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Research Article

AI-Based Expert System Framework for Product Development Stage Gate Decisions

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Abstract

The automotive industry is characterized by rapid technological advancements and increasing market competition, necessitating effective product development strategies. This paper presents an AI-based expert system designed to enhance decision-making at each stage of the product development process, utilizing a stage-gate framework. By integrating machine learning algorithms and data analytics, the expert system aids in evaluating project feasibility, risk assessment, and prioritization of product features. The system's effectiveness is demonstrated through a case study involving multiple automotive projects, showcasing its potential to optimize decision-making and improve project outcomes.

Keywords: Stage Gates, Expert System, Artificial Intelligence, Development Decisions, Machine Learning Algorithms, Python

1. Introduction

Artificial Intelligence (AI) and its underlying methodologies have taken a prominent place in the transformation of all organizational practices, thus also becoming indispensable components in projects and project-oriented organizations, accelerating effectiveness and efficiency in decision making and ensuring strategic direction in achievement of project goals and enhancing overall project performance.

The complexity of product development in the automotive industry calls for structured methodologies to ensure efficiency and effectiveness. The stage-gate process offers a framework for managing product development, dividing the process into stages with decision points (gates) to review progress. However, traditional methods often lack the agility required in contemporary markets. This study introduces an AI-based expert system that enhances the stage-gate model by providing data-driven insights, thereby facilitating more informed decision-making.

AI- Based Stage-Gate is a strategic approach for new Product Project Management and can be smart compass, guiding OEM 's to reduced time to market and minimized risks much better than traditional Stage – Gate. The Stage-Gate process consists of distinct stages (development phases) separated by gates (decision points). At each gate, projects are evaluated to decide whether to continue, pivot, or terminate. The proposed hybrid model integrates deep learning to analyze data and provide predictive insights, while the expert system applies rules and domain knowledge to guide decision-making.

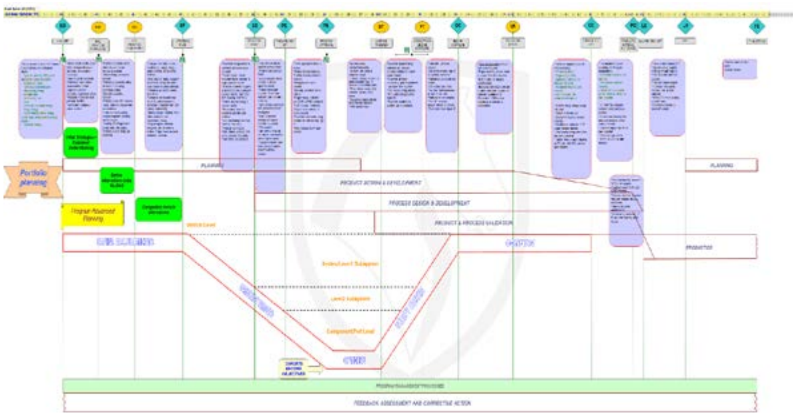


Figure 1: Generic OEM Stage-Gate

The development of the AI-based expert system involved the following steps:

1. Data Collection: Historical data from previous automotive projects were collected, including project timelines, budgets, success rates, and market trends.

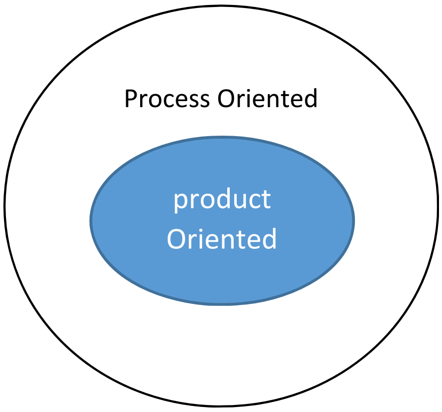
2. Model Development: Machine learning models were developed using classifiers such as Random Forest and Support Vector Machines to predict project outcomes based on input variables.

3. System Integration: The components of the expert system were integrated into a cohesive platform using Python and relevant libraries (e.g., Pandas, Scikit-Learn, Matplotlib).

4. Validation: The system was tested on several ongoing projects, with outcomes compared to traditional decision-making methods.

