87%, and all 174 questionnaires were retained for analysis after data cleaning. Men accounted for 64.4% of the sample. The most frequent age group was 30–40 years (42.5%), the most frequent work-experience category was 5–10 years (39.1%), and bachelor's degree holders constituted the largest educational group (38.5%). Participants from federations F1, F2, and F3 represented 33.3%, 36.8%, and 29.9% of the sample, respectively.

In the qualitative phase, semi-structured interviews lasting 45–75 minutes were conducted, audio-recorded with participants' informed consent. In the quantitative phase, two questionnaires were administered: (a) the Psychological Capital Questionnaire (PCQ) developed by Luthans et al. (2007), consisting of 24 items rated on a six-point scale and

comprising four six-item dimensions; and (b) a 25-item organizational behavior questionnaire rated on a five-point scale and comprising five five-item indicators: organizational commitment, organizational trust, job satisfaction, organizational citizenship behavior, and deviant behavior.

Content validity was evaluated by eight specialists. The content validity ratio (CVR) for all items exceeded the critical value of 0.75, ranging from 0.78 to 1.00, and the content validity index (CVI) was 0.92. Confirmatory factor analysis indicated satisfactory fit for the measurement models. For the PCQ, RMSEA = 0.058, CFI = 0.94, GFI = 0.91, and SRMR = 0.049, with factor loadings ranging from 0.54 to 0.87. For the organizational behavior questionnaire, RMSEA = 0.062, CFI = 0.92, GFI = 0.90, and SRMR = 0.052, with factor loadings ranging from 0.52 to 0.85. The average variance extracted (AVE) exceeded 0.50 for all constructs, and discriminant validity was confirmed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT) (Fornell & Larcker, 1981; Henseler et al., 2015). Composite reliability exceeded 0.70 for all constructs, while the Spearman–Brown coefficients for the two questionnaires were 0.88 and 0.86, respectively. Cronbach’s alpha coefficients are presented in Table 1.

Table 1

Cronbach’s Alpha Coefficients for the Research Instruments

Construct	Number of Items	Cronbach’s Alpha
Psychological capital (total)	24	0.91
Self-efficacy	6	0.87
Hope	6	0.85
Resilience	6	0.83
Optimism	6	0.86
Organizational behavior (total)	25	0.89
Organizational commitment	5	0.84
Organizational trust	5	0.82
Job satisfaction	5	0.86
Organizational citizenship behavior	5	0.85
Deviant behavior	5	0.81

The qualitative data were analyzed through thematic analysis involving three stages of open, axial, and selective coding using MAXQDA software. The trustworthiness of the findings was evaluated based on Lincoln and Guba’s (1985) criteria. Peer debriefing was conducted by two university professors familiar with qualitative research methods, resulting in the consolidation of three repetitive codes and revision of the labels of two subcategories. Member checking was also performed, whereby five interviewees confirmed the accuracy of the researchers’ interpretations. In addition, a complete audit trail of the research procedures and reflexive notes was maintained.

In the quantitative phase, prior to running the algorithms, questionnaires containing more than 20% unanswered items were excluded ($n = 8$). Multivariate outliers were identified using Z scores with a threshold of ± 3 ($n = 4$), and missing values of less than 2% were replaced with the corresponding item means. Normality was assessed using the Kolmogorov–Smirnov test. Classification algorithms, including decision tree, random forest, artificial neural network, and support vector machine, were evaluated for predicting each employee’s membership in one of three organizational behavior categories—favorable, moderate, or unfavorable—using 10-fold cross-validation and a 20% holdout test set comprising 35 cases. For comparison with conventional statistical approaches, logistic regression and multiple linear regression were also used as baseline models. The optimal number of clusters in K-Means clustering was determined using the elbow method and silhouette coefficient. For the Apriori algorithm, continuous scores were discretized into three levels—low, moderate, and high—with a minimum

support threshold of 0.10 and a minimum confidence threshold of 0.70. Feature importance was estimated using random forest. Differences among the federations were examined using one-way analysis of variance and Tukey's post hoc test. The analyses were conducted in Python using Scikit-learn, Pandas, and NumPy, as well as SPSS Version 26.

