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The Impact of Artificial Intelligence Technologies on Employees' Quality of Work Life in the Energy Sector: An Applied Study Using Partial Least Squares Structural Equation Modeling (PLS-SEM) in an Algerian Organization in North Africa

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Abstract:
Artificial intelligence (AI) technologies have become a crucial tool widely used across various fields, particularly in the workplace, to enhance performance efficiency. However, the relationship between adopting AI technologies and professional quality of life remains unclear among employees in the energy sector within Algerian institutions in North Africa. This study aims to assess the impact of AI technologies (expert systems, intelligent agents, and neural networks) on professional quality of life using structural equation modeling (PLS-SEM). To achieve this objective, the study employed a descriptive and analytical field methodology, collecting data from employees in an energy sector institution through both paper-based and electronic questionnaires. The current study revealed several significant findings, including a positive impact of intelligent agents, neural networks, and expert systems on professional quality of life. The study recommends enhancing the use of AI technologies to improve employees' professional quality of life.
Keywords : Artificial Intelligence, Expert Systems, Intelligent Agents, Neural Networks, Professional Quality of Life.

Introduction

Artificial intelligence (AI) technologies have become an integral part of modern work environments, being employed in various daily tasks, from decision-making to automating routine activities. These technologies are not merely technical tools; they directly influence the work environment by affecting productivity, facilitating work-life balance, and introducing challenges related to job stress. Therefore, exploring the relationship between AI technologies (neural networks, expert systems, and intelligent agents) and professional quality of life is crucial to understanding how these technologies contribute to creating a supportive work environment.

This research aims to examine the dynamics of the relationship between AI technologies and professional quality of life among employees in an Algerian energy sector institution in North Africa. Specifically, it investigates whether expert systems enhance the work environment, whether intelligent agents contribute positively to workplace conditions, and the relationship between neural networks and professional quality of life. This raises the central research question: To what extent do AI technologies (neural networks, expert systems, and intelligent agents) impact the professional quality of life of employees in an Algerian energy sector institution in North Africa?

The primary objective of this study is to assess the impact of AI technologies (neural networks, expert systems, and intelligent agents) on the professional quality of life of employees in the Algerian energy sector. To achieve this, structural equation modeling (SEM) was used to analyze the relationships between the study variables.

The significance of this study lies in its potential to enrich academic research while providing guidance to policymakers and organizations on the importance of adopting AI technologies, highlighting their role in enhancing professional quality of life.

Intelligent agents

The concept of artificial intelligence (AI) was first introduced in the 1950s and is defined as the ability of machines to understand, reason, and learn in a manner similar to humans(Trappey et al., 2019a, p. 478). More specifically, artificial intelligence focuses on the study of machines capable of perceiving their environment and acting accordingly in order to increase their likelihood of achieving a specific objective(Hammam et al., 2019, p. 2). Additionally, artificial intelligence is defined as a field that emphasizes the simulation of human intelligence processes through machines—particularly computer systems—to perform tasks that are traditionally associated with human intelligence, such as natural language understanding, image recognition, and data-driven decision-making(Rani, 2020, p. 1991).

An intelligent agent is defined as an autonomous software entity equipped with sensing mechanisms and actuators that operate within a specific electronic environment in order to achieve a predefined objective(Eggert et al., 2019, p. 115). It is also described as a software system capable of operating either fully or partially autonomously to perform tasks in complex and dynamic environments(Ramu & Haldorai, 2023, p. 92).

Moreover, intelligent agents are commonly conceptualized as computer-based systems that perceive their environment and act autonomously within complex, dynamic settings, with the aim of accomplishing a set of tasks for which they are specifically designed(Sokas, 2012, p. 113).

An intelligent agent integrates three fundamental aspects. First, it acquires new information about selected components of its environment through sensing mechanisms. Second, it links and integrates this newly acquired information with prior knowledge about the environment.

Third, it utilizes the integrated information to derive inferences that support goal achievement and to execute actions through actuators(Eggert et al., 2019, p. 115).

Modern intelligent systems can be classified into five main types as follows(Botti, 2025, pp. 6–8):

- **Simple reactive systems:** These systems act directly based on current percepts using condition–action rules, without relying on memory or internal models.
- **Model-based systems:** These systems maintain an internal representation of the state of the environment, which is continuously updated based on incoming percepts.
- **Goal-based systems:** These systems select actions to be performed based on explicitly defined goals, employing search and planning techniques.
- **Utility-based systems:** These systems use utility functions to evaluate different possible outcomes and select the optimal option from a set of alternatives.
- **Learning systems:** Representing the most advanced category, these systems are capable of improving their performance over time through experience and learning.

Expert systems

Expert systems are considered among the earliest and most advanced intelligent system technologies. They are based on embedding the knowledge possessed by human experts into computer programs, where such knowledge is represented in the form of rules(Kostal et al., 2019, p. 3). Expert systems are rule-based systems that enable logical reasoning comparable to human reasoning. These systems are characterized by high performance, reliability, and rapid response(Isabel Cristina, 2021, p. 3). Expert systems represent a type of symbolic artificial intelligence techniques that enhance the knowledge possessed by human experts, thereby enabling improvements in the decision-making process across various domains(Rahman & Mehnaz, 2024, p. 3).

Expert systems are knowledge-based systems that process data and knowledge with the aim of generating new knowledge derived from existing knowledge(Zimmermann, 2024, p. 4). Expert systems are pre-designed software tools that encapsulate specialized expertise and domain-specific knowledge, which are used to solve problems within a particular field(Barker et al., n.d., p. 65), In another definition, expert systems are described as knowledge-based systems that simulate human decision-making processes(Vigo et al., 2022, p. 2).

A major challenge facing expert systems lies in knowledge acquisition, representation, and updating. To address this challenge, neural network technology has been developed, which will be discussed in the subsequent section of this study(Zimmermann, 2024, p. 4). Expert systems are systems that utilize a knowledge base, rules, and reasoning methods to solve problems within a specific domain of expertise, such as medicine, finance, or engineering(Dimkina & Hristov, 2024, p. 44).

Neural networks

Neural networks are computer-based systems designed in a manner analogous to human cognition. These systems consist of a set of artificial neural elements interconnected in various ways to solve problems. The connections within a neural network are formed through a training process, after which the trained neural network is applied to the problem domain for which it was specifically designed(Barker et al., n.d., p. 65).

The first single-layer neural network was introduced in 1960 and was called the perceptron. Subsequently, several improvements were made to neural networks, and during the 1980s, new enhanced types emerged, including recurrent neural networks and convolutional neural networks, designed to address specific problems. After 2000, and with the rapid advancement of technology, deep neural networks appeared in fields such as speech recognition, face recognition, and financial forecasting(Trappey et al., 2019b, p. 479).

Neural networks are computer-based systems characterized by their ability to perform deep learning and solve complex problems. They have wide-ranging applications across numerous fields, including medical diagnosis, face recognition, and finance(Jäger, 2021, p. 164). A neural network is an interconnected network of neurons in which communication channels exist between these neurons. The neural network can generate outputs in response to environmental stimuli, analogous to how the human brain responds to various changes in its environment(Rong et al., 2020, p. 291).

Neural networks are computer-based architectures composed of interconnected artificial neurons that mimic the properties of biological neurons. They are used to process large volumes of data using rules and logical inference(Vatovec, 2011, p. 607), Neural networks are a machine learning model inspired by the functioning of the human brain, used in various tasks such as image recognition, speech understanding, and time series forecasting(Dimkina & Hristov, 2024, p. 44).

Artificial neural networks are used for pattern recognition and classification, medical diagnosis, object and face recognition, as well as applications in sectors such as banking. One of the main drawbacks of artificial neural networks is their opacity, as operators do not know what each neuron represents, which can lead to misclassification and inaccurate results.

Neural networks have significantly contributed to improving the performance of artificial intelligence systems by enhancing the capabilities of intelligent systems across several domains, such as image recognition and speech processing(Zhang et al., 2025, p. 7).

Quality of Work Life

Quality of work life is a multidimensional concept that emerged in the late 1960s and focuses on how surrounding work conditions affect employees' job performance, satisfaction, and well-being. It encompasses both subjective elements (such as job satisfaction) and objective elements (such as compensation and occupational safety). The concept of quality of work life is among the concepts of significant interest to both profit and non-profit organizations, as organizations have begun to recognize that, in addition to production and profit, the human factor is one of the most important determinants of increased productivity and competitiveness(Çetinkanat & Kösterelioğlu, 2016, p. 1779).