1.1 Literature Review and Methodology for AI Based Stage – Gate

Extensive research exists on product development methodologies, particularly the stage-gate process [1]. However, the integration of AI in decision-making processes is still emerging. Studies have shown that AI can decision-making efficiency, enhance predictive analytics, iPMO as an assistant tools, Egor Sarafanov, Omid Fatahi Valilai & Hendro Wicaksono proposes a causal model describing multivariate causal relationships between the driving factors, and the willingness to adopt AI [2-5]. The Relevance of Artificial Intelligence in Project Management [6]. This literature underscores advances in AI adoption and Some challenges, One of the important challenges is trusting the output and replacing it with expert decisions and information systems of organizations and the need for adaptive expert systems that leverage data and AI in high-stakes environments like automotive development [7]. In some classifiction the is three type of AI: Narrow AI, General AI and Super AI. In some researches The role of artificial intelligence in project management has considered and from Narrow AI to Strong AI provide four type AI based project [8-10]. In our Methodology we defined this role as Product oriented and Process oriented.



The AI-Based Expert System for stage- gate decisions intersect in this two domain and integrates several components in stage – gate decisions:

1. Input Module: Gathers data from various sources, including market research, customer feedback, and historical project data.

2. Analysis Engine: Applies machine-learning algorithms to analyse the input data, assessing feasibility, risks, and opportunities.

3. Decision Support Module: Offers recommendations based on analysis results, guiding the project team through each stage and gate.

4. Output Module: Presents findings and recommendations in a user-friendly interface, complete with visualizations and reports.

In the followings we detail each stage – gate milestones in automotive industry, focusing on AI based area in automotive development process and defined AI assistance in each gate [11].

1. Kick Off

o Objective: Determine if the project/program is viable.

o AI Assistance: Analyze market trends, assess feasibility reports, and evaluate potential risks using natural language processing (NLP) on project documentation.

o Data Inputs: Market analysis data, cost estimates, project timelines, stakeholder analysis.

o Output: Viability report highlighting strengths, weaknesses, and recommendations.

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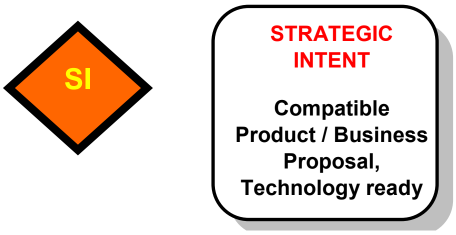


2. Strategic Plan

o Objective: Ensure the product/business proposal is compatible and technology is ready.

o AI Assistance: Evaluate technological readiness through historical data on similar projects and assess alignment with business goals.

o Data Inputs: Technical specifications, market compatibility studies, resource availability.

o Output: Compatibility scorecard with actionable insights.

3. Strategy Ready

o Objective: Confirm powertrain selection and Tier 1 suppliers are acceptable.

o AI Assistance: Optimize supplier selection and powertrain performance using predictive analytics and optimization algorithms.

o Data Inputs: Supplier performance history, cost analyses, technical evaluations of powertrains.

o Output: Supplier and powertrain selection report.

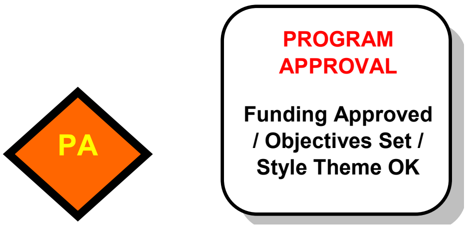
4. Package Sign Off

o Objective: Freeze package and hardpoints; Level 2 targets need to be validated.

o AI Assistance: Validate design parameters against performance criteria and previous case studies.

o Data Inputs: Design specifications, engineering change requests, simulation data.

o Output: Package validation report with risk assessments.



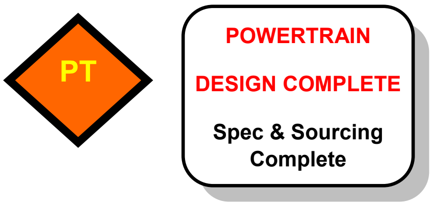
5. Program Approval

o Objective: Ensure funding is approved, objectives are set, and style themes are acceptable.

o AI Assistance: Financial forecasting and impact analysis on the budget and objectives alignment.