Findings and Results

A total of 341 initial concepts were extracted from the 18 interviews. After removing duplicate items and merging conceptually similar concepts, these were reduced to 82 open codes. During axial coding, the codes were organized into 21 subcategories and six main categories, as shown in Table 2. Examples of participants' statements included: "An employee who has hope for his or her occupational future will never leave the organization" (Expert 4); "Unfortunately, our employees' behavioral data are not recorded or stored" (Expert 9); "Foreign algorithms are not compatible with Iranian organizational culture" (Expert 11); and "Employees do not trust algorithmic outputs; we need transparency" (Expert 7).

Table 2

Axial Coding Structure: Main Categories and Examples of Subcategories

Main Category	Subcategories (Examples)
Causal conditions	International competitive pressures, frequent managerial changes, shortage of skilled human resources, increasing performance expectations
Central phenomenon	Lack of an indigenous organizational behavior prediction model, weaknesses in behavioral data analysis, gap between psychological capital and performance
Contextual factors	Organizational structure of federations, organizational culture, ethical climate, type of federation (team/individual sport)
Intervening factors	Technological readiness, senior management support, financial resources, administrative laws and regulations
Strategies	Application of data-mining algorithms, enhancement of employees' psychological capital, development of a decision-support system, implementation of empowerment programs
Consequences	Improved job satisfaction, increased organizational commitment, enhanced organizational citizenship behavior, reduced deviant behavior, increased productivity

During selective coding, the core category was identified as "developing an intelligent organizational behavior model based on the integration of psychological capital and data mining." This category reflects the federations' need to transition from conventional approaches toward a data-driven yet human-centered model in which artificial intelligence functions not as a substitute for employees' psychological capital but as a facilitator of it. Following peer debriefing and member checking, the preliminary qualitative model was confirmed without substantive modification.

The mean scores for the dimensions of psychological capital ranged from 3.92 to 4.26 on a six-point scale and were therefore above the midpoint. Self-efficacy had the highest mean, whereas resilience had the lowest. Among the organizational behavior indicators measured on a five-point scale, organizational commitment had the highest mean (3.56), whereas deviant behavior had the lowest mean (2.56), as shown in Table 3. Skewness and kurtosis values for all variables were within ± 2 , and the Kolmogorov–Smirnov test indicated no significant deviation from normality for any variable ($p > .05$).

Table 3

Descriptive Statistics for the Main Variables (N = 174)

Variable	Minimum	Maximum	Mean	SD	Skewness	Kurtosis
Psychological capital (range: 1–6)						
Self-efficacy	1.83	6.00	4.26	0.84	–0.32	0.15
Hope	1.50	6.00	4.05	0.91	–0.45	0.28
Resilience	1.67	6.00	3.92	0.88	–0.21	0.03
Optimism	2.00	6.00	4.18	0.79	–0.38	0.42
Organizational behavior (range: 1–5)						
Organizational commitment	1.45	5.00	3.56	0.76	–0.25	0.19
Organizational trust	1.25	5.00	3.28	0.82	–0.11	–0.05

Job satisfaction	1.50	5.00	3.45	0.74	-0.18	0.26
Organizational citizenship behavior	1.33	5.00	3.37	0.80	-0.09	0.11
Deviant behavior	1.00	4.80	2.56	0.85	0.35	-0.22

The elbow method indicated a breakpoint at three clusters, and the silhouette coefficient also reached its maximum value at three clusters (0.52), compared with 0.38, 0.45, 0.41, and 0.38 for two, four, five, and six clusters, respectively. The three behavioral clusters were labeled according to their mean profiles, as presented in Table 4. Cluster 1, “Hopeful Resilients” (38%), exhibited the highest levels of hope and resilience, high levels of organizational commitment and job satisfaction, and the lowest level of deviant behavior. Cluster 2, “Optimistic Self-Efficacious Employees” (42%), demonstrated the highest levels of self-efficacy and optimism and favorable organizational citizenship behavior. Cluster 3, “Employees at Risk of Deviant Behavior” (20%), displayed the lowest scores across all dimensions of psychological capital, very low organizational commitment and citizenship behavior, and the highest level of deviant behavior.