During the 1980s, the concept of quality of work life evolved and was defined as a socio-economic relationship between the organization and its employees. It was expressed by the following equation:

QWL = f(O, E), meaning that quality of work life is a function of organizational characteristics and the work environment, where organizational characteristics refer to workplace attributes within the organization, and the environment reflects its impact on employees' well-being(Ilgan, 2014, p. 116), Quality of work life is considered one of the key aspects of human resource management and is positively associated with job performance and the development of human capabilities within the work environment(Dissanayake et al., 2021, p. 68).

Since the mid-1990s, greater attention has been given to quality of work life within organizations and human resource management, alongside increased employee awareness of work quality. Consequently, the concept of quality of work life has been viewed from a psychosocial perspective and is defined as the effect of the work environment on job satisfaction, family and personal satisfaction, and overall life satisfaction(Ilgan, 2014, p. 116).

It is difficult to establish a universally agreed-upon definition of the concept of quality of work life. According to Walton (1973), one of the leading scholars in this field, the concept is characterized by its comprehensiveness and is not limited solely to labor unions, workers, or labor laws(Ilgan, 2014, p. 115).

Quality of work life encompasses multiple aspects, such as working conditions, working hours, wage payment methods, health risks, and the responsiveness of management to employees' needs(Mily Velayudhan & Yameni, 2017, p. 7). Accordingly, quality of work life can be said to be associated with both financial and non-financial benefits.

In this context, Walton (1973) proposed eight conceptual categories used to assess quality of work life, namely(Parvar et al., 2013, pp. 136–138):

- **Fair and adequate compensation**, reflecting the effort exerted by employees.
- **Safe and healthy working conditions**, requiring the provision of appropriate occupational environments for employees.
- **Opportunities for the development and utilization of human capacities**, enabling employees to enhance and apply their skills.
- **Opportunities for continued growth and job security**, ensuring future career development and employment stability.
- **Social integration in the workplace**, through creating an environment in which employees feel a sense of belonging to the organization.
- **Protection of employees' rights**, by ensuring objective and legal factors such as privacy, freedom of expression, fairness, and due process, which contribute to better quality of work life.
- **Work–life balance**, ensuring harmony between professional responsibilities and personal life.
- **The social relevance of work life**, emphasizing the societal importance of work and its outcomes.

Review of relevant prior research and scholarly works:

The relationship between intelligent agents and quality of work life

Intelligent systems contribute to increasing employee productivity, as they have begun to replace humans in many routine activities, allowing employees to allocate more time to developmental tasks within the organization, thereby reducing fatigue and psychological stress(Wuczyński, 2020), In addition, intelligent systems are not limited to task execution; they also have the ability to improve work–life balance by simplifying tasks, enhancing time management, and reducing workload burdens(Kakkad & Suresh, 2023).

Studies also indicate that the implementation of intelligent agent systems has led to significant improvements in employees' job satisfaction and contributed to enhancing their well-being and overall satisfaction at work, which reflects a clear positive effect of intelligent agent systems on quality of work life(Valeriya et al., 2024), Intelligent agent technology, like other artificial intelligence technologies, contributes to motivating employees and alleviating routine workload, which leads to reduced stress and anxiety, improved job performance and commitment, and consequently enhances employees' organizational commitment(Loureiro et al., 2023).

Other studies also indicate that artificial intelligence systems may have negative effects on employees, particularly with regard to privacy concerns,(Hickok & Maslej, 2023; Jetha et al., 2025) and may lead to feelings of isolation and a loss of control over work(Rick et al., 2024).

First Hypothesis (H1): There Is No Positive Effect Of Intelligent Agents On Quality Of Work Life At The 5% Significance Level.

The relationship between neural networks and quality of work life

Neural networks have been applied in various aspects of quality of work life research to explore human behavior within organizations. In this context, multilayer neural networks were used to identify the key factors influencing job satisfaction, and the findings indicated that opportunities for professional development are among the most important contributors to hotel employees' job satisfaction(Chandrasekar et al., 2015).

Researchers have also developed neural network models to predict job burnout and employee turnover. These models analyze psychological factors affecting employees' well-being and have achieved prediction accuracy rates exceeding 96%, which confirms the strength and effectiveness of neural networks in predictive tasks(Li, 2022).

Another study also applied neural network models to predict career paths and job success among primary school teachers. These models were used to analyze how personality traits influence job satisfaction, and the results indicated that lower levels of neuroticism and impulsivity were among the strongest predictors of longer job tenure(Hollett et al., 2021).

In another study, neural networks demonstrated good predictive accuracy across various quality of work life measures. In the healthcare sector, multilayer neural networks revealed that anxiety levels, functional capacity, and depression are among the most important indicators of quality of work life(Kanchanatawan et al., 2019). Neural networks also showed strong performance in predicting employee satisfaction levels using genetic algorithms integrated with artificial neural networks(Syed et al., 2023).

The studies reviewed above indicate a positive impact relationship between neural networks and quality of work life. Accordingly, the following null hypothesis can be proposed:

Second Hypothesis (H2): There Is No Positive Effect Of Neural Networks On Quality Of Work Life At The 5% Significance Level.

The relationship between expert systems and quality of work life

Expert systems contribute directly to quality of work life in several ways, including reducing professional errors and enabling operation in different environments and at any time(Agus et al., 2018). Expert systems also provide significant operational advantages that help reduce occupational stress, as they enable access by multiple users simultaneously through system terminals. This reduces reliance on individual employees during their leave periods, upon their departure from the organization, and in situations where there is a shortage of available experts(Martín-Ruiz et al., 2013).

In another study, it was found that modern expert systems with interactive interfaces, such as electronic systems equipped with chatbots, contribute to enhancing team cohesion and increasing user engagement and satisfaction(Fatani & Banjar, 2024).

On the other hand, one study indicates that expert systems can have a negative impact on quality of work life. According to this study, reliance on expert systems may lead to fear of job loss or a perceived devaluation of professions, with concerns that expert systems could replace computer programmers and human experts(Oravec, 2014).

Despite the concerns and challenges posed by expert systems regarding employee satisfaction and stability, most studies indicate a positive relationship between expert systems and quality of work life. Accordingly, the following null hypothesis can be proposed:

Third Hypothesis(H3): There Is No Positive Effect Of Expert Systems On Quality Of Work Life At The 5% Significance Level.

The research gap between the current study and previous studies

Our study aims to address the gaps in existing research regarding the impact of artificial intelligence (AI) technologies on quality of work life in North Africa. The reviewed studies reveal positive outcomes concerning the effect of AI technologies on quality of work life. Some studies also highlighted the use of AI technologies as tools or models to predict factors influencing quality of work life. However, these studies do not sufficiently examine the causal relationship between the independent variables under study (intelligent agents, neural networks, and expert systems) and the dependent variable (quality of work life). Therefore, this study seeks to fill this research gap by investigating the impact of each independent variable on quality of work life.

Academic research confirms the positive effect of AI on quality of work life across various fields. At the same time, studies indicate concerns and challenges posed by AI regarding employee job satisfaction, as employees may fear that machines and systems will replace them, potentially leading to job insecurity. Our study aims to reaffirm the positive relationship between AI technologies and quality of work life in the North African context, thereby enriching the literature on this topic.

In summary, this research seeks to address gaps in existing studies by conducting an applied study on employees in the energy sector in North Africa. Specifically, it examines the impact of AI technologies (neural networks, intelligent agents, and expert systems) on employees' quality of work life.

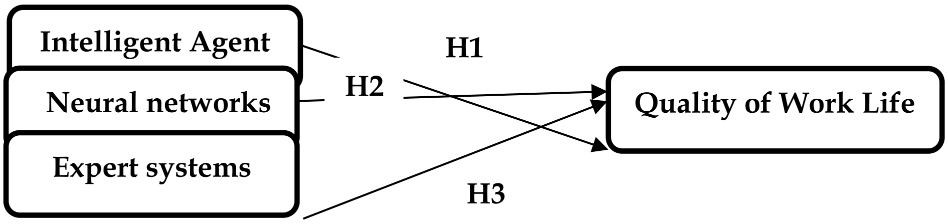

Figure 01. Theoretical framework

Methodology

Research Design and Methodology

This study adopts a quantitative research design to examine the impact of artificial intelligence technologies on the quality of work life among employees in the energy sector. Structural equation modeling was employed to identify and explain the relationships among the study variables. This approach is considered appropriate for assessing the effect of artificial intelligence technologies on employees' quality of work life.

data Collection Methods

A questionnaire was designed to collect quantitative data from a sample of employees. The questionnaire includes multiple-choice questions and five-point Likert scale items. The main constructs measured by the survey instrument are artificial intelligence technologies, quality of work life, and demographic and social information.