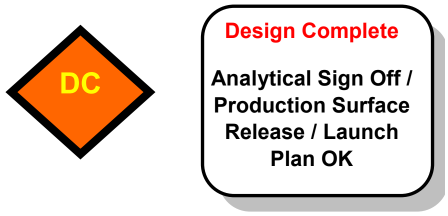
o Data Inputs: Budget forecasts, financial risk assessments, project objectives.

o Output: Program feasibility report and approval checklist.



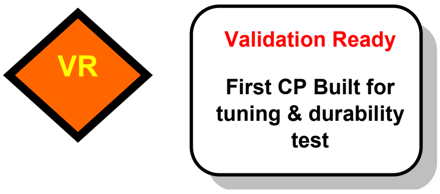
6. Powertrain: Design Complete

o **Objective:** Ensure specifications and sourcing are finalized.
o **AI Assistance:** Compare design specifications with industry benchmarks and compliance standards.
o **Data Inputs:** Design documents, sourcing contracts, compliance regulations.
o **Output:** Design compliance and sourcing readiness report.



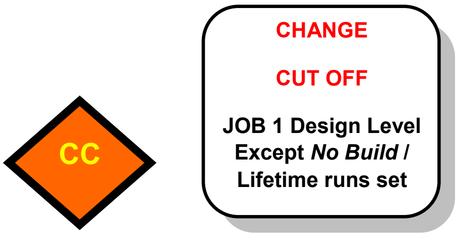
7. Design Complete

o **Objective:** Achieve analytical sign-off and establish a launch plan.
o **AI Assistance:** Use simulation tools to predict manufacturing outcomes and validate design against performance criteria.
o **Data Inputs:** Analytical models, production readiness data.
o **Output:** Launch readiness report.



8. Validation Ready

o **Objective:** Ensure the first prototype (CP) is ready for tuning and durability testing.
o **AI Assistance:** Analyze testing protocols based on historical data and anticipated performance metrics.
o **Data Inputs:** Testing strategies, past performance data, prototype specifications.
o **Output:** Validation strategy report.

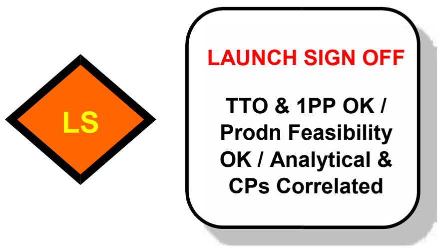


9. Change Cut Off

o **Objective:** Ensure design levels are set, and lifetime runs are established.
o AI Assistance: Benchmark against previous projects to minimize changes at this stage.
o **Data Inputs:** Change requests, design freeze data, lifecycle assessments.
o **Output:** Change management report.

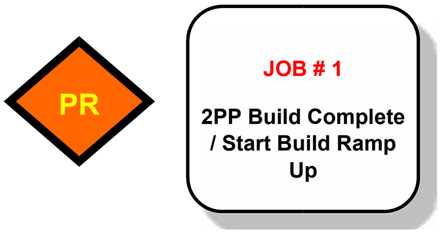
10. Pre-Prod Ready

o **Objective:** Confirm readiness for production.
o **AI Assistance:** Track parts readiness and production assembly tools using real-time data analytics.
o **Data Inputs:** Parts status, assembly tool assessments.
o **Output:** Pre-production readiness report.



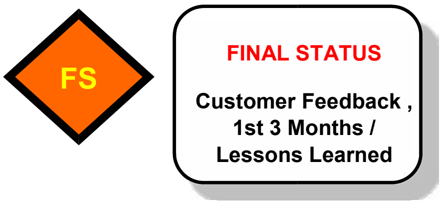
11. Launch Sign Off

o **Objective:** Evaluate production feasibility and validate analytical results.
o **AI Assistance:** Correlate analytical models with actual production capabilities to predict success.
o **Data Inputs:** Production metrics, analytical data, market feedback.
o **Output:** Launch sign-off report summarizing feasibility.



12. JOB #1

o **Objective:** Complete the second production process (2PP) build and ramp up production.
o **AI Assistance:** Monitor production processes and provide insights on ramp-up efficiency.
o **Data Inputs:** Production schedules, output reports.
o **Output:** Production performance analysis.



13. Final

o **Objective:** Gather customer feedback and lessons learned from the first three months of launch.
o **AI Assistance:** Analyze customer feedback and identify trends using sentiment analysis.
o **Data Inputs:** Customer feedback surveys, performance data.
o **Output:** Final report with insights and recommendations for future projects.