Table 4

Behavioral Cluster Profiles of Employees: Mean Scores

Cluster	Percentage	Self-Efficacy	Hope	Resilience	Optimism	Commitment	Satisfaction	Citizenship Behavior	Deviance
1: Hopeful Resilients	38%	4.52	4.81	4.63	4.40	4.05	3.92	3.85	2.03
2: Optimistic Self-Efficacious Employees	42%	5.03	4.25	3.87	4.85	3.82	3.74	3.68	2.34
3: Employees at Risk of Deviant Behavior	20%	2.94	2.76	2.85	2.91	2.45	2.53	2.38	3.81

The distribution of clusters varied across the federations, as shown in Table 5. Federation F2 had the largest proportion of employees in Cluster 1 (45%) and the smallest proportion in the high-risk cluster (17%), whereas Federation F3 had the largest proportion of employees at risk of deviant behavior (25%).

Table 5

Percentage Distribution of Behavioral Clusters by Federation

Cluster	F1	F2	F3
1: Hopeful Resilients	32%	45%	35%
2: Optimistic Self-Efficacious Employees	48%	38%	40%
3: Employees at Risk of Deviant Behavior	20%	17%	25%

The Apriori algorithm extracted 28 meaningful association rules, of which 12 exhibited relatively high levels of support and confidence. The lift value exceeded 1 for all rules, indicating that the associations between the antecedents and consequents were non-random. Table 6 presents the most important rules. The highest confidence (88%) and lift (3.12) were observed for the rule linking low self-efficacy and low hope to high deviant behavior. At the federation level, the rule “high hope → high organizational commitment” was stronger in F2, with 90% confidence, whereas the rule related to deviant behavior in F3 exhibited 92% confidence and support of 0.22, consistent with the clustering findings.

Table 6

Most Important Association Rules Identified

No.	Rule (If → Then)	Support	Confidence	Lift
1	High self-efficacy and high hope → High organizational citizenship behavior	0.22	0.85	2.41
2	High resilience and high optimism → High organizational commitment	0.18	0.82	2.23
3	Low self-efficacy and low hope → High deviant behavior	0.14	0.88	3.12
4	High hope → High job satisfaction	0.26	0.78	1.95

5	Low optimism and low resilience → Low organizational commitment	0.12	0.80	2.56
6	High self-efficacy → High organizational trust	0.20	0.75	1.87

Random forest feature-importance analysis indicated that hope was the strongest predictor of organizational commitment (0.34), while self-efficacy ranked first in predicting job satisfaction (0.31). The combination of self-efficacy (0.28) and hope (0.26) contributed most strongly to the prediction of organizational citizenship behavior. Resilience was the most important factor associated with lower deviant behavior, with an importance score of 0.33 and an inverse relationship. Overall, hope (0.26) and self-efficacy (0.24) made the largest contributions to the prediction of organizational behavior, whereas demographic variables, including age, work experience, and education, collectively accounted for less than 15% of total feature importance.

The artificial neural network with a 12–8–3 architecture—comprising an input layer, one hidden layer with eight neurons, and an output layer with three neurons—was selected as the best-performing prediction algorithm. ReLU activation was used in the hidden layer and Softmax activation in the output layer, while the Adam optimizer was employed with a learning rate of 0.001. Table 7 presents the network's performance during training, cross-validation, and testing. The relatively small decline in accuracy from the training set to the test set indicated an absence of substantial overfitting and acceptable generalizability of the model.

Table 7

Performance of the Artificial Neural Network Across Evaluation Stages

Stage	Accuracy	Sensitivity	Specificity	AUC
Training	91.4%	0.903	0.926	0.938
10-fold cross-validation	90.2%	0.889	0.907	0.920
Test set (n = 35)	88.6%	0.875	0.892	0.905

Compared with the other algorithms, the artificial neural network achieved the highest accuracy, followed by random forest, decision tree, and support vector machine. Conventional statistical approaches, including logistic regression and multiple linear regression, performed substantially less well, as shown in Table 8.

