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Use of machine learning to predict creativity among nurses: a multidisciplinary approach

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Abstract

Background In this era of rapid development in science and technology, creativity has become an important requirement in nursing to satisfy the daily needs of their patients. However, nurses' creativity and related aspects are rarely studied in nursing research. This study was aimed to explore the factors influencing nurses' creativity and to develop a decision support system using machine learning to predict creativity levels among nurses.

Methods A multidisciplinary design comprising machine learning algorithms mixed with a descriptive, cross-sectional, correlational design was implemented to enhance data analysis and decision-making. A convenience sample of 191 registered nurses from eight hospitals– representing the broader nursing community in Jordan- was recruited to complete the online survey.

Results revealed that staff nurses reported a high level of creativity (M = 44.95). The machine learning model achieved good prediction performance with high precision. Specifically, Naïve Bayes achieved a recall of 99% for predicting psychological safety, around 98% for both gender and time commitment, 96% for years of experience, 92% for nurse age, and 82% for humble leadership. A decision support system was successfully developed based on these findings. Additionally, a multiple linear regression revealed five main predictors of nurses' creativity: humble leadership, psychological safety, experience, quality initiatives, and education level, together explaining about 30% of the variance in perceived creativity among staff nurses.

Conclusions To augment nurses' creativity, managers are advised to adopt flexible leadership styles, create a safe work environment, and encourage staff development. The developed decision support system may be valuable for helping nurse managers evaluate creativity among nurses; this allows for more informed decisions about staff allocation, development, and resource optimization. Researchers are encouraged to use machine learning models because they achieve good prediction performance with high precision.

Clinical trial number Not applicable.

Keywords Decision support system, Humble leadership, Machine learning, Multidisciplinary design, Nurses' creativity, Psychological safety

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Introduction

Recently, healthcare services have undergone vast advances in knowledge and technology, which has made healthcare systems more complex than ever before. This necessitated healthcare system reform and generated major challenges for clinicians, administrators, researchers, and policy-makers. Staying updated with new knowledge and technologies is essential for improving organizational performance and developing effective policies. Creativity plays a critical role in achieving organizational success by facilitating the generation and acceptance of innovative ideas [1–9]. It requires an open mind, critical thinking, and a supportive environment. While the significance of creativity in nursing is recognized—especially as nurses encounter situations for which they have never been prepared- nurse managers require deeper insights into the psychological and social factors influencing creativity [9, 10]. In an era of rapid scientific progress, enhancing nurses' creativity is vital for addressing patient needs and improving organizational outcomes.

Leadership style is a crucial factor influencing organizational behavior. Research has explored how various styles—such as transformational, authentic, empowering, and shared leadership—affect follower creativity [11, 12]. Recent studies emphasize the importance of leader humility in fostering follower creativity [4, 8, 13–16]. Humility involves a focus away from oneself, a realistic understanding of one's abilities, and an acknowledgment of limitations. With the advent of the Fourth Industrial Revolution, characterized by rapid technological advancements and a high demand for competencies, the need for humble leaders has become increasingly evident. These leaders embrace their limitations, encourage new ideas, value their followers' strengths, prioritize continuous learning, and take responsibility [8, 15–18]. This approach cultivates a psychologically safe environment, motivating followers to express and share innovative ideas, thereby enhancing their creativity [8, 14, 16].

In essence, humble leadership has been consistently linked to improved psychological safety in the workplace [8, 14, 16]. Psychological safety is an important element in a healthcare environment, significantly reducing errors and enhancing safety. It fosters a culture where employees feel safe to voice their opinions, take interpersonal risks, and express new ideas [19, 20]. This environment encourages cooperation, feedback, and open-mindedness, leading to improved team performance and individual learning [19]. Research shows that employees' perception of psychological safety not only boosts performance and respect among team members but also enhances creativity and innovation [13, 20]. By prioritizing psychological safety, organizations can achieve better outcomes for both employees and the organization as a whole.

Creativity is a dynamic quality that can be nurtured and developed over time. Recent research highlights the growing interest in understanding creativity within organizational contexts, yet the roles of humble leadership and psychological safety, particularly in healthcare, remain underexplored. Studies indicate that humble leadership positively influences follower creativity through psychological safety and knowledge sharing [8]. In medical education, enhanced psychological safety fosters creativity in simulation-based learning [21]. Moreover, humble leadership contributes to employee well-being and engagement, mediated by psychological safety [22, 23]. In nursing, it significantly boosts innovative behavior through work engagement [24], and recent findings demonstrate that it enhances creativity alongside educational attainment and proactive initiatives [14]. Despite these insights, the creativity of nurses and its influencing factors remain inadequately addressed in nursing research. This study aims to assess the level of creativity among nurses and explore its associated factors, emphasizing the need for further investigation in this vital area.

Previous studies have employed various statistical methodologies to yield robust results. In this research, the authors introduced a blended approach using statistical methods alongside machine learning (ML) techniques, marking a trial application of artificial intelligence (AI) in nursing research. Creativity is a multidimensional human attribute shaped by a variety of psychological, social, and environmental influences, which makes it challenging to predict through conventional methods. Given its dynamic and non-linear characteristics, machine learning (ML) presents a robust approach to analyzing creativity. Machine Learning can identify hidden patterns and relationships within extensive datasets, effectively modeling the complex interactions that contribute to creative expression. This capability is especially valuable in fields such as nursing, where numerous factors interact to influence creative behaviors.