2. AI-Based Expert System Framework

2.1 Knowledge Base

Store expert knowledge, regulatory standards, design principles, and best practices drawn from historical data, guidelines, and domain expertise.

2.2 Inference Engine

Utilize decision trees or rule-based reasoning to draw conclusions based on the data and knowledge base. For example, the system can assist designers in determining optimal material choices based on given constraints.

2.3 User Interface

Create an interactive dashboard that allows project managers and engineers to input parameters, view simulations, and receive automated insights regarding design choices, production schedules, and market opportunities.

2.4 Learning Component

Implement ML algorithms to continuously learn from new data, adjusting recommendations based on market trends, consumer feedback, and performance metrics, thereby refining the model over time.

2.5 Some Considerations

➢ **Collaboration:** Ensure collaboration between domain experts and data scientists during development to accurately capture the necessary knowledge.
➢ **Data Privacy:** Adhere to regulations regarding data privacy and protection, especially when handling consumer data for feedback and preferences.
➢ **Scalability:** Build your AI system with scalability in mind, allowing it to grow as more data becomes available or when new features are added to the vehicle product line.

By incorporating these AI-based expert systems and techniques, your project can achieve more efficient design processes, enhanced user experiences, and improved operational efficiencies, ultimately leading to a successful electric vehicle launch. Combining deep learning and expert systems into a hybrid model for a Stage-Gate process can significantly enhance decision-making during the product development cycle, such as for electric vehicles. Below is a detailed example of how this could work at various stages of the Stage-Gate model.

2.6 Integration of AI Features

• **Decision Support:** Use machine learning algorithms to predict success rates at each stage based on historical data.
• **Natural Language Processing (NLP):** Analyze text from reports and meetings to gauge sentiment and identify concerns.
• **Data Visualization:** Implement dashboards for real-time monitoring of project stages and deliverables.
• **Collaboration Tools:** Integrate with existing communication platforms (e.g., Slack, Microsoft Teams) for notifications and updates.

By implementing these features, the AI-based expert system can significantly streamline the automotive project management process, enhancing decision-making and improving project outcomes.

3. Scenario: Electric Vehicle (EV) Development Decisions by Hybrid Deep Learning & Expert System

3.1 Stage 1: Discovery

Objective: Identify opportunities and conduct preliminary market research.

• **Deep Learning:** Use deep learning models (like CNNs or LSTMs) to analyze images and text from social media, customer reviews, and market reports to identify trends and unmet needs in the EV market.

• **Expert System:** Compile rules based on market strategies and expert insights to evaluate the relevance of identified opportunities, filtering out those that do not meet certain criteria (e.g., profitability, alignment with corporate goals).

Decision: Proceed to Gate 1 if there's a feasible opportunity.

3.1.1 Gate 1: Initial Evaluation

Criteria: Market potential, alignment with business strategy.

• **Deep Learning Insights:** Present findings from the analysis regarding market trends and customer preferences.

• **Expert System Evaluation:** Check against predefined criteria, including alignment with corporate objectives and budget constraints.

Decision: Go or no-go based on analysis and expert evaluation.

3.2 Stage 2: Scoping

Objective: Conduct a more detailed investigation of market and technical feasibility.

• **Deep Learning:** Use regression models to predict sales and market size based on historical data and trends. Neural networks could also analyze potential technical challenges associated with the new vehicle design.

• **Expert System:** Develop a framework using decision rules to assess technical risks (e.g., availability of technologies, supplier reliability).

Decision: Proceed to Gate 2 if the scope seems promising.

3.2.1 Gate 2: Technical Feasibility

Criteria: Feasibility, resource capability, and risk assessment.

• **Deep Learning Outputs:** Evaluate predicted sales against resource capabilities. Utilize reinforcement learning models to suggest optimal resource allocation.

• **Expert System Decision Rules:** Use historical data to evaluate potential success rates, considering risk assessment rules.

Decision: Proceed or terminate based on risk versus reward analysis.

3.3 Stage 3: Development

Objective: Develop the prototype, conduct testing, and refine designs.

• **Deep Learning:** Implement computer vision using deep learning to monitor quality control during manufacturing. Predictive maintenance algorithms could analyze sensor data from prototypes to prevent failures.