Table 8

Comparison of Algorithm Accuracy in Predicting Organizational Behavior Category

Algorithm	Accuracy
Artificial neural network	91.4%
Random forest	88.6%
Decision tree	85.7%
Support vector machine	82.9%
Logistic regression	68%
Multiple linear regression	Approximately 65%

One-way analysis of variance revealed significant differences among the three federations in self-efficacy and hope and in four organizational behavior indicators: organizational commitment, organizational trust, job satisfaction, and organizational citizenship behavior, as shown in Table 9. Differences in resilience, optimism, and deviant behavior did not reach statistical significance at the .05 level, although they approached significance, with p values ranging from .051 to .059. Tukey's post hoc test indicated that F2 differed significantly from F3 in self-efficacy ($p = .036$), from both F1 ($p = .009$) and F3 ($p = .007$) in hope, and from both F1 ($p = .023$) and F3 ($p = .011$) in organizational commitment. The difference between F1 and F3 in

organizational commitment was not statistically significant ($p = .562$). Federation F2 had the highest mean scores on all positive indicators and the lowest mean score for deviant behavior.

Table 9

Comparison of Means (Standard Deviations) for Psychological Capital Dimensions and Organizational Behavior Indicators Across the Three Federations

Component/Indicator	F1	F2	F3	F	p
Psychological capital					
Self-efficacy	4.18 (0.81)	4.45 (0.76)	4.09 (0.89)	3.24	.042*
Hope	3.94 (0.88)	4.32 (0.74)	3.85 (0.95)	5.67	.004**
Resilience	3.83 (0.85)	4.12 (0.80)	3.76 (0.92)	2.98	.053
Optimism	4.09 (0.77)	4.35 (0.71)	4.05 (0.84)	3.01	.051
Organizational behavior					
Organizational commitment	3.48 (0.74)	3.78 (0.69)	3.35 (0.80)	4.81	.009**
Organizational trust	3.22 (0.80)	3.51 (0.75)	3.08 (0.86)	4.23	.016*
Job satisfaction	3.39 (0.72)	3.67 (0.68)	3.25 (0.79)	4.56	.012*
Organizational citizenship behavior	3.31 (0.79)	3.58 (0.74)	3.18 (0.85)	3.92	.022*
Deviant behavior	2.64 (0.84)	2.38 (0.79)	2.71 (0.91)	2.88	.059

Note. $p < .05$. $p < .01$.

The final model was developed by integrating the qualitative findings—the core category and paradigmatic model—with the quantitative findings derived from clustering, association rules, and the prediction algorithm. The model comprises three layers: (1) a technological-contextual layer, including data mining as the analytical and decision-support engine together with contextual variables such as gender, age, work experience, education, and federation type; (2) a psychological capital layer consisting of the four psychological capital dimensions; and (3) a behavioral outcomes layer comprising five organizational behavior indicators. The model includes three operational components that can be directly used by human resource managers: (a) “if-then” rules, presented in Table 6, as guidelines for managerial action; (b) three standardized employee profiles accompanied by corresponding managerial recommendations, presented in Table 10; and (c) a prediction algorithm for estimating each employee’s organizational behavior category based on scores on the four psychological capital dimensions and demographic variables.

Table 10

Standardized Employee Profiles and Managerial Recommendations

Profile	Characteristics	Managerial Recommendation
T1: Hopeful Resilients (38%)	High hope and resilience, high commitment, low deviance	Maintain current conditions; assign leadership and mentoring roles
T2: Optimistic Self-Efficacious Employees (42%)	High self-efficacy and optimism, favorable organizational citizenship behavior	Further empowerment and greater participation in decision-making
T3: Employees at Risk of Deviant Behavior (20%)	Low scores across all dimensions of psychological capital and high deviance	Immediate integrated intervention involving counseling, training, and job redesign