Sampling Technique

To ensure a comprehensive representation of various demographic factors such as age, gender, and geographic location in North Africa, specifically in Algeria, a random sampling technique was employed.

Data Collection Procedure

The questionnaire instrument, in both paper-based and electronic formats, was used to collect the required data from the study sample. Electronic questionnaires were distributed via email and social media platforms, while paper-based questionnaires were administered in cooperation with local companies operating in the energy sector. It should be noted that prior informed consent was obtained from participants, and data confidentiality was ensured in order to encourage honest and candid responses.

Variables and Measures:

Artificial Intelligence Technologies: A set of statements was designed and addressed to employees to elicit their perceptions regarding the extent of their use of artificial intelligence technologies (neural networks, intelligent agents, and expert systems).

Quality of Work Life: A set of statements was designed and addressed to employees to capture their perceptions of the quality of work life.

Rationale for the Chosen Methods:

The quantitative approach is considered appropriate for the present study, as it allows for the analysis of data to identify relationships and correlations among the study variables through questionnaires distributed to the study sample.

The partial least squares structural equation modeling (PLS-SEM) technique was employed using the SmartPLS software, allowing for the examination of the various relationships among the variables.

The random sampling technique ensures the representation of all groups without bias, thereby enhancing the validity and quality of the results.

The questionnaire facilitates the data collection process from the study sample, enabling the conduct of statistical analyses to test the hypotheses and draw robust conclusions.

The methodology adopted in the present study allows for the generation of empirical evidence that identifies the relationship between artificial intelligence technologies and quality of work life among employees in the energy sector, thereby contributing to a broader understanding of the extent to which artificial intelligence technologies influence quality of work life.

Data Presentation and Analysis:

First: Measurement Model Assessment

Structural equation modeling using the SmartPLS software is employed to verify the validity of the measurement instrument and the research model. SmartPLS is distinguished by its ability to model latent variables under conditions of non-normal data distribution and small sample sizes, as it imposes minimal restrictions on measurement scales and residual distributions(Chin et al., 2003; Hair et al., 2011).

This section of the study examines the quality of the variables in the model using **Smart PLS**. The assessment of the measurement model includes:

- **Convergent Validity Tests:** These tests ensure that the indicators adequately represent the constructs to which they belong and that the measurements remain reliable under different conditions.
- **Discriminant Validity Tests:** These tests verify that there is no linear overlap between the study's constructs, ensuring that each construct is distinct from the others.

Convergent Validity:

In the SmartPLS software, the assessment of convergent validity is based on three fundamental criteria that work together to demonstrate that the indicators accurately represent their intended latent constructs(Chen et al., 2022; Hamari et al., 2020).

The first criterion examines factor loadings (also referred to as outer loadings), which should exceed 0.7 to indicate that the shared variance between the construct and its indicators is greater than the error variance. However, loadings ranging between 0.5 and 0.6 may be acceptable in certain cases, particularly in exploratory research(Hair et al., 2019).

The second criterion is the **Average Variance Extracted (AVE)**. Latent variables or constructs with AVE values exceeding 0.5 are considered to exhibit high convergent validity(Diamantopoulos & Winklhofer, 2001). AVE is interpreted as indicating that the construct explains more than half of the variance in its indicators(Chen et al., 2019; Drexel

University et al., 2000; Hamari et al., 2020; Riar et al., n.d.; S. Yaakub & Nik Abdullah, 2018).This threshold ensures that the construct or latent variable captures a greater proportion of variance from its indicators than that attributable to measurement error.

The third criterion is Composite Reliability (CR), which should be at least 0.7 to establish internal consistency among the indicators measuring the construct. When the AVE value is slightly below 0.5 but composite reliability exceeds 0.6, convergent validity may still be considered acceptable.

Table 01: Results Of The Convergent Validity Tests Of The Model

	Cronbach's Alpha	Composite Reliability (Rho_A)	Composite Reliability (Rho_C)	Average Variance Extracted (AVE)
Intelligent Agent	0.777	0.786	0.870	0.690
Neural Networks	0.834	0.847	0.889	0.668
Expert Systems	0.854	0.855	0.912	0.775
Quality Of Work Life	0.939	0.940	0.948	0.672

Source : Prepared By The Authors Based On The Outputs Of Smartpls 4

As shown **in Table 01**, the reliability assessment based on Cronbach's alpha for the latent variables ranges from 0.777 to 0.939, indicating high and statistically acceptable reliability, as all values exceed the recommended threshold of 0.70. Similarly, the composite reliability (CR) values are above 0.70, with all coefficients ranging between 0.870 and 0.948, confirming a high level of construct reliability. These findings suggest that the measurement instrument demonstrates adequate consistency and would yield stable results if the study were replicated.

Moreover, the average variance extracted (AVE) values for all study constructs exceed the threshold of 0.50, indicating satisfactory convergent validity and allowing for further hypothesis testing. Overall, the results confirm that all constructs exhibit strong internal consistency reliability.

The following figure also presents the results of the factor loadings:

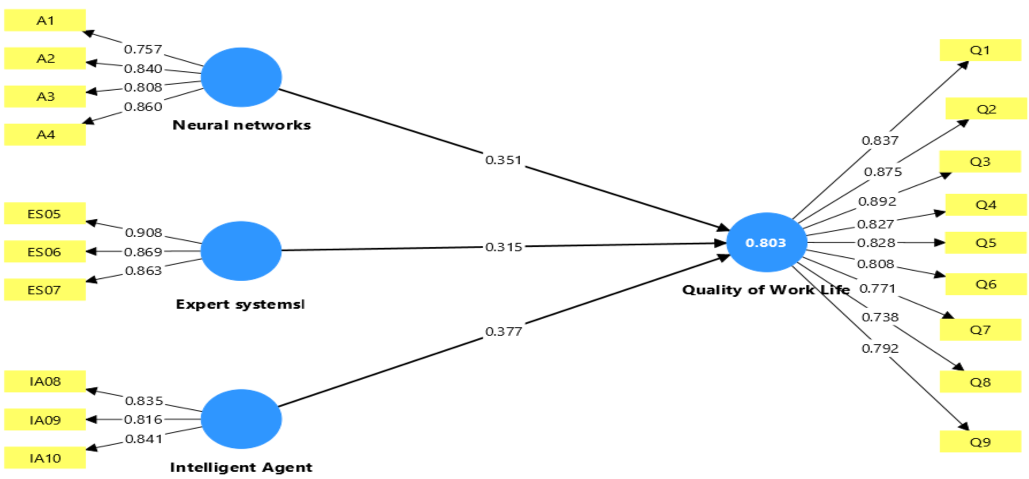

Figure 02: Results of the factor loadings for the indicators of the study variables
Source: Prepared By The Authors Based On The Outputs Of Smartpls 4

Figure 02 illustrates the results of the convergent validity assessment based on outer loadings for the artificial intelligence techniques constructs (neural networks, intelligent agents, and expert systems). The results presented in the figure show that most indicator outer loading values exceed the recommended threshold of 0.70, with values ranging from 0.757 to 0.908.

Similarly, the outer loading values for the quality of work life construct range between 0.771 and 0.892, all of which are above the 0.70 threshold.

Overall, the outer loading values are statistically acceptable, as they exceed the minimum acceptable level of 0.70, indicating that the indicators explain their respective constructs to an adequate and high degree.

Discriminate Validity

The assessment of discriminant validity involves a set of statistical tests that have been proposed by researchers in the field of statistics. Among the commonly used criteria are the Fornell–Larcker criterion, the cross-loadings criterion, and the HTMT ratio. Studies examining discriminant validity have indicated that both the Fornell–Larcker criterion and the cross-loadings approach exhibit very weak performance in accurately detecting discriminant validity problems in variance-based structural equation modeling(Henseler et al., 2015).