• **Expert System:** Establish guidelines for quality assurance and assess compliance with regulatory standards, ensuring all design principles are followed.

Decision: Proceed to Gate 3 if prototypes meet performance and quality standards.

3.3.1 Gate 3: Development Completion

Criteria: Prototype performance, compliance, and market readiness.

• **Deep Learning Analysis:** Present performance metrics of prototypes compared to industry benchmarks using analytical models.

• **Expert System Evaluation:** Check adherence to safety standards and customer expectations, and evaluate whether feedback from initial testing aligns with industry guidelines.

Decision: Move to the next stage or revisit development.

3.4 Stage 4: Testing & Validation

Objective: Test the product in real-world conditions and validate customer feedback.

• **Deep Learning:** Analyze extensive feedback from testers using NLP to gauge sentiment and common issues. Predict user behavior and preferences using historical user data.

• **Expert System:** Define rules for assessing test results and customer feedback, enabling a comprehensive evaluation of the product's viability.

Decision: Proceed to Gate 4 if the product passes testing.

3.4.1 Gate 4: Launch Decision

Criteria: Market readiness, sales forecasts, operational readiness.

• **Deep Learning Forecasting Models:** Provide predictive models for market performance, sales forecasts, and potential customer adoption rates.

• **Expert System Assessment:** Review compliance with pre-established launch criteria, ensuring all operational aspects are aligned.

Decision: Launch if all criteria are met.

3.5 Benefits of the Hybrid Model

1. Comprehensive Insights: Deep learning models provide data-driven predictions, while expert systems leverage domain knowledge, resulting in well-rounded decision-making.

2. Continuous Learning: The hybrid model allows for continuous improvement. New data can refine both deep learning models and the rules of the expert system over time.

3. Improved Risk Management: The combined approach enhances risk assessment through predictive analytics and established expert knowledge.

3.6 Implementation Considerations in Python

• **Integration:** Ensure seamless integration between deep learning algorithms and the expert system for fluid data exchange.

• **Training:** Train deep learning models on historical data relevant to the electric vehicle industry. Engage domain experts to help create a well-defined rule set for the expert system.

• **Validation:** Continuously validate both systems through real-world outcomes to improve accuracy and reliability.

This hybrid model serves as a powerful framework for guiding critical design decisions in the electric vehicle development process, maximizing both innovation and market viability.

Citation: Zarei, A., Faridnia, R. (2024). AI-Based Expert System Framework for Product Development Stage Gate Decisions. *J Adv Civil Mech Eng, 1*(1), 1- 9.

Creating a complete implementation scenario that combines deep learning, an expert system, and provides analysis and plots in Python is complex and involves multiple steps. Below is a simplified outline and code snippets to help you get started with a basic framework. Note that this is illustrative and would require refinement for a real-world application.

4. Required Libraries

You'll need several libraries. Install them via pip if you haven't done so:

Pip install numpy pandas scikit-learn tensorflow matplotlib seaborn

Scenario for an Electric Vehicle (EV) Development Process. The Tasks Include:

1. Deep Learning Model: To predict sales based on features.

2. Expert System: A rule-based system to evaluate feasibility.

3. Data Visualization: Using matplotlib and seaborn.

4.1 Step 1: Data Generation

We'll create synthetic data representing various features for the EVs and their corresponding sales.

```
import numpy as np
import pandas as pd

# Seed for reproducibility
np.random.seed(42)

# Generate synthetic data
data_size = 1000
data = {
    'price': np.random.uniform(20000, 50000, data_size),
    'battery_capacity': np.random.uniform(50, 100, data_size),  # kWh
    'range': np.random.uniform(100, 400, data_size),  # miles
    'charging_time': np.random.uniform(0.5, 5, data_size),  # hours
    'sales': np.random.randint(1, 500, data_size)  # Random sales figures
}

df = pd.DataFrame(data)
df.head()
```

4.2 Step 2: Deep Learning Model

We'll create a simple neural network that predicts sales based on the features.

```
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

# Splitting data
X = df[['price', 'battery_capacity', 'range', 'charging_time']]
y = df['sales']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Building the neural network
model = Sequential()
model.add(Dense(64, activation='relu', input_dim=X_train.shape[1]))
model.add(Dense(32, activation='relu'))
model.add(Dense(1))  # Output layer

# Compiling the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Training the model
model.fit(X_train, y_train, epochs=100, batch_size=32, verbose=0)

# Evaluate the model
loss = model.evaluate(X_test, y_test)
print(f"Model Loss: {loss:.2f}")
```