Quantitative validation of the model was performed using the test set of 35 cases that had not been used during model training. The resulting performance indices are reported in Table 7, including AUC = 0.905 and a reduction in accuracy of less than 3 percentage points relative to the training stage. Qualitative validation was conducted by presenting the model and research findings to three experts who had participated in the qualitative phase: a professor of sport management, a senior federation manager, and an artificial intelligence specialist. The experts’ mean score across eight evaluation dimensions—including comprehensibility of the model structure, comprehensibility of the rules and clusters, contextual appropriateness

for sports federations, consistency of the clusters with empirical observations, feasibility of implementation, usefulness of the rules, and applicability of the algorithm—was 4.23 out of 5, while mean scores across the individual dimensions ranged from 4.00 to 4.33. The lowest score was assigned to the applicability of the prediction algorithm; the second expert attributed this limitation to the need for appropriate technical infrastructure. The experts recommended implementing the model in the form of a managerial dashboard, initially piloting it in one federation, providing awareness and training programs for senior managers, and incorporating objective indicators of deviant behavior, such as absenteeism, tardiness, and complaints, into the model. The model was approved after minor revisions were incorporated.

Table 11

Summary of Hypothesis Testing Results

Hypothesis	Main Evidence	Result
H1	Significant positive correlations between psychological capital dimensions and positive organizational behavior indicators and negative correlations with deviant behavior ($r = -.42$ to $.68$, $p < .01$); association rules; differences among clusters	Supported
H2	Artificial neural network performance; feature importance scores (hope = 0.26, self-efficacy = 0.24); association rules	Supported
H3	Superior performance of the artificial neural network (91.4%) relative to multiple linear regression (approximately 65%); identification of rules involving interactions among components	Supported
H4	Artificial neural network accuracy of 91.4% compared with 68% for logistic regression; AUC = 0.905 on the test set	Supported
H5	Analysis of variance and Tukey's post hoc test; cluster distributions; federation-specific association rules	Supported
H6	Statistical validation using the test set and expert validation with a mean score of 4.23 out of 5	Supported

Discussion and Conclusion

The present study developed and validated an artificial intelligence–based organizational behavior model for selected Iranian sports federations by integrating psychological capital theory with qualitative expert knowledge and data-mining techniques. The findings showed that employees' organizational behavior could be meaningfully differentiated according to configurations of hope, self-efficacy, resilience, and optimism, and that these psychological resources were strongly associated with organizational commitment, trust, job satisfaction, organizational citizenship behavior, and deviant behavior. The qualitative phase identified the need for a context-sensitive and data-driven model that could bridge the gap between employees' psychological resources and observable workplace behavior, while the quantitative phase demonstrated that this relationship could be operationalized through behavioral clustering, association-rule mining, feature-importance analysis, and predictive algorithms. These findings are consistent with the theoretical foundations of positive organizational behavior, which emphasize measurable and developable psychological capacities as important determinants of employee functioning [4]. They also support the broader conceptualization of psychological capital as a strategic resource that extends beyond conventional human and social capital by influencing how employees interpret challenges, persist toward goals, recover from adversity, and maintain positive expectations regarding work outcomes [5]. The present results therefore reinforce the view that psychological capital is not merely an attitudinal construct but an operationally relevant resource for predicting important patterns of organizational behavior.

One of the principal findings was the identification of three distinct employee profiles: "Hopeful Resilients," "Optimistic Self-Efficacious Employees," and "Employees at Risk of Deviant Behavior." This clustering result is important because it demonstrates that employees cannot be adequately understood only in terms of isolated average scores on individual psychological variables. Instead, combinations of psychological resources appear to produce distinct behavioral profiles with different implications for human resource management. The first cluster, characterized by high hope and resilience, showed high organizational commitment and job satisfaction and the lowest level of deviant behavior. This pattern is compatible with

hope theory, which conceptualizes hope as the joint capacity to generate pathways toward valued goals and sustain the motivational agency required to pursue those pathways [8]. Employees with higher hope are therefore more likely to interpret workplace barriers as challenges for which alternative routes can be developed rather than as reasons for disengagement. The high resilience observed in this cluster further supports this adaptive pattern because resilience facilitates recovery and continued functioning under pressure, uncertainty, and organizational disruption [10]. From a resource perspective, employees possessing multiple reinforcing psychological resources are also better positioned to preserve and accumulate valued resources, thereby reducing vulnerability to stress and withdrawal behavior [11]. The combination of hope and resilience may thus explain why this cluster simultaneously demonstrated stronger commitment and satisfaction and lower deviance.