The goal of ML, a subfield of AI, is to enable computers to learn from data without needing explicit programming for every scenario [25–28] by creating algorithms that can self-learn by examining a very large number of variables (probably identified previously) to develop a decision support system (DSS) that allows the prediction of specific outcomes based on known patterns [29, 30], which will assess and/or solve problems in the work environment. Important concepts in this field include "algorithm," which refers to the sequence of rules or instructions that guide the system; "model," the result generated from the learning process; and "training data," the information utilized to educate the system. With experience, machine learning systems become adept at

identifying patterns and can predict outcomes or make decisions based on new, unfamiliar data. Machine Learning is used in a broad range of industries and applications to solve complex problems, automate tasks, and make data-driven decisions [25–31].

A Decision Support System (DSS) is an information system designed to assist in decision-making by providing relevant data, analysis, and insights. It is particularly useful for complex decisions involving uncertain or unstructured problems. A DSS integrates data from multiple sources, processes it with analytical models, and presents the outcomes in an accessible format, such as reports or visual dashboards. In nursing management, for instance, a DSS can enhance patient care, optimize resource allocation, and improve operational efficiency through real-time, data-driven recommendations [25–30].

Although the DSS provides nurse managers with tools to enhance and accelerate effective decisions regarding management functions, some managers and clinicians are reluctant and anxious about using these tools because of the complex nature of ML algorithms, which lends to the black–box AI phenomenon [25–27]. This study is expected to support nurse managers with a model that may help in assessing and understanding creativity among nurses in the work environment. This approach will enable nurse managers and policy-makers to make decisions related to different processes in the organization, such as planning, organizing activities, designing work, and staffing.

This study is expected to deepen our understanding of creativity among nurses, identifying crucial factors that influence it, often overlooked in practice. By combining statistical methods with machine learning (ML) techniques, it offers a unique, data-driven approach to evaluation. This not only enhances our insight into creativity's role in nursing but also sets the stage for further research on its significant impact on patient care and outcomes. Embracing these findings and methodology can lead to transformative improvements in nursing practices and research. Therefore, the current study aims to answer the following research questions:

- What is the level of creativity perceived by Jordanian nurses?
- Can we predict creativity levels among nurses using ML methods?
- What are the most important factors in the work environment that can predict creativity?
- Can we use the DSS, which will be developed based on the proposed predictive model, to assess, classify, and understand creativity among nurses?

The study methods

Aims

To examine the level of creativity among nurses, to explore the factors influencing nurses' creativity and to develop a DSS using ML to predict creativity level among nurses.

Design

A multidisciplinary design was used: ML algorithms were blended into descriptive, cross-sectional, correlational designs to understand and assess nurses' creativity.

Sample and setting

The sample size for the study was estimated using the formula $N \geq 10(k) + 50$, where N is the sample size and k represents the number of explanatory variables. With two major variables and ten personal and work traits, a minimum sample size of 170 participants was determined [31]. Inclusion criteria required participants to be registered nurses who graduated from a four-year nursing program, were proficient in English, could use electronic platforms, and were employed at the hospitals involved in the study. Out of approximately 350 eligible registered nurses, 245 (70%) responded, and 191 (55% response rate) met the inclusion criteria, while 54 were excluded. Data were collected from eight hospitals (both private and public) across four major governorates in Jordan.

In machine learning, the sufficiency of 191 participants depends on:

- Model complexity: Simpler models like linear regression or logistic regression might require fewer data points, whereas complex models like deep neural networks typically need much larger datasets.
- Dimensionality (number of features): More features usually demand more data to avoid overfitting (when the model learns noise instead of the underlying patterns).
- Task type: For classification, regression, clustering, or other tasks, the performance of the machine learning model can be influenced by both the number of observations and features.
- Therefore, in small datasets the techniques like cross-validation and regularization help mitigate overfitting when you have fewer data points [25, 26].

Ethical considerations

The Institutional Review Board (IRB) of Hashemite University approved the research, with the reference number 11/8/2021/2022. All procedures were conducted in accordance with the ethical standards established in the Declaration of Helsinki, revised in Brazil in 2013.

At the beginning of the online survey, participants were presented with a consent form, outlining their rights and

providing them with the option to accept or decline participation, only participants who provided consent were able to proceed with the survey. Hence, the consent was obtained from all participants. To ensure anonymity, the questionnaire deliberately excluded any identifying information about the participants, with only aggregate results being reported. Additionally, the consent form included detailed guidelines on data management, highlighting that all responses would be collected securely and stored in encrypted formats. Participants were informed that their involvement was entirely voluntary and that they could withdraw at any time without facing any penalties.