Accordingly, the Heterotrait–Monotrait ratio (HTMT) was proposed. This measure represents the average of the correlations between indicators across constructs that measure different phenomena (heterotrait–heteromethod correlations), relative to the average of the correlations between indicators within the same construct (monotrait–heteromethod correlations). Because two submatrices of heterotrait–heteromethod correlations are involved, the geometric mean of their averages is calculated(Henseler et al., 2015).

HTMT is estimated as a correlation-based value, and its interpretation is straightforward: the correlation between two constructs should be sufficiently below one to conclude that they are empirically distinct. There are two main approaches for using HTMT to assess discriminant validity:

The first approach treats HTMT as a criterion, whereby the obtained value is compared with a pre-specified threshold. If the HTMT value exceeds this threshold, a lack of discriminant validity can be inferred. The exact threshold remains debated, with some scholars proposing a cutoff value of 0.85(Clark & Watson, 1995), while others suggest 0.90(Gold et al., 2001; Teo et al., 2008).

The second approach treats HTMT as a statistical test. Bootstrapping procedures can be used to generate confidence intervals for HTMT in order to test the null hypothesis ($H0$: HTMT $\geq$ 1) against the alternative hypothesis ($H1$: HTMT $<$ 1). A confidence interval that includes the value of one (i.e., H0 is supported) indicates the absence of discriminant validity. Conversely, if the value lies outside the interval, this suggests that the two constructs are empirically distinct(Shaffer Juliet Popper, 1995).

In this study, the HTMT criterion was used exclusively to assess discriminant validity, as it is one of the statistical tests recommended in the recent literature due to its strong ability to detect discriminant validity issues compared to the Fornell–Larcker criterion and the cross-loadings approach. The following table presents the results of the discriminant validity assessment among the study variables according to the HTMT criterion.

Table 02: HTMT ratio results for assessing the discriminant validity of the study variables

	Intelligent Agent	**Neural networks**	**Quality of Work Life**	**Expert systems**
Intelligent Agent				
Neural networks	0.616			
Quality of Work Life	0.886	0.838		
Expert systems	0.816	0.776	0.891	

Source : Prepared By The Authors Based On The Outputs Of Smartpls 4

As shown in the table, all HTMT values for the study constructs are below the 0.90 threshold, ranging between 0.616 and 0.891. This finding indicates the presence of adequate discriminant validity among the latent constructs in the current research model, thereby confirming the absence of multicollinearity or overlap among the constructs of the measurement model.

Second: Structural Model Assessment (Inner Model Testing)

This part focuses on evaluating the relationships between the independent and dependent variables within the structural model to test the hypothesized effects.

The systematic evaluation of structural models follows established procedures, beginning with an assessment of multicollinearity using the Variance Inflation Factor (VIF), where values below 5.0 indicate the absence of potential multicollinearity problems(Ooi et al., 2022; Saptioratri Budiono et al., 2021; Yang & Lin, 2022). The evaluation of the structural model further includes examining path coefficients, t-statistics, p-values, effect sizes, the coefficient of determination (R^2), and measures of predictive relevance(Guzman et al., 2022; Ooi et al., 2022).

Below are the results of the multicollinearity assessment using the Variance Inflation Factor (VIF):

Table 03: Variance Inflation Factor (VIF) results among the study variables

	Quality of Work Life
Intelligent Agent	1.857
Neural networks	1.772
Expert systems	2.410

Source: Prepared By The Authors Based On The Outputs Of Smartpls 4

As observed in the table, all VIF values are below the threshold of 5, with values of 1.857, 1.772, and 2.410 for the intelligent agents, neural networks, and expert systems constructs, respectively. Accordingly, multicollinearity among the artificial intelligence constructs does not pose any issues in examining their effect on the quality of work life construct. Therefore, the results obtained in subsequent analyses can be considered reliable and interpretable.

After verifying the absence of multicollinearity among the variables using the Variance Inflation Factor (VIF), the remaining statistical tests are conducted.

Predictive accuracy is a fundamental element in evaluating structural models, where the coefficient of determination (R^2) is used as a primary measure of the model's predictive power(Adinyira et al., 2020; Zeng et al., 2021). R^2 indicates the amount of variance explained in the endogenous variables by the exogenous variables, with commonly accepted thresholds of 0.75, 0.50, and 0.25 representing high, moderate, and weak levels of predictive accuracy, respectively(Henseler & Sarstedt, 2013; Zeng et al., 2021).

With regard to the effect size coefficient (f^2) used to assess the adequacy of the structural model in structural equation modeling research, the commonly accepted reference values are 0.02, 0.15, and 0.35, representing small, medium, and large effect sizes, respectively. Cohen's seminal work on statistical power analysis serves as the primary reference for these thresholds(Duchi et al., 2020; Lauriola et al., 2019; Liu et al., 2020; Müller-Pérez et al., 2025). In other streams of research, slightly different threshold ranges have been proposed, whereby values between 0.15 and 0.20 indicate weak effects, values between 0.20 and 0.35 reflect moderate effects, and values exceeding 0.35 are considered strong effects(Karaboga et al., 2023).

Values below 0.02 are generally regarded as indicating no meaningful or only negligible effects. Interpreting the f^2 effect size provides researchers with a clear methodological basis for determining whether an exogenous construct exerts a substantively significant influence on an endogenous construct. The widespread reporting of f^2 threshold values across numerous scientific studies and methodological papers reflects their broad acceptance within the research community(Belouadah, 2025; Chen et al., 2025; Mutonyi et al., 2021; Valle et al., 2022).

The following table presents the results of the R^2 and f^2 coefficients used to evaluate the adequacy of the structural model.

Table 04: Results of R^2 and F^2values

	R^2	F^2
Neural Networks	/	0.353
Expert Systems	/	0.209
Intelligent Agent	/	0.389
Quality of Work Life	0.803	/

Source: Prepared By The Authors Based On The Outputs Of Smartpls 4

Table 4 presents the evaluation of the structural model, focusing on the coefficient of determination (R^2) and the effect size (f^2) for the latent variables: intelligent agent, neural networks, expert systems, and quality of work life, using the PLS-SEM approach. The R^2 value represents the proportion of variance in each endogenous variable explained by its corresponding exogenous variables. For quality of work life, the R^2 value is 0.803, indicating that the model explains 80.3% of the variance in quality of work life, which reflects a high level of predictive accuracy.

Similarly, the effect size f^2 indicates the magnitude of the impact of the exogenous variables on the endogenous constructs within the model. The effect size for the intelligent agent is 0.353, representing a strong effect. For neural networks, the effect size is 0.209, which falls within the range of 0.20 to 0.35, indicating a moderate effect; in other words, the neural networks variable moderately predicts quality of work life with a value of 0.209. Regarding expert systems, the effect size is 0.389, indicating a strong effect.

Discussion of testing the study hypotheses

The bootstrap method is considered the primary approach for evaluating structural models, as it relies on non-parametric procedures that generate subsamples to assess statistical significance without depending on specific distributional assumptions(Guzman et al., 2022). The standard application uses 5,000 bootstrap samples at a 5% confidence level, and *t*-values greater than 1.96 indicate statistical support for the hypotheses(Adinyira et al., 2020; Chuang & Chen, 2022; Huang et al., 2022).

Among the specialized software applications used to assess structural models based on variance-based partial least squares is SmartPLS, which estimates path coefficients by minimizing the sum of squared differences between observed and predicted values. This provides estimates of path coefficients, levels of statistical significance, model-fit statistics, and predictive capability measures, including Q^2 values(Adinyira et al., 2020; Guzman et al., 2022; Huang et al., 2022; Jnr & Petersen, 2023; Siqueira et al., 2021).

Acceptance or rejection of hypotheses in SmartPLS is based on established statistical criteria derived from *t*-statistics and *p*-values obtained through the bootstrapping resampling procedure. Typically, alternative hypotheses are accepted and null hypotheses are rejected when the *t*-value exceeds 1.96 and the *p*-value is below 0.05. In other studies, *t*-values greater than 2 with *p*-values less than 0.05 are likewise considered statistically significant(Choi et al., 2020; Suyudi et al., 2020).