The second profile, “Optimistic Self-Efficacious Employees,” exhibited the highest levels of self-efficacy and optimism and relatively strong organizational citizenship behavior. This result is theoretically plausible because self-efficacy influences whether individuals initiate challenging tasks, how much effort they invest, and how persistently they continue in the face of obstacles [7]. Employees who believe strongly in their ability to perform effectively are more likely to take initiative, contribute voluntarily, and engage in discretionary behaviors that extend beyond minimum formal job requirements. Optimism may reinforce this tendency by encouraging positive expectations about the consequences of effort and by reducing the likelihood that temporary setbacks will be interpreted as permanent or pervasive failures [9]. The broader positive psychology literature similarly argues that adaptive psychological strengths can facilitate effective functioning and constructive engagement rather than merely reduce dysfunction [3]. The observed pattern is also consistent with meta-analytic evidence showing that psychological capital is positively associated with desirable employee attitudes, behaviors, and performance [12]. Accordingly, the present study extends previous findings by showing that specific combinations of psychological capital dimensions may be associated with particular organizational behavior outcomes and can be empirically identified through cluster analysis.

The third cluster, “Employees at Risk of Deviant Behavior,” had the lowest scores on all psychological capital dimensions, the lowest organizational commitment and citizenship behavior, and the highest level of deviant behavior. This finding was reinforced by the strongest *Apriori* association rule, according to which low self-efficacy combined with low hope was associated with high deviant behavior with 88% confidence and the highest lift value. This result suggests that workplace deviance may be particularly likely when employees simultaneously lack confidence in their capacity to influence work outcomes and perceive few viable pathways toward valued occupational goals. Such a combination may contribute to frustration, disengagement, withdrawal, or counterproductive responses. Robinson and Bennett’s conceptualization of workplace deviance emphasizes that deviant behavior represents voluntary violations of important organizational norms that can harm the organization or its members [2]. The present findings add a predictive psychological dimension to this perspective by indicating that low levels of positive psychological resources may function as warning indicators for elevated behavioral risk. This interpretation is also consistent with resource-based explanations, according to which individuals facing resource depletion or insufficient adaptive resources are more vulnerable to stress and maladaptive coping [11]. Importantly, the findings should not be interpreted as suggesting that low psychological capital inevitably causes deviant behavior; rather, they indicate a probabilistic pattern that can assist managers in identifying employees who may benefit from support before more serious behavioral problems emerge.

The feature-importance analysis further demonstrated that hope and self-efficacy were the most influential predictors of organizational behavior overall. Hope was the strongest predictor of organizational commitment, while self-efficacy ranked first in predicting job satisfaction, and the combination of self-efficacy and hope had the greatest importance for organizational citizenship behavior. Resilience was the most important factor associated with reduced deviant behavior. These findings align closely with the conceptual structure of psychological capital and with previous evidence that the four components jointly contribute to desirable employee outcomes [6]. The particularly strong role of hope in organizational commitment may reflect the importance of perceived future pathways in sustaining attachment to an organization. Employees are more likely to remain psychologically invested in an organization when they believe that valued occupational goals remain attainable within it. Similarly, self-efficacy may contribute to job satisfaction because employees who feel competent and capable of handling their responsibilities are more likely to experience mastery, autonomy, and positive feedback from their work environment. The importance of resilience in reducing deviance is also understandable in settings such as sports federations, where employees may face competitive pressures, managerial turnover, public scrutiny, resource limitations, and changing expectations. Employees who can recover effectively from setbacks may be less likely to respond through withdrawal, hostility, or other counterproductive forms of behavior. These findings therefore suggest that psychological capital interventions should not necessarily treat all four dimensions as equally important in every behavioral context; targeted interventions may be more effective when they are aligned with the specific organizational outcome of concern.