Data collection procedures

The data for this study were collected remotely. An online English Google form was developed. The form was shared through Messenger and WhatsApp with the head nurses of different departments of each included hospital; then, it was shared with colleagues of the same department through official groups developed by each department. To enhance response rates and ensure a more representative sample, a follow-up strategy was introduced. Participants received reminder messages at consistent intervals. This method effectively encouraged participation and contributed to a more thorough and diverse sample. Although these applications allow for high levels of anonymity and accessibility and can be administered widely; quickly, and inexpensively, remote data collection can impact response rates, particularly for populations with limited access to technology or low digital literacy, leading to potential underrepresentation and skewed samples. Moreover, the lack of direct interaction may affect data quality, resulting in misinterpretations or incomplete responses that compromise the reliability of the findings [33]. However, these challenges were effectively addressed through the design of an electronic tool. The tool was available online from September to November 2022.

Measurement

The variables of this study include the scalar (dependent) variable followers' (nurses') creativity and the explanatory (independent) variables humble leadership, psychological safety, staff nurses, and work environment traits.

Follower creativity

Zhou and George's (2001) 13-item supervisory rating scale was modified to individuals' self-rated creativity scale (SRCS) [34] and used to measure followers' creativity. In this study, the SRCS was used to empirically assess followers' (Jordanian nurses') creativity. Nurses responded to 12 items on a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The summation of the responses for the total scale represents the level of the nurses' creativity. Nurses who provided scores ≥ 40 were more likely to perceive themselves as creative. Scores ranging from 20 to 39 indicated moderate scores. However, scores < 20 reflect a low level of creativity. A sample of the scale items would be "I suggest new ways to increase the quality of work".

Several studies have supported the reliability and convergent validity of the SRCS [33]. The Cronbach's alpha coefficient (internal consistency) was 0.829 in [34], 0.84 in [35], and 0.92 in the present study.

Humble leadership

The humble leadership scale was developed by Owens et al. (2013) [36]. It is a nine-item Likert scale with responses ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Nurses reflected on their perception of leader humbleness. Humble leadership scores ranged from 9 to 45. The phrase "This leader often compliments others' strengths" is an example of a scale item. The internal consistency of this instrument was $\alpha = 0.88$ according to [8] and 0.91 in the present study.

Psychological safety

Edmondson developed a seven-item Likert scale to measure psychological safety. Responses ranged from 1 (*strongly disagree*) to 5 (*strongly agree*), with total score ranging from 7 to 35 [19]. Nurses reflected their perception of their psychological safety level in their work environment; an example item is "Organizational members can bring up problems and tough issues". This scale was developed using strict scale-building standards and implemented through rigorous validation testing, which revealed robust content, construct, and criterion validity and consistent reliability [19–20]. The Cronbach's alpha for this scale in [8] was 0.76, whereas it was 0.75 in the present study.

Participants and work environment traits

The participants' traits in this study included: gender, age, marital status, education level, and number of years of experience. *Work environment traits* included hospital type, department type, official accreditation, official quality initiatives, type of work commitment (full-time, part-time), and teamwork size.

The 11 personal and work traits were selected as explanatory variables based on their relevance to creativity, as identified in existing research across various fields, including nursing and organizational studies. The inclusion of these variables allows for a comprehensive exploration of the factors that may drive or hinder creativity in nursing practice.

Analysis

The screening data revealed no missing data or incomplete questionnaires; the data were collected online where the researcher indicated each item as a required response, and incomplete responses were automatically dismissed. To answer the research questions, the researchers used two analytic methodologies: the Statistical Package for Social Sciences (SPSS) version 25 (IBM, Inc., Armonk, NY, USA) and the machine learning algorithm.

SPSS was used to calculate **the descriptive statistics** (frequency (n), percentage (%), mean (M), and standard deviation (SD) used to describe nurses' and work traits in the sample and perceptions of followers' (nurses') creativity. **Inferential statistics** (Pearson correlation coefficient (Pearson *r*), independent sample t test, one-way analysis of variance (ANOVA), and stepwise regression analysis) were used to determine the influence of humble leadership, psychological safety, and work and nurses' traits on nurses' creativity. The researchers calculated (1) Pearson correlation coefficients (Pearson *r*) for the independent continuous variables (humble leadership and psychological safety) and (2) ANOVA and t tests for the categorical independent variables. Post hoc analysis (Bonferroni) was also conducted to determine significant differences among groups. (3) A stepwise regression model was used and the data for multiple regression assumptions were tested before running the regression model. The results were considered to be statistically significant at an alpha level of $p < 0.05$ in all the tests conducted [32].

A machine learning algorithm was used to develop the DSS to assess, predict, and classify creativity levels among nurses using a set of variables relevant to creativity. The first step was to prepare the corpus from the dataset, which was used for training the developed machine learning classifier. For each instance of the studied dataset, a value related to each considered factor was extracted. Then, a model was developed that combines supervised learning.

A. Creating the corpus

The main step in carrying out classification is to create the corpus that represents the input of machine learning classifiers. In this study, the corpus takes into account the extracted values related to every classification factor for each instance of the studied dataset. These values are extracted from the nurses' responses to the SRCS. In this study, we considered six variables (classification factors): humble leadership, psychological safety, gender, time commitment, years of experience, and age.