The hypothesis-testing process involves comparing the calculated *t*-statistic with the critical tabulated *t*-value at a 95% confidence level; alternative hypotheses are accepted when the calculated *t* exceeds the tabulated value. The adopted significance level of $p < 0.05$ is applied throughout all SmartPLS analyses to assess the validity of the hypotheses, whereby *p*-values below 0.05 are regarded as statistically significant(Yikilmaz et al., 2023; Yulinda et al., 2021; Zhang et al., 2022).

Table 05: Results of the study hypotheses testing (H1, H2, H3)

Hypothesis	Paths	**Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
H1	**Intelligent Agent -> Quality of Work Life**	0.377	0.379	0.089	4.228	0.000
H2	**Neural networks -> Quality of Work Life**	0.351	0.355	0.068	5.143	0.000

H3	**Expert systems -> Quality of Work Life**	0.315	0.308	0.083	3.801	0.000

Source : Prepared By The Authors Based On The Outputs Of Smartpls 4

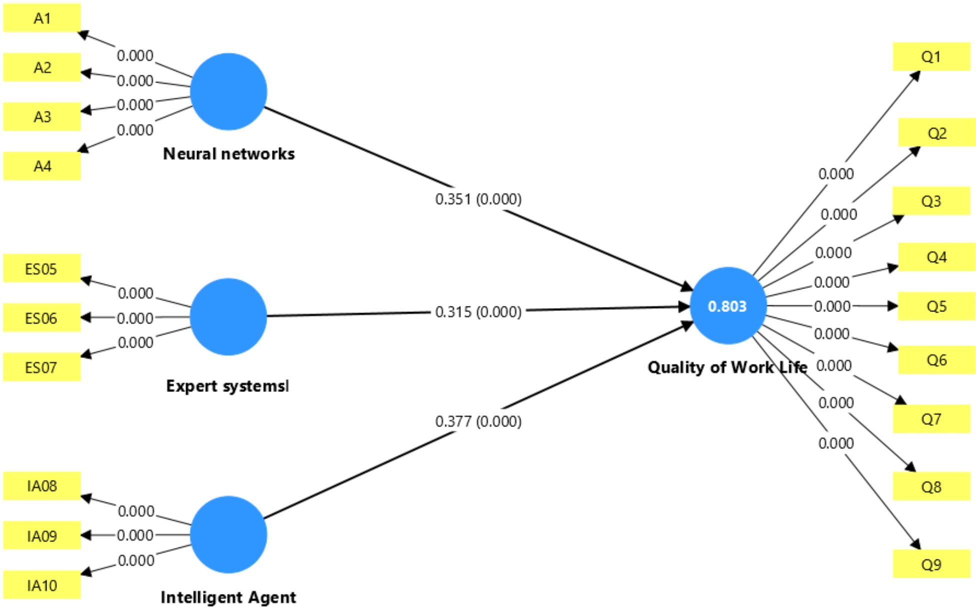

Figure 03: Structural Model Of The Study
Source : Prepared By The Authors Based On The Outputs Of Smartpls 4

As shown in the table above, the direct effect of the intelligent agents construct on quality of work life was positive, with a path coefficient of 0.377. The corresponding t-value was 4.228, with a significance level of 0.000, which is below the conventional threshold of 0.05. This indicates that the effect of intelligent agents on quality of work life is statistically significant. These results suggest that intelligent agents positively influence the quality of work life of employees in the energy sector organization under study. Specifically, a one-unit increase in the intelligent agents construct is associated with a 0.377-unit positive change in quality of work life. Accordingly, the null hypothesis is rejected, and the alternative hypothesis is accepted, indicating a significant positive effect of intelligent agents on employees' quality of work life at the 0.05 significance level.

Similarly, the direct effect of the neural networks construct on quality of work life was positive, with a path coefficient of 0.351. The t-value was 5.143, and the significance level was 0.000, which is below 0.05, indicating a statistically significant effect. These results show that neural networks positively contribute to supporting employees' quality of work life in the energy sector organization. A one-unit change in the neural networks construct corresponds to a 0.351-unit increase in quality of work life. Thus, the null hypothesis is rejected, and the alternative hypothesis is accepted, confirming a significant positive effect at the 0.05 significance level.

Furthermore, the direct effect of the expert systems construct on quality of work life was positive, with a path coefficient of 0.315. The t-value was 3.801, with a significance level of 0.000, again below 0.05, indicating a statistically significant effect. This suggests that expert systems positively impact the quality of work life of employees in the energy sector organization. Specifically, a one-unit increase in the expert systems construct leads to a 0.315-unit positive change in quality of work life. Therefore, the null hypothesis is rejected, and the alternative hypothesis is accepted, confirming a significant positive effect at the 0.05 significance level.

Discussion

Interpretation of the Results

This study aims to examine the impact of artificial intelligence technologies—namely intelligent agents, neural networks, and expert systems—on employees' quality of work life in an organization operating in the energy sector in North Africa, using variance-based structural equation modeling (PLS-SEM) implemented through the SmartPLS software.

The results of the proposed structural model demonstrate strong explanatory power, as the coefficient of determination (R^2) for quality of work life reached 0.803, indicating that the independent variables (intelligent agents, neural networks, and expert systems) explain more than 80% of the variance in quality of work life. This represents a very high value in behavioral and organizational research and reflects the robustness and adequacy of the proposed model for analyzing the causal relationships under investigation.

Furthermore, the effect-size results (f^2) reveal that both intelligent agents and expert systems exert strong effects on quality of work life, whereas neural networks exhibit a moderate effect on the dependent variable. This finding indicates heterogeneity in the magnitude of influence exerted by different artificial intelligence technologies within the organization.

The results indicate that artificial intelligence technologies exert strong effects on quality of work life, which can be attributed to the strategic role these technologies play within organizations, as they contribute to reducing operational burdens and routine tasks, thereby alleviating occupational stress and job burnout, which in turn positively affects both employee performance and organizational performance.

The strong effects of intelligent agents and expert systems on quality of work life among the study sample in the energy sector can be explained by the fact that these technologies are used directly by employees in operational processes, making their impact on the work environment more visible. In contrast, the moderate effect of neural networks may be due to their predominant use for analytical or predictive purposes at the senior management level, as confirmed by several prior studies that employed neural networks primarily as forecasting tools. Consequently, their influence on employees' daily work experiences is more indirect compared with that of intelligent agents and expert systems.

Comparison with Previous Studies

The results of the study are consistent with the previous research discussed in the literature review for all three hypotheses:

First Hypothesis (H1): There Is No Positive Effect Of Intelligent Agents On Quality Of Work Life At The 5% Significance Level.

The findings of this study are consistent with the majority of previous research reviewed in the introduction, as both the current and prior studies confirm a positive relationship between the independent variable, intelligent agents, and the dependent variable, quality of work life, with intelligent agents contributing to higher levels of job satisfaction among employees and reducing routine tasks, thereby enhancing overall quality of work life, which aligns with the studies of(Kakkad & Suresh, 2023; Loureiro et al., 2023; Valeriya et al., 2024; Wuczyński, 2020); however, the findings differ from those reported by (Hickok & Maslej, 2023; Jetha et al., 2025; Rick et al., 2024), which highlight potential negative effects of intelligent agent technologies, particularly concerns about job displacement, a discrepancy that may be explained by differences in geographical context and the sector under study.

Second Hypothesis (H2): There Is No Positive Effect Of Neural Networks On Quality Of Work Life At The 5% Significance Level.

The results of this study are consistent with most previous research that has confirmed the positive effect of neural networks on quality of work life. Studies by(Chandrasekar et al., 2015; Hollett et al., 2021; Kanchanatawan et al., 2019; Li, 2022; Syed et al., 2023) indicated that neural networks are used by organizations to predict employees' career paths in order to enhance quality of work life, which aligns with the findings of the present study demonstrating that neural networks have a positive impact on employees' quality of work life in the energy sector.

Third Hypothesis (H03): There Is No Positive Effect Of Expert Systems On Quality Of Work Life At The 5% Significance Level.

The results of the third hypothesis in the present study are consistent with most previous research that has examined the relationship between expert systems and quality of work life. Prior studies by(Agus et al., 2018; Martín-Ruiz et al., 2013), and (Fatani & Banjar, 2024) indicated that expert systems directly contribute to improving quality of work life, particularly by reducing professional errors, which in turn alleviates work-related stress. Although (Oravec, 2014) highlighted the challenges and concerns that expert systems may create for employees—such as fear of job loss and the replacement of human experts—the majority of studies have agreed on the positive contribution of expert systems and artificial intelligence technologies in enhancing employees' quality of work life.