Another major finding was the superior predictive performance of the artificial neural network. The neural network achieved 91.4% training accuracy and 88.6% accuracy on the independent test set, with an AUC of 0.905. It outperformed random forest, decision tree, support vector machine, logistic regression, and multiple linear regression. The relatively small decline from training to testing also suggested acceptable generalizability and limited overfitting. This result supports the use of advanced machine-learning techniques for organizational behavior prediction when relationships among predictors are complex, multidimensional, or nonlinear. Traditional regression models are highly useful for estimating average associations and testing theoretically specified relationships, but they may not fully capture interactive or nonlinear combinations among psychological and contextual variables. The superiority of the neural network in the present study suggests that organizational behavior categories may emerge from complex patterns that are better represented by flexible nonlinear models. This conclusion aligns with the growing literature on artificial intelligence in organizations, which emphasizes that AI-based methods can extend organizational research by detecting multilevel and complex patterns not easily captured by traditional analytical procedures [14]. In sports management specifically, recent research has also demonstrated the usefulness of data-driven approaches such as decision trees and machine learning for predicting managerial decision-making styles [15]. The present study extends this line of research from managerial decision style to employee organizational behavior.

The findings also support the increasing role of data analytics within sports organizations. Although data analytics has been widely adopted for athlete performance, recruitment, tactical planning, and competition analysis, its use for internal organizational and human resource decision-making is still comparatively less developed. Research on professional clubs and national federations has shown substantial growth in analytical practices, alongside continuing differences in infrastructure, expertise, and integration of analytics into routine organizational processes [19]. The present study demonstrates that similar analytical principles can be applied to employees' psychological and behavioral data. The final model translates data analysis

into three operational products: standardized employee profiles, association rules, and an individual-level prediction algorithm. This structure may be particularly valuable because it combines interpretability with predictive accuracy. The association rules provide managers with understandable “if–then” patterns, the clusters provide intuitive employee typologies, and the neural network provides an individualized predictive mechanism. Such a combination can help overcome a common limitation of AI systems in management, namely the tension between accurate prediction and practical interpretability.

The observed differences among the three federations further demonstrate the importance of organizational context. Federation F2 had the highest scores on positive indicators and the lowest mean deviant behavior, while F3 had the greatest proportion of employees in the high-risk behavioral cluster. Significant differences were found in self-efficacy, hope, organizational commitment, trust, job satisfaction, and organizational citizenship behavior. These results indicate that psychological capital and employee behavior are not determined solely by individual characteristics; they are also shaped by the organizational environment in which employees operate. Recent research in the sports sector has suggested that artificial intelligence and information technology influence human capital partly through organizational structure, indicating that technology and organizational context are closely interdependent [20]. Similarly, positive sport organization scholarship highlights the importance of organizational climates, leadership systems, and institutional conditions in supporting positive employee functioning [18]. The differences observed in the present study may therefore reflect variation in leadership quality, technology readiness, resource availability, ethical climate, decision-making practices, or organizational stability across federations. This interpretation is also consistent with the qualitative findings, in which structural characteristics, organizational culture, senior management support, and technological readiness emerged as important contextual and intervening factors.

The study also contributes to the emerging discussion about the relationship between artificial intelligence and psychological capital. Rather than treating AI merely as a monitoring or control technology, the final model positions it as a decision-support system that can identify developmental needs and guide targeted interventions. This perspective is consistent with recent arguments that AI may enhance psychological capital by supporting personalized learning, timely feedback, and adaptive employee development [17]. For example, an employee classified as being at risk because of low hope and self-efficacy should not simply be labeled as problematic; the classification can instead trigger interventions focused on goal-setting, skills development, coaching, mentoring, or job redesign. In this way, algorithmic prediction becomes a mechanism for strengthening human resources rather than merely categorizing them. This human-centered orientation is particularly important because the use of AI in employment contexts raises ethical concerns related to fairness, autonomy, transparency, accountability, and surveillance [16]. The practical value of the model therefore depends on managers treating algorithmic outputs as advisory evidence rather than deterministic judgments about employees.