Each instance of the corpus was labeled with the associated creativity level by calculating the summation of all participant responses and divided into three categories (A- low creativity level (12–28), B- moderate creativity level (29–44), and C- high creativity level (45–60)). Prediction 1: Humble leaders classified their answers into three classes (A (9–15), B (16–30), and C (31–45)). Likewise, Prediction 2: Psychological safety (A(7–10), B(11–20), C(21–35)).

B. Prediction models and evaluation metrics

Classification is a type of supervised machine learning task where the goal is to predict the categorical class label of new instances based on past observations of data. Several machine learning algorithms were used for classification, each with its own strengths, weaknesses, and suitable applications:

- Naïve Bayes is a simple but powerful classification algorithm based on Bayes' Theorem, which provides a probabilistic framework for classification. It's called "naïve" because it makes the assumption that all features (attributes) are independent, which often doesn't hold in practice. Despite this simplifying assumption, Naïve Bayes performs well in many real-world applications, especially for text classification and spam detection [30, 31].
- IBk stands for Instance-Based k-Nearest Neighbor, which is a variant of the k-Nearest Neighbor (k-NN) algorithm. In this approach, classification is based on the closest training examples in the feature space. It's an example of an instance-based learning method where learning only occurs at the time of prediction, and the algorithm does not create an explicit model [30, 31].
- K-Star is a non-parametric instance-based classification algorithm, which is similar to k-NN but incorporates entropy-based distance rather than just Euclidean distance. It is based on the k-nearest neighbor principle but uses information gain and distance measures to improve classification accuracy, especially in cases with categorical data [28].
- Random Tree is a decision tree-based classification algorithm, which is an ensemble method similar to Random Forest. However, unlike a traditional decision tree, Random Tree introduces randomness during the construction of individual decision trees, improving the diversity of the trees and making the overall model more robust [31] (Fig. 1).

Several good-quality SVM operations were available. The Waikato Environment for Knowledge Analysis (WEKA) toolkit was used to construct the model (University of Waikato, Craig Nevill-Manning, Mark Hall, New Zealand). Different supervised classifiers divide the dataset into a training set that is used to train the classifier and a test set that is used to measure the accuracy of the model. The decision regarding dataset classification

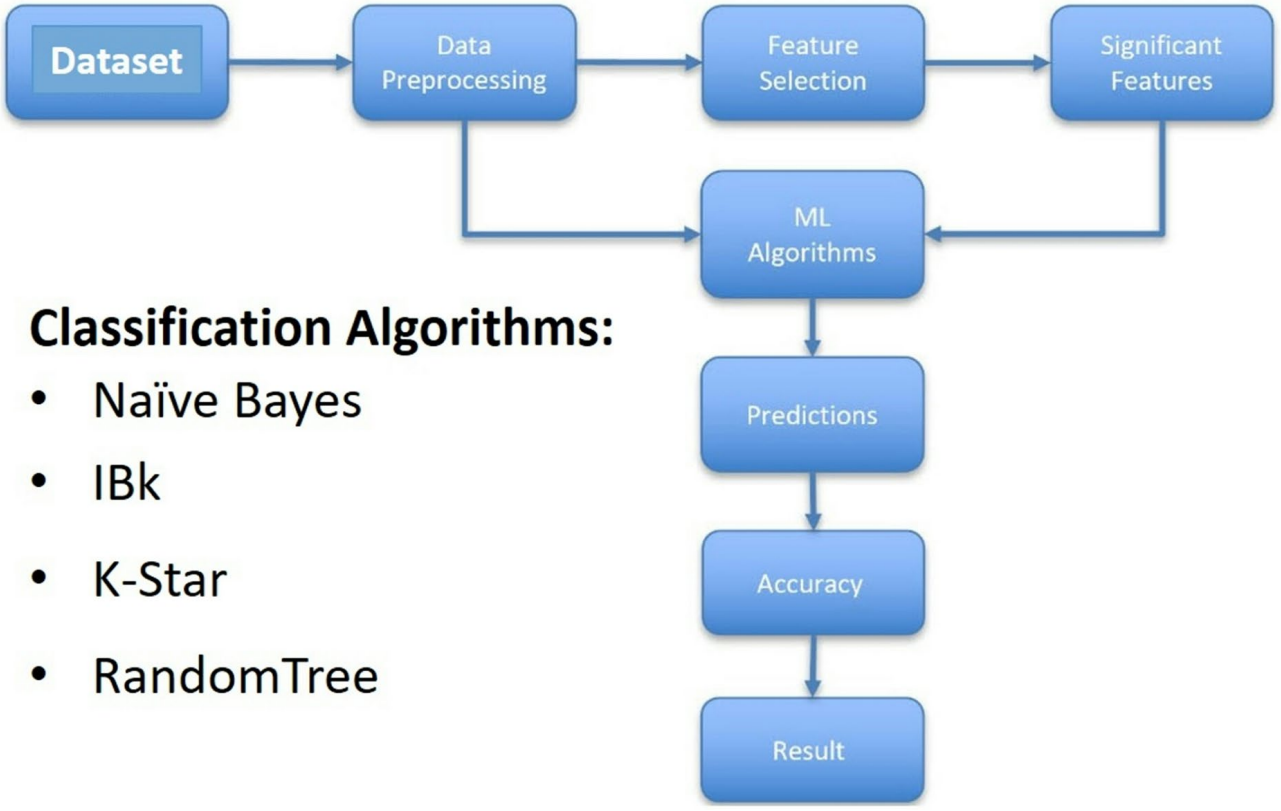

Fig. 1 Machine learning workflow

was controlled by a 10-fold cross-validation technique [26–31].