4.3 Step 3: Expert System

We'll create a simple rule-based system to evaluate whether an EV meets certain criteria for market potential.

```
def expert_evaluation(row):
    if row['price'] < 35000 and row['range'] > 250 and row['battery_capacity'] > 70:
        return "High Potential"
    elif row['price'] < 45000:
        return "Moderate Potential"
    else:
        return "Low Potential"

df['potential'] = df.apply(expert_evaluation, axis=1)
```

4.4 Step 4: Sales Prediction Function

A function to predict sales using the trained model.

```
def predict_sales(input_data):
    return model.predict(np.array(input_data).reshape(1, -1)).flatten()[0]

# Example input
input_features = np.array([30000, 80, 300, 2])  # Sample features
predicted_sales = predict_sales(input_features)
print(f"Predicted Sales for input features {input_features}: {predicted_sales:.2f}")
```

4.5 Step 5: Data Visualization

We'll visualize the results to analyze the sales and potential.

```
import matplotlib.pyplot as plt
import seaborn as sns

# Sales vs Price
plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='price', y='sales', hue='potential', palette='viridis')
plt.title('Sales vs Price with Market Potential')
plt.xlabel('Price ($)')
plt.ylabel('Sales (Units)')
plt.show()

# Sales Distribution
plt.figure(figsize=(10, 5))
sns.histplot(df['sales'], bins=30, kde=True)
plt.title('Sales Distribution')
plt.xlabel('Sales')
plt.ylabel('Frequency')
plt.show()
```

5. Result & Conclusion

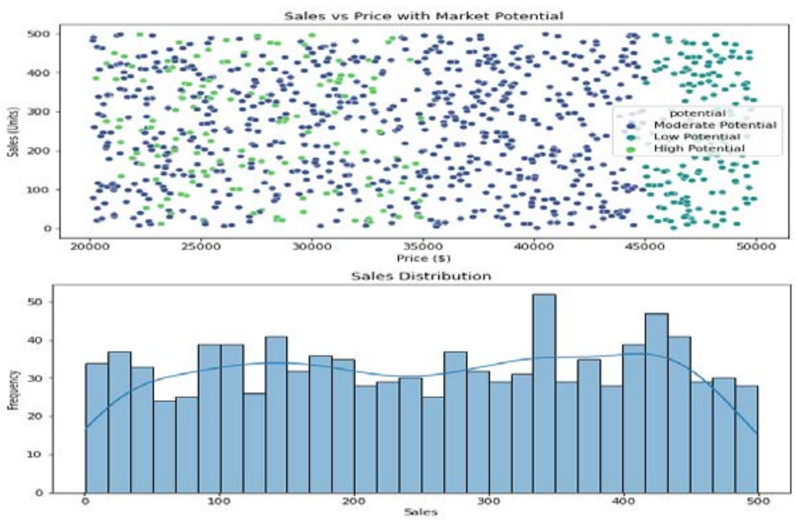


Figure 2: Predict Sales Based on Features. By Evaluate Feasibility by Deep Learning and Expert System by General Data Set

This implementation creates a basic framework for an EV development scenario using deep learning for sales predictions alongside an expert system for evaluating market potential. For a real-world application, we would need more extensive data, refine models, and possibly include more sophisticated decision-making processes [12-21].

6. References

1. Cooper, R. G. (1990). Stage-gate systems: a new tool for managing new products. *Business horizons, 33*(3), 44-54.
2. Chen, J., et al. (2012). The Role of Big Data in Business: A New Era for Decision-Making. *International Journal of Business and Management, 7*(5), 1-10.
3. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard business review, 96*(1), 108-116.
4. Mikhaylov, A. (2021, September). A Survey of Artificial Intelligence Tools in Project Management. In World Congress of the International Project Management Association (pp. 99-105). Cham: Springer Nature Switzerland.
5. Sarafanov, E., Valilai, O. F., & Wicaksono, H. (2023,

September). Causal Analysis of Artificial Intelligence Adoption in Project Management. In Proceedings of SAI Intelligent Systems Conference (pp. 245-264). Cham: Springer