The statistical validation of the measurement models and the confirmation of discriminant validity also strengthen confidence in the conceptual distinctiveness of the constructs included in the model. The acceptable factor loadings, AVE values, composite reliability, and HTMT results indicate that the measured components were sufficiently differentiated while remaining theoretically related. This is especially important in psychological capital research because its dimensions are conceptually connected but should not be empirically interchangeable. The use of HTMT is consistent with contemporary recommendations for evaluating discriminant validity among closely related latent constructs [13]. Consequently, the strong

predictive results are unlikely to be solely attributable to measurement redundancy among hope, self-efficacy, resilience, and optimism. Instead, each dimension appears to contribute distinctive information, even though some dimensions were more predictive than others for specific behavioral outcomes.

Finally, the overall pattern of findings supports the use of AI-enhanced human resource management in sports federations while also highlighting the need for organizational readiness. Previous research has emphasized that AI can improve the administrative performance of sports federations by strengthening efficiency, decision quality, and responsiveness [21]. The current study provides more specific evidence by showing how AI can be linked to employee psychological resources and organizational behavior. However, the expert validation findings also indicated that the applicability of the prediction algorithm received the lowest evaluation score because of technical infrastructure requirements. Thus, the successful implementation of the model depends not only on algorithmic performance but also on data quality, managerial literacy, staff acceptance, governance mechanisms, and the capacity to integrate analytics into established HR processes. The model's value therefore lies in combining psychological theory, organizational context, and machine-learning capability within a single decision-support framework rather than treating any of these components in isolation.

The present study has several limitations. First, the quantitative phase was conducted in only three Iranian sports federations, which limits the generalizability of the findings to other federations, sport organizations, governmental agencies, or private-sector institutions. Second, most variables were measured using self-report questionnaires, which may be affected by social desirability, common method variance, and respondents' subjective perceptions. Third, although the sample size was adequate for the planned analyses, larger samples would allow more stable training of complex machine-learning models and more detailed subgroup analyses. Fourth, the cross-sectional nature of the quantitative data prevents strong conclusions regarding causal direction and does not capture changes in psychological capital or behavior over time. Fifth, the prediction algorithm relied primarily on questionnaire scores and demographic variables and did not incorporate objective behavioral indicators such as absenteeism, lateness, complaints, disciplinary records, performance evaluations, or digital work patterns. Finally, although the artificial neural network demonstrated high predictive accuracy, its internal decision process is less interpretable than simpler models such as decision trees, which may create challenges for managerial transparency and employee acceptance.

Future research should replicate the model across a larger and more diverse range of sports federations, clubs, Olympic committees, and sport-related public and private organizations to assess external validity. Longitudinal studies are recommended to examine whether changes in psychological capital precede changes in organizational behavior and whether the predictive model maintains accuracy over time. Future studies could also incorporate objective administrative and behavioral indicators, performance records, absenteeism, turnover intentions, complaint data, and organizational network measures to improve predictive validity. Comparative studies across countries and cultural settings would be useful for determining which association rules are universal and which are context-specific. Researchers should also compare additional machine-learning and explainable-AI techniques, including gradient boosting, SHAP-based interpretation, ensemble models, and hybrid models combining structural equation modeling with machine learning. Intervention studies could further examine whether employees identified as high risk subsequently improve after targeted programs designed to enhance hope, self-efficacy, resilience, or optimism.

In practice, sports federations should implement the model as a decision-support rather than an automated decision-making system. Human resource units can use the three employee profiles to tailor development strategies, assign mentoring or leadership roles to psychologically stronger employees, and provide early support to employees showing risk patterns. Periodic assessment of psychological capital can be integrated into employee development and organizational climate monitoring, provided confidentiality and informed use of data are ensured. Federations should also invest in secure HR information systems, data governance, staff training, and managerial analytics literacy before implementing predictive algorithms. A pilot implementation in one federation is advisable before organization-wide adoption, with regular evaluation of predictive accuracy and employee acceptance. Objective indicators such as absenteeism, lateness, grievances, and performance records should gradually be incorporated into the system. Most importantly, algorithmic classifications should never be used as the sole basis for disciplinary, promotion, or employment decisions; they should be interpreted alongside managerial judgment, contextual information, and direct communication with employees.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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