To evaluate the efficacy of each classifier, four performance metrics were used:

(1) Precision: the percentage between true positives and all positives. It is calculated as (P = true positives/(true positives + false-positives)) [25–31, 37].
(2) Recall: the percentage of correctly identified true positives and hence it is computed as (R = True Positives/(True Positives + False-Negatives)) [25–31, 37].
(3) F-Measure: a metric that depends on both recall and precision of a model and thus calculated by a combination of these two metrics as ((2 * Recall * Precision) / (Recall + Precision)). The value of this metric is between 0 and 1 [25–31, 37].
(4) The ROC curve is a metric that represents the number of predictions that are incorrectly categorized positive and incorrectly categorized negative and is calculated as (R= (True Positives + True Negative) / (True Positives + True Negative + False Negatives + False Positive)) [25–31, 37].

Both statistical and machine learning models offer distinct advantages and challenges, each playing a vital role in data analysis. While machine learning models often excel at making accurate predictions, their primary focus is on forecasting future outcomes or classifying data without delving deeply into the relationships between variables. These models are judged by their predictive prowess, measured through important metrics like accuracy, F1-score, and mean squared error, emphasizing their ability to generalize to new, unseen data. In contrast, statistical models shine in parameter estimation and hypothesis testing, providing critical insights into causal relationships and the interplay of various factors [38]. Understanding both approaches equips us to choose the right tools for our data analysis needs.

After model training and validation, the sample size in this study was deemed sufficient for applying machine learning techniques. The dataset provided enough statistical power to ensure reliable model training and testing, which minimized the risk of overfitting and allowed the model to generalize effectively to unseen data. Furthermore, the sample size was large enough to facilitate proper validation through a training/test split, ensuring the robustness and accuracy of the model's predictions.

Table 1 Staff nurses' creativity level in relation to nurses' and work traits as reflected by nurses (*N* = 191)

Nurses' and work traits	*n*	%	Nurses' creativity level	
			Mean (SD)	F/ T-test
Nurses' Traits				
Gender				0.494
Male	60	31.41	45.38 (8.00)	
Female	131	68.59	44.76 (8.20)	
Marital Status				2.354
Single	79	41.36	43.77 (8.77)	
Married	104	54.45	45.50 (7.50)	
Widowed / Separated	8	4.19	49.50 (7.93)	
Level of Education				3.464**
Baccalaureate	132	69.11	43.63 (8.30)	
Master	59	30.89	47.92 (6.91)	
Age				2.493*
Less than 25 years	52	27.23	43.10 (7.62)	
25–34 years	50	26.18	44.00 (9.99)	
35–44 years	62	32.46	46.10 (6.40)	
45–54 years	27	14.13	47.67 (8.24)	
Work Conditions				
Work Commitment				1.980*
Full-time	158	82.72	45.48 (8.19)	
Part-time	33	17.28	42.42 (7.42)	
Years of experience				4.011**
Less than one year	52	27.23	42.94 (8.50)	
1–2 years	17	8.90	44.94 (6.46)	
3–4 years	26	13.61	42.04 (10.68)	
5–9 years	28	14.66	44.32 (7.57)	
10 years or more	68	35.60	47.87 (6.43)	
Department				0.488
Units	79	41.36	45.34 (7.11)	
Wards	112	58.64	44.76 (8.79)	
Nurses' Team Size				0.628
1–5	97	50.79	45.59 (8.07)	
6–10	69	36.13	44.42 (9.00)	
11–15	25	13.08	43.96 (5.41)	
Hospital Accreditation				1.484
Yes	170	89.01	45.26 (7.81)	
No	21	10.99	42.48 (10.23)	
Hospital Quality Initiatives				3.500**
Yes	166	86.91	45.73 (7.57)	
No	25	13.09	39.80 (9.85)	
Hospital Type				0.553
Public	148	77.49	45.13 (7.37)	
Private	43	22.51	44.35 (10.40)	

*ANOVA or t-testis significant at α = 0.05, 2-tailed test **ANOVA or t-testis significant at α = 0.01, 2-tailed test

Results

Nurses' and work traits

The sample in this study included 191 registered nurses. The majority of the nurses were females, 131 [68.59%]; married, 104 [54.45%]; and varied in age; two-thirds had a baccalaureate degree. Regarding work conditions, most of the nurses worked full-time (158, 82.72%), and in public settings (148, 77.49%). According to the participants' opinions, most of these settings were accredited 170 (89%) and had quality initiatives 166 (87%). Nurses in the sample varied in their years of experience, and most of them worked in small teams (1–5 members) (Table 1).