In summary, the results of this study are consistent with previous academic research, thereby confirming the positive impact of artificial intelligence technologies (intelligent agents, neural networks, and expert systems) on quality of work life. Both intelligent agents and expert systems were found to exert a strong effect on quality of work life. The findings are of considerable importance for managers and professionals in the energy sector as well as in other industries seeking to enhance employees' quality of work life.

Moreover, the present study is among the few that have examined the combined and direct effects of multiple artificial intelligence technologies within a single model in the context of North Africa and the energy sector, thus constituting a valuable contribution to the existing literature.

Conclusion

This study aimed to examine the impact of artificial intelligence technologies (intelligent agents, neural networks, and expert systems) on quality of work life. It provides positive evidence regarding the relationships among the studied variables in an energy-sector organization in Algeria, North Africa.

The main findings can be summarized as follows. The study shows that intelligent agents are among the most important contemporary artificial intelligence technologies, as they are now widely used across many fields. The results indicate that intelligent agents exert a strong and positive effect on employees' quality of work life in the Algerian energy-sector organization, by reducing professional errors and facilitating employees' work through the automation of administrative processes and the provision of solutions to specific problems. Consequently, intelligent agents enhance quality of work life by alleviating work pressure and improving the work environment, thereby strengthening employees' sense of organizational belonging.

Another important finding is that neural networks also contribute positively to employees' quality of work life in the same context. Although their effect was found to be of moderate magnitude, neural networks remain an important artificial intelligence technology. This moderate effect can be attributed to the fact that neural networks are mainly used for predictive purposes by top management rather than being directly employed by all staff, unlike other AI technologies. Nevertheless, neural networks still improve quality of work life by reducing randomness in managerial decision-making and increasing job satisfaction and productivity.

Finally, the study reveals a strong and positive effect of expert systems on quality of work life among employees in the Algerian energy-sector organization. Expert systems are widely used to guide decisions and solve employees' problems effectively, thereby contributing to a better work environment. Accordingly, they enhance managerial effectiveness and help reduce employees' work pressures.

The practical implications and recommendations of the study are as follows:

The study yielded important implications for various stakeholders, including public and private economic institutions, in light of the global shift toward the use of technology in the workplace. The positive impact of artificial intelligence technologies—namely expert systems, intelligent agents, and neural networks—on quality of work life enables national decision-makers to adopt and disseminate these technologies across different fields and sectors in order to enhance employees' quality of work life and, consequently, improve workforce performance and institutional productivity. Providing an appropriate work environment generates benefits at both the organizational and national levels, as it is reflected in increased corporate profitability and revenues on the one hand, and higher state revenues on the other, which can then be directed toward serving the public interest through the financing of social and economic projects such as investments in infrastructure and public services.

In addition, recognizing the critical importance of artificial intelligence technologies underscores the necessity of adopting and implementing them across diverse domains. The application of expert systems and intelligent agents can help simplify administrative processes within organizations, while neural networks can be used by top management as predictive tools to support decision-making.

This study contributes to the academic literature by offering practical recommendations to enhance the deployment of artificial intelligence technologies across different work settings in order to improve quality of work life in energy-sector organizations in Algeria, North Africa. By acknowledging the positive relationship between artificial intelligence technologies—expert systems, intelligent agents, and neural networks—and quality of work life, governments and organizations alike can adopt these technologies to create more supportive and productive work environments for employees.

References

1. Adinyira, E., Agyekum, K., Danku, J. C., Addison, P., & Danku, J. C. (2020). Influence of Subcontractor Risk Management on Quality Performance of Building Construction Projects in Ghana. *Journal of Construction in Developing Countries*, *25*(2), 175–197. https://doi.org/10.21315/jcdc2020.25.2.7
2. Agus, F., Wulandari, H. E., & Astuti, I. F. (2018). Expert System With Certainty Factor For Early Diagnosis Of Red Chili Peppers Diseases. *Journal of Applied Intelligent System*, *2*(2), 52–66. https://doi.org/10.33633/jais.v2i2.1455
3. Barker, P., Richards, S., & Banerji, A. (n.d.). *Intelligentapproaches to performance support*.
4. Belouadah, F. (2025). Impact of corporate social responsibility disclosure on quality of health care institutions: Field study on Al-Kharj province ,. *Decision Science Letters*, *14*(2), 239–250. https://doi.org/10.5267/j.dsl.2025.2.003
5. Botti, V. (2025). *Agentic AI and Multiagentic: Are We Reinventing the Wheel?*
6. Çetinkanat, A. C., & Kösterelioğlu, M. A. (2016). Relationship between Quality of Work Life and Work Alienation: Research on Teachers. *Universal Journal of Educational Research*, *4*(8), 1778–1786. https://doi.org/10.13189/ujer.2016.040806
7. Chandrasekar, T., Chidambaram, V., Venkatraman, S., & Venugopal, V. (2015). The viability of neural network for modeling the impact of individual job satisfiers on work commitment in Indian manufacturing unit. *Verslas: Teorija Ir Praktika*, *16*(3), 326–333. https://doi.org/10.3846/btp.2015.522
8. Chen, M.-C., Hsu, C.-L., & Chen, M.-M. (2019). How Transportation Service Quality Drives Public Attitude and Image of a Sustainable City: Satisfaction as A Mediator and Involvement as A Moderator. *Sustainability*, *11*(23), 6813. https://doi.org/10.3390/su11236813
9. Chen, W., Gao, Y., Ren, R., Bi, Y., & Liao, Y. (2025). Socioeconomic status and internet addiction: Double-mediated moderation. *BMC Public Health*, *25*(1), 48. https://doi.org/10.1186/s12889-024-21153-w
10. Chen, W.-K., Chen, C.-W., & Silalahi, A. D. K. (2022). Understanding Consumers' Purchase Intention and Gift-Giving in Live Streaming Commerce: Findings from SEM and fsQCA. *Emerging Science Journal*, *6*(3), 460–481. https://doi.org/10.28991/ESJ-2022-06-03-03
11. Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). *A PARTIAL LEAST SQUARES LATENT VARIABLE MODELING APPROACH FOR MEASURING INTERACTION*

EFFECTS: RESULTS FROM A MONTE CARLO SIMULATION STUDY AND VOICE MAIL EMOTION/ADOPTION STUDY. *14*(02), 189–217.

12. Choi, D., Chung, C. Y., Seyha, T., & Young, J. (2020). Factors Affecting Organizations' Resistance to the Adoption of Blockchain Technology in Supply Networks. *Sustainability*, *12*(21), 8882. https://doi.org/10.3390/su12218882
13. Chuang, H.-M., & Chen, C.-I. (2022). Sustaining the Well-Being of Wearable Technology Users: Leveraging SEM-Based IPMA and VIKOR Analyses to Gain Deeper Insights. *Sustainability*, *14*(13), 7799. https://doi.org/10.3390/su14137799
14. Clark, L. A., & Watson, D. (1995). Constructing Validity:Basic Issues in Objective Scale Development. *Psychological Assessment*, *7*(3), 309–319.
15. Diamantopoulos, A., & Winklhofer, H. M. (2001). *Index construction with formative indicators: An alternative to scale develo... 38*(5), 269–277.
16. Dimkina, N., & Hristov, G. (2024). The Answer of the Question „Is Artificial Intelligence Artificial?". *Science, Engineering and Education*, *9*(1), 41–47. https://doi.org/10.59957/see.v9.i1.2024.6
17. Dissanayake, D. F., Wachissara, P., & De Silva, P. O. (2021). The Impact of Emotional Intelligence and Quality of Work- Life on Organizational Citizenship Behaviour. *Peradeniya Management Review*, *3*(1), 64–93. https://doi.org/10.4038/pmr.v3i1.50
18. Drexel University, Gefen, D., Straub, D., & Georgia State University. (2000). The Relative Importance of Perceived Ease of Use in IS Adoption: A Study of E-Commerce Adoption. *Journal of the Association for Information Systems*, *1*(1), 1–30. https://doi.org/10.17705/1jais.00008
19. Duchi, L., Lombardi, D., Paas, F., & Loyens, S. M. M. (2020). How a growth mindset can change the climate: The power of implicit beliefs in influencing people's view and action. *Journal of Environmental Psychology*, *70*, 101461. https://doi.org/10.1016/j.jenvp.2020.101461
20. Eggert, J., Deigmöller, J., Fischer, L., & Richter, A. (2019). Memory Nets: Knowledge Representation for Intelligent Agent Operations in Real World: *Proceedings of the 11th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management*, 115–126. https://doi.org/10.5220/0008068101150126
21. Fatani, M., & Banjar, H. (2024). Web-based Expert Bots System in Identifying Complementary Personality Traits and Recommending Optimal Team Composition. *International Journal of Advanced Computer Science and Applications*, *15*(2). https://doi.org/10.14569/IJACSA.2024.0150213
22. Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge Management: An Organizational Capabilities Perspective. *Journal of Management Information Systems*, *18*(1), 185–214. https://doi.org/10.1080/07421222.2001.11045669
23. Guzman, J., Recoco, G. A., Pandi, A. W., Padrones, J. M., & Ignacio, J. J. (2022). Evaluating workplace safety in the oil and gas industry during the COVID-19 pandemic using occupational health and safety Vulnerability Measure and partial least square Structural Equation Modelling. *Cleaner Engineering and Technology*, *6*, 100378. https://doi.org/10.1016/j.clet.2021.100378

24. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (Eighth edition). Cengage.
25. Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a Silver Bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202
26. Hamari, J., Hanner, N., & Koivisto, J. (2020). "Why pay premium in freemium services?" A study on perceived value, continued use and purchase intentions in free-to-play games. *International Journal of Information Management*, *51*, 102040. https://doi.org/10.1016/j.ijinfomgt.2019.102040
27. Hammam, A. A., Soliman, M., & Hassanien, A. E. (2019). *A Proposed Artificial intelligence Model for Real-Time Human Action Localization and Tracking* (arXiv:1911.04469). arXiv. https://doi.org/10.48550/arXiv.1911.04469
28. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
29. Henseler, J., & Sarstedt, M. (2013). Goodness-of-fit indices for partial least squares path modeling. *Computational Statistics*, *28*(2), 565–580. https://doi.org/10.1007/s00180-012-0317-1
30. Hickok, M., & Maslej, N. (2023). A policy primer and roadmap on AI worker surveillance and productivity scoring tools. *AI and Ethics*, *3*(3), 673–687. https://doi.org/10.1007/s43681-023-00275-8
31. Hollett, R. C., McMahon, M., & Monson, R. (2021). Associating Psychological Factors With Workplace Satisfaction and Position Duration in a Sample of International School Teachers. *Frontiers in Psychology*, *11*, 601554. https://doi.org/10.3389/fpsyg.2020.601554
32. Huang, H., Gao, L., Deng, X., & Fu, H. (2022). The Relationship Between Emotional Intelligence and Expatriate Performance in International Construction Projects. *Psychology Research and Behavior Management*, *Volume 15*, 3825–3843. https://doi.org/10.2147/PRBM.S387287
33. Ilgan, A. (2014). Validity and reliability study of Quality of School Work Life (QSWL) scale. *International Journal of Human Sciences./ Uluslararası İnsan Bilimleri Dergisi*, 114–137. https://doi.org/10.14687/ijhs.v11i2.2866
34. Isabel Cristina, A. P. (2021). Opportunities for the digital transformation of the banana sector supply chain based on software with artificial intelligence. *Metaverse*, *2*(1), 13. https://doi.org/10.54517/met.v2i1.1870
35. Jäger, G. (2021). Using Neural Networks for a Universal Framework for Agent-based Models. *Mathematical and Computer Modelling of Dynamical Systems*, *27*(1), 162–178. https://doi.org/10.1080/13873954.2021.1889609
36. Jetha, A., Crouch, M., Vold, K., Peters, S. E., Vietas, J., Sriharan, A., & Irvin, E. (2025). *Artificial Intelligence in the Workplace: A Living Systematic Review Protocol on*

Worker Safety, Health, and Well-being Implications. SSRN. https://doi.org/10.2139/ssrn.5124436

37. Jnr, B. A., & Petersen, S. A. (2023). Using an extended technology acceptance model to predict enterprise architecture adoption in making cities smarter. *Environment Systems and Decisions*, *43*(1), 36–53. https://doi.org/10.1007/s10669-022-09867-x
38. Kakkad, D. P., & Suresh, N. (2023). *Artificial Intelligence and Work Life Balance of Faculties: An Attempt to Review the Optimistic Angles*.
39. Kanchanatawan, B., Sriswasdi, S., & Maes, M. (2019). Supervised machine learning to decipher the complex associations between neuro-immune biomarkers and quality of life in schizophrenia. *Metabolic Brain Disease*, *34*(1), 267–282. https://doi.org/10.1007/s11011-018-0339-7
40. Karaboga, T., Erdal, N., Karaboga, H. A., & Tatoglu, E. (2023). Creativity as a mediator between personal accomplishment and task performance: A multigroup analysis based on gender during the COVID-19 pandemic. *Current Psychology*, *42*(15), 12517–12529. https://doi.org/10.1007/s12144-021-02510-z
41. Kostal, P., Mudrikova, A., & Michal, D. (2019). Possibilities of intelligent flexible manufacturing systems. *IOP Conference Series: Materials Science and Engineering*, *659*(1), 012035. https://doi.org/10.1088/1757-899X/659/1/012035
42. Lauriola, M., Tomai, M., Palma, R., La Spina, G., Foglia, A., Panetta, C., Raniolo, M., & Pontone, S. (2019). Intolerance of Uncertainty and Anxiety-Related Dispositions Predict Pain During Upper Endoscopy. *Frontiers in Psychology*, *10*, 1112. https://doi.org/10.3389/fpsyg.2019.01112
43. Li, X. (2022). Psychological Health Assessment Model of Enterprise Employees Based on DNN Technology. *Wireless Communications and Mobile Computing*, *2022*(1), 4824038. https://doi.org/10.1155/2022/4824038
44. Liu, L., Xie, J., Li, K., & Ji, S. (2020). Exploring How Media Influence Preventive Behavior and Excessive Preventive Intention during the COVID-19 Pandemic in China. *International Journal of Environmental Research and Public Health*, *17*(21), 7990. https://doi.org/10.3390/ijerph17217990
45. Loureiro, S. M. C., Bilro, R. G., & Neto, D. (2023). Working with AI: Can stress bring happiness? *Service Business*, *17*(1), 233–255. https://doi.org/10.1007/s11628-022-00514-8
46. Martín-Ruiz, M., Valero Duboy, M. A., & Pau De La Cruz, I. (2013). Deployment and Validation of a Smart System for Screening of Language Disorders in Primary Care. *Sensors*, *13*(6), 7522–7545. https://doi.org/10.3390/s130607522
47. Mily Velayudhan, T. K., & Yameni, M. D. (2017). Quality of Work Life – A Study. *IOP Conference Series: Materials Science and Engineering*, *197*, 012057. https://doi.org/10.1088/1757-899X/197/1/012057
48. Müller-Pérez, J., Acevedo-Duque, Á., García-Salirrosas, E. E., Escobar-Farfán, M., Esponda-Pérez, J. A., Cachicatari-Vargas, E., Álvarez-Becerra, R., & Alcina De Fortoul, S. (2025). Factors influencing healthy product consumer behavior: An

integrated model of purchase intention. *Frontiers in Public Health*, *13*, 1576427. https://doi.org/10.3389/fpubh.2025.1576427