Table 2 Correlations between nurses' creativity in relation to humble leadership and psychological safety as perceived by registered nurses (*N* = 191)

The variables	Nurses' perception of their creativity		
	Mean (Standard deviation)	Description of level	Pearson *r*
Humble Leadership	32.38 (7.51)	High	0.374**
Psychological Safety	21.63 (4.69)	Moderate	0.295**
Nurses' Creativity	44.95 (8.127)	High	1

*Correlation is significant at α = 0.05, 2-tailed test **Correlation is significant at α = 0.01, 2-tailed test

Followers' (Nurses') creativity

Jordanian nurses reported a relatively high level of creativity in general (M = 44.95, SD = 8.127) (Table 2). Additionally, they had a relatively high level of humble leadership and moderate levels of psychological safety.

The results presented in Tables 2 and 3 reveal seven factors influencing nurses' creativity. Nurses' creativity was positively correlated with humble leadership ($r = 0.374$, $p \leq 0.01$) and psychological safety ($r = 0.295$, $p \leq 0.01$). However, no significant correlation was detected between humble leadership and psychological safety.

According to the total score of creativity, there were significant differences in followers' creativity in relation to education level ($t = 3.464$, $p \leq 0.01$; more highly educated), age ($F = 2.493$, $p \leq 0.05$; more older), time commitment ($t = 1.980$, $p \leq 0.05$; more full-time), nurses' years of experience ($F = 4.011$, $p \leq 0.01$; nurses' creativity increased with increasing years of experience) and, ultimately, hospital quality initiatives ($F = 3.500$, $p \leq 0.01$; nurses in hospitals with quality improvement programs reported better creativity levels) (Table 1) and (Table 2).

Prediction of nurses' creativity using regression analysis

Multiple linear regression analyses were implemented to identify statistically significant predictors of nurses' creativity. All the variables that were significantly correlated with nurses' creativity were entered into the regression model in step one. The overall model revealed five important factors that could predict nurses' creativity as perceived by staff nurses: *humble leadership*, *psychological safety*, *nurses' years of experience*, *official quality initiatives*, *and education level.* These factors were responsible for approximately 30% of the variance (Table 3).

Table 3 Predictors of nurses' creativity as perceived by Jordanian nurses ($n = 191$)

	Predictors	B	Adjusted r^2	r^2 - Change	F	*p*
Nurses' Creativity	Humble Leadership	0.365	0.136	0.140	30.823	0.000
	Psychological Safety	0.257	0.225	0.093	22.900	0.000
	Nurses' Experience	0.150	0.262	0.040	10.273	0.002
	Official Quality Initiatives	-0.167	0.287	0.029	7.689	0.006
	Nurses' Education	0.136	0.300	0.016	4.263	0.040

Predictors of nurses' creativity final model produced at α = 0.05

Table 4 Classification results of **Input variables** using machine learning algorithms

Learner	Recall	Precision	F-measure	ROC
Humble Leadership				
Naïve Bayes	0.824	0.811	0.817	0.787
IBk	0.816	0.810	0.813	0.784
K-Star	0.896	0.794	0.842	0.784
RandomTree	0.808	0.802	0.805	0.714
Psychological Safety				
Naïve Bayes	0.995	0.995	0.994	0.990
IBk	0.861	0.833	0.847	0.834
K-Star	0.848	0.949	0.896	0.975
RandomTree	0.824	0.924	0.871	0.910
Gender (Female)				
Naïve Bayes	0.985	0.977	0.981	0.984
IBk	0.947	0.919	0.932	0.882
K-Star	0.756	0.728	0.742	0.606
RandomTree	0.885	0.879	0.882	0.809
Time Commitment (Full Time)				
Naïve Bayes	0.987	0.981	0.984	0.988
IBk	0.968	0.950	0.959	0.884
K-Star	0.892	0.860	0.876	0.760
RandomTree	0.975	0.957	0.966	0.881
Tenure (2- Less than one year & 6–10 years or more)				
Naïve Bayes	0.962	0.962	0.962	0.997
IBk	0.558	0.690	0.617	0.766
K-Star	0.662	0.714	0.687	0.800
RandomTree	0.735	0.694	0.714	0.778
Age (1- Less Than 25 Years)				
Naïve Bayes	0.923	1.000	0.960	0.993
IBk	0.673	0.778	0.722	0.823
K-Star	0.673	0.660	0.667	0.859
RandomTree	0.788	0.774	0.781	0.851

Prediction of nurses' creativity using ML models

Several ML approaches and evaluation metrics were employed to construct the prediction models. The results obtained from the classification experiments are presented. The evaluation results showed that the studied approach achieved a recall of 0.99% when the Naïve Bayes classifier was applied for psychological safety and approximately 0.98% for both gender and time commitment. In addition, the recalls were 0.96 and 0.92 for years of experience and age, respectively, as shown in Table (4).

By examining the proposed classifiers that were trained using a combination of all the factors given in Table 4, a comparison between several classification techniques was performed. A comparison with a baseline approach was also conducted. The performance results of the employed models (classifiers) are shown in Table (4). The obtained results show improvement in prediction when the developed classifier is compared with the baseline model in terms of all the evaluation metrics. For instance, when comparing the Naïve Bayes classifier to the baseline model, the improvement ratio is 0.99 in terms of recall and 0.99 in terms of precision. That is, we can construct highly precise prediction models to predict the ratio of creativity through machine learning methods. The second observation in this study was the K-star and Naïve Bayes classifiers, which provide better classification accuracy and F-measure than other machine learning classifiers. For example, Naïve Bayes computes a probability for each class depending on the probability distribution in the training dataset. Therefore, for each training example, the prior and the probability can be updated dynamically to achieve flexibility and robustness to classification errors. On the other hand, the K-star learner achieved a better F-measure because of the increase in the dimensionality of the data until the data points were differentiable in some dimensions.

The decision support system (DSS)

The DSS is integrated into the results by providing a predictive model that analyzes various factors influencing creativity in the nursing context. These factors include: psychological safety, gender, time commitment, staff experience, age and humble leadership.

The Decision Support System (DSS) in this study is designed to help nurse managers predict and assess the creativity levels of their nursing staff. Creativity in nursing is vital for developing innovative solutions to patient care challenges, improving workflows, and adapting to changing healthcare environments. By utilizing the DSS, nurse managers receive data-driven insights that enable them to predict which nurses are more likely to engage in creative problem-solving and contribute innovative solutions.

The DSS enhances the role of nurse managers by providing valuable tools to assess creativity patterns among nurses. By analyzing various data points—such

as psychological safety, gender, time commitment, staff experience, age and humble leadership —the DSS can identify trends and make predictions about individual nurses' creativity levels. This allows managers to target specific areas where creativity can be nurtured, ensuring they can offer the appropriate support, resources, and encouragement to foster innovation within their teams.

Moreover, the DSS empowers nurse managers to make more informed and proactive decisions. Instead of relying solely on subjective assessments, the system provides an objective, data-driven method for predicting creativity. This enables managers to allocate tasks based on creativity levels, optimize team composition, and identify opportunities for professional development that encourage creative thinking. With this predictive capability, managers can also anticipate potential challenges and address them before they escalate.

In summary, the DSS enhances the decision-making process by equipping nurse managers with the foresight needed to harness and nurture creativity within their teams. By improving their ability to predict and support creative behaviors, the DSS strengthens managerial effectiveness and contributes to a more innovative and adaptive nursing workforce, ultimately leading to improved patient care and operational efficiency.

Discussion

This study reveals that Jordanian nurses exhibit high levels of creativity in their work, a finding supported by [7] and [13]. However, there is a significant gap in research focusing on the creativity levels within the nursing profession. Addressing this gap is essential, as fostering creativity among nurses can lead to innovative ideas and technologies in patient care, ultimately enhancing quality, saving costs, and improving the work environment. Creative contributions can range from developing new healthcare devices to advancing nursing research and education. As emphasized by many researchers, promoting creativity in nursing is crucial for enhancing organizational outcomes and overall patient care [1–9].

Regarding the third research question, the focus of this study was mostly on the variables impacting Jordanian nurses' creativity. A multiple regression model extracted five factors related to nurses' and work traits that could predict nurses' creativity: humble leadership, psychological safety, years of experience, official quality initiatives, and education level.

The level of creativity was significantly associated with humble leadership. Humble leaders appreciate employees' knowledge and abilities and allow them to participate in new creative ideas and suggestions related to the work process and work environment. This will consequently enhance organizational outcomes. This result is consistent with most previous studies that linked humble leadership to creativity [4, 13–17, 36].

The study found that psychological safety is a crucial factor in enhancing creativity among nurses. It fosters continuous quality improvement, collaboration, and innovative problem-solving, while an unsafe environment leads to stress and distraction from organizational goals. This aligns with existing research linking psychological safety to creativity [8, 19, 20]. Notably, unlike previous studies that identified a mediating role of psychological safety between humble leadership and creativity, this study found no significant relationship between humble leadership and psychological safety.

Based on demographic traits, creativity significantly increases with higher education levels and becomes more prevalent as nurses age. This result is congruent with some studies [8, 13] and contradicts that of Mert and Kok [39]. Indeed, creativity implies the generation of new ideas and wise demonstration of updated knowledge and technology; an increase in education level and age means more experience and greater competencies.

In addition, three work conditions—full-time commitment, years of experience, and hospital quality initiatives—positively and significantly affected nurses' creativity. Full-time nurses and experienced nurses feel stable and settled and have the right to express feelings and new ideas or take the risk of trying new methodologies. Moreover, hospital quality initiatives increase staff members' feelings of responsibility and accountability toward performing their job at higher standards; hence, nurses increase their potential and share their creative ideas. Actually, structured programs aimed at improving care quality may encourage nurses to innovate and contribute ideas.