49. Mutonyi, B. R., Slåtten, T., & Lien, G. (2021). Fostering innovative behavior in health organizations: A PLS-SEM analysis of Norwegian hospital employees. *BMC Health Services Research*, *21*(1), 470. https://doi.org/10.1186/s12913-021-06505-1
50. Ooi, W. T., Tan, O. K., & Low, M. P. (2022). Workplace safety and hazards awareness among the China construction companies in Malaysia. *E3S Web of Conferences*, *347*, 05012. https://doi.org/10.1051/e3sconf/202234705012
51. Oravec, J. A. (2014). Expert Systems and Knowledge-Based Engineering (1984-1991): Implications for Instructional Systems Research. *International Journal of Designs for Learning*, *5*(2). https://doi.org/10.14434/ijdl.v5i2.12891
52. Parvar, M. R. F., Allameh, S. M., & Ansari, R. (2013). Effect of Quality of Work Life on Organizational Commitment by SEM (Case Study: OICO Company). *International Journal of Academic Research in Business and Social Sciences*, *3*(10), Pages 135-144. https://doi.org/10.6007/IJARBSS/v3-i10/285
53. Rahman, P., & Mehnaz, S. (2024). International Journal for Multidisciplinary Research (IJFMR). *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5054029
54. Ramu, A., & Haldorai, A. (2023). The Characteristics, Methods, Trends and Applications of Intelligent Systems. *Journal of Computing and Natural Science*, 91–102. https://doi.org/10.53759/181X/JCNS202303009
55. Rani, P. (2020). A Comprehensive Survey of Artificial Intelligence (AI): Principles, Techniques, and Applications. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)*, *11*(3), 1990–2000. https://doi.org/10.17762/turcomat.v11i3.13596
56. Riar, M., Morschheuser, B., Hamari, J., & Zarnekow, R. (n.d.). *How game features give rise to altruism and collective action? Implications for cultivating cooperation by gamification*.
57. Rick, V. B., Stebner, M., Dräger, L., Franken, A., Mertens, A., & Nitsch, V. (2024). Effects of AI-based technologies on employees' work engagement: Implications for the human-centered design of digital work. *Zeitschrift Für Arbeitswissenschaft*, *78*(3), 323–334. https://doi.org/10.1007/s41449-024-00438-1
58. Rong, G., Mendez, A., Bou Assi, E., Zhao, B., & Sawan, M. (2020). Artificial Intelligence in Healthcare: Review and Prediction Case Studies. *Engineering*, *6*(3), 291–301. https://doi.org/10.1016/j.eng.2019.08.015
59. S. Yaakub, S. Y., & Nik Abdullah, N. A. H. (2018). The Moderating Effects of Logistics and Supply Chain Issues on the Relationship Between Organisational Innovations, Entrepreneurial Orientation and Market Orientation of Smes in Malaysia. *The Journal of Social Sciences Research*, (SPI6), 973–985. https://doi.org/10.32861/jssr.spi6.973.985
60. Saptioratri Budiono, H. D., Nurcahyo, R., & Habiburrahman, M. (2021). Relationship between manufacturing complexity, strategy, and performance of manufacturing

industries in Indonesia. *Heliyon*, *7*(6), e07225. https://doi.org/10.1016/j.heliyon.2021.e07225

61. Shaffer Juliet Popper. (1995). *Multiple hypothesis testing*. 561–580.
62. Siqueira, G. D., Adeel, A., Pasha, P., Balushi, A. A., & Shah, S. A. R. (2021). Sustainable Transportation and Policy Development: A Study for Impact Analysis of Mobility Patterns and Neighborhood Assessment of Walking Behavior. *Sustainability*, *13*(4), 1871. https://doi.org/10.3390/su13041871
63. Sokas, A. (2012). Software Agent Finds Its Way in the Changing Environment. In H. Xu (Ed.), *Practical Applications of Agent-Based Technology*. InTech. https://doi.org/10.5772/37742
64. Suyudi, M., Suyatno, S., Rahmatullah, A. S., & Rachmawati, Y. (2020). Investigating the Influence of Entrepreneurial Leadership on Students' Entrepreneurial Intentions: Teacherpreneurship as a Mediating Variable. *European Journal of Educational Research*, *volume–9–2020*(volume–9–issue–4–october–2020), 1605–1614. https://doi.org/10.12973/eu-jer.9.4.1605
65. Syed, S. M., Subbalakshmi, A. V. V. S., Singh, D., Emani, S., & Basava, R. K. (2023). Design and Analysis of Human Resources Using Artificial Intelligence. *Journal of Law and Sustainable Development*, *11*(9), e829. https://doi.org/10.55908/sdgs.v11i9.829
66. Teo, T. S. H., Srivastava, S. C., & Jiang, L. (2008). Trust and Electronic Government Success: An Empirical Study. *Journal of Management Information Systems*, *25*(3), 99–132. https://doi.org/10.2753/MIS0742-1222250303
67. Trappey, A. J. C., Trappey, C. V., & Lin, S. C.-C. (2019a). Detecting Trademark Image Infringement Using Convolutional Neural Networks. In K. Hiekata, B. R. Moser, M. Inoue, J. Stjepandić, & N. Wognum (Eds.), *Advances in Transdisciplinary Engineering*. IOS Press. https://doi.org/10.3233/ATDE190155
68. Trappey, A. J. C., Trappey, C. V., & Lin, S. C.-C. (2019b). Detecting Trademark Image Infringement Using Convolutional Neural Networks. In K. Hiekata, B. R. Moser, M. Inoue, J. Stjepandić, & N. Wognum (Eds.), *Advances in Transdisciplinary Engineering*. IOS Press. https://doi.org/10.3233/ATDE190155
69. Valeriya, G., John, V., Singla, A., Yamini Devi, J., & Kumar, K. (2024). AI-Powered Super-Workers: An Experiment in Workforce Productivity and Satisfaction. *BIO Web of Conferences*, *86*, 01065. https://doi.org/10.1051/bioconf/20248601065
70. Valle, L., Costan, E., Costan, F., General, E., Alcantara, G., Kilat, R. V., Batican, I., Olivar, G. M., & Avila, D. (2022). Community extension MSME's entrepreneurial activities in relation to poverty reduction. *Frontiers in Sociology*, *7*, 1038006. https://doi.org/10.3389/fsoc.2022.1038006
71. Vatovec, E. (2011). Intelligent Value Chain Networks: Business Intelligence and Other ICT Tools and Technologies in Supply/Demand Chains. In S. Renko (Ed.), *Supply Chain Management—New Perspectives*. InTech. https://doi.org/10.5772/18850
72. Vigo, R., Zeigler, D. E., & Wimsatt, J. (2022). Uncharted Aspects of Human Intelligence in Knowledge-Based "Intelligent" Systems. *Philosophies*, *7*(3), 46. https://doi.org/10.3390/philosophies7030046

73. Wuczyński, M. (2020). The use of cognitive agent programs in management support. *Informatyka Ekonomiczna*, *2020*(3), 73–82. https://doi.org/10.15611/ie.2020.3.06
74. Yang, H.-H., & Lin, Y.-T. (2022). How Knowledge Sharing and Cohesion Become Keys to a Successful Graduation Project for Students from Design College. *Sage Open*, *12*(3), 21582440221121785. https://doi.org/10.1177/21582440221121785
75. Yikilmaz, İ., Güleryüz, İ., & Efe, Y. (2023). Workplace Fear of Missing Out and Telepressure: How Digital Workplace Challenges Contribute to Employee Burnout? *Üniversite Araştırmaları Dergisi*, *6*(3), 347–355. https://doi.org/10.32329/uad.1343420
76. Yulinda, E., Supian, K., & Saad, M. (2021). The Effect of Trust on the Fishing Industry Supply Chain Performance in Rokan Hilir Regency Riau Province, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *934*(1), 012044. https://doi.org/10.1088/1755-1315/934/1/012044
77. Zeng, N., Liu, Y., Gong, P., Hertogh, M., & König, M. (2021). Do right PLS and do PLS right: A critical review of the application of PLS-SEM in construction management research. *Frontiers of Engineering Management*, *8*(3), 356–369. https://doi.org/10.1007/s42524-021-0153-5
78. Zhang, J., She, L., Wang, D., & Shafiq, A. (2022). Chinese Consumers' E-Learning Satisfaction and Continuance Purchase Intention on Paid Online Python Course. *Frontiers in Psychology*, *13*, 849627. https://doi.org/10.3389/fpsyg.2022.849627
79. Zhang, Y., Qiao, S., Zhang, J., Lin, T.-H., Gao, C., & Li, Y. (2025). *A Survey of Large Language Model Empowered Agents for Recommendation and Search: Towards Next-Generation Information Retrieval* (arXiv:2503.05659). arXiv. https://doi.org/10.48550/arXiv.2503.05659
80. Zimmermann, G. (2024). What makes systems intelligent. *Discover Psychology*, *4*(1), 127. https://doi.org/10.1007/s44202-024-00245-z