The ML models demonstrated strong performance in predicting creativity levels among nurses, based on six factors: humble leadership, psychological safety, gender, age, time commitment, and staff experience. While some factors aligned with statistical results (humble leadership, psychological safety, staff experience), others (age, gender, time commitment) did not, and level of education and hospital quality initiatives were excluded. Statistical models explain relationships between variables, while ML models focus on making accurate predictions, often lacking interpretability [38]. Also, factors exclusion like education level and hospital quality initiatives as predictors in the ML model, despite their significance in statistical analysis, can be attributed to the model's automated feature selection process. Machine learning algorithms assess the predictive power of each variable based on its relationship with the target outcome. This exclusion does not negate their overall importance but reflects the model's focus on the most relevant variables for accurate predictions [38].

In this study, machine learning (ML) models demonstrated high precision in predicting creativity among

nurses, with most receiving ROC values exceeding 0.9. This highlights the effectiveness and reliability of an AI-based decision support system (DSS) for assessing creativity levels. The research outlines the correlations between variables using statistical methods and emphasizes the DSS's significance for nurse managers, educators, and researchers in evaluating and predicting nurses' creativity.

Creativity isn't solely inherent in individuals; rather, creative people often share traits like proactivity, self-development, open-mindedness, autonomy, enthusiasm, and tenacity [7]. The work environment significantly influences the enhancement and development of creativity [8, 13, 39]. To better understand creativity, it's essential to study both personal and environmental factors. Additionally, developing more decision support systems (DSSs) using machine learning with a broader range of independent variables could yield a more accurate model for predicting creativity.

Strengths and limitations

Nursing, like other health-related disciplines, has undergone massive advancements in terms of knowledge and technology, leading to more complex roles that require critical thinking and creativity. Despite this, research on creativity among nurses remains limited. This study aims to inform nursing researchers, policymakers, and managers about factors that may enhance creative behavior and offers a Decision Support System (DSS) for assessing creativity levels among nurses. However, the study has limitations that may affect the generalizability of its results. The nonprobability sampling method was necessary due to the large target population, complicating randomization. Additionally, uncontrolled variables in this outcome study could impact creativity. Though statistical methods were employed to address these challenges, the limited number of input variables in machine learning (ML) stemmed from a lack of evidence in the nursing field. Further research is essential to identify factors influencing creativity (e.g., cultural factors, interdisciplinary teamwork), and a more robust DSS should be developed and examined. An additional challenge is the complexity of understanding and applying ML-based AI in nursing research, despite its precision and potential benefits. Consequently, both the primary variable and ML methodology in this study represent innovative approaches in nursing that warrant further exploration.

Conclusion

This study examined the influence of selected personal and work-related factors on nurses' creativity. Both statistical methods and ML models were employed. Using AI, the ML models predicted nurses' creativity through six factors: humble leadership, psychological safety, gender, age, time commitment, and staff experience. The developed DSS based on ML models was found to be effective at investigating and categorizing creativity levels among nurses.

Implication for the profession

Nurses' creativity significantly influences care quality, organizational outcomes, and professional growth. This study emphasizes that enhancing knowledge, fostering a safe work environment, and adopting a humble leadership style can boost creativity. To support this, nurses should engage in continuing education, attend nursing conferences, participate in evidence-based practices, and contribute to policy development for advanced nursing roles.

Nurse Managers can enhance psychological safety and humble leadership by implementing targeted training programs and fostering open communication, establish peer support network, promote a culture of recognition and appreciation, and encourage reflective practices. Regular team-building activities can build trust and lower hierarchical barriers, creating a safe space for idea-sharing. Encouraging policies that promote creativity and professional growth supports innovation. Additionally, establishing regular feedback channels through performance reviews and one-on-one meetings allows for assessing leadership effectiveness. By demonstrating humility—acknowledging mistakes, valuing staff input, and engaging in reflective practices—managers can cultivate an environment that encourages openness and improves team dynamics and decision-making.

The developed decision support system could be integrated into nursing workflows through an easy-to-use mobile app or software, allowing nurse managers to evaluate creativity among nurses. This integration would help make more informed decisions on staff allocation, development, and resource optimization, ultimately improving patient outcomes and operational efficiency. Additionally, the adoption of machine learning models in nursing research is recommended for accurately predicting creativity.

Abbreviations

IRB	Institutional Review Broad
ML	Machine Learning
AI	Artificial Intelligence
DSS	Decision Support System
SRCS	Self Rated Creativity Scale
SPSS	Statistical Package for Social Science
M	Mean
SD	Standard Deviation
r	Pearson Correlation Coefficient
ANOVA	One-way Analysis of variance
SVM	Support Vector Machine learning
WEKA	Waikato Environment for Knowledge Analysis
P	Precision

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Author contributions
All authors wrote the main manuscript text, R.M and M.K prepared tables and analyzed results, R.M and M.M reviewed the manuscript.

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Data availability
Data supporting this study's findings will be available upon reasonable request due to privacy/ethical restrictions.

Declarations

Ethics approval and consent to participate
The Institutional Review Board (IRB) of Hashemite University approved the research, with the reference number 11/8/2021/2022. The informed consent was obtained from all participants. All procedures were conducted in accordance with the ethical standards established in the Declaration of Helsinki, revised in Brazil in 2013.

Consent for publication
Not relevant.

No patient or public contribution
The patients and public were not involved in this study.

Competing interests
The authors declare no competing interests.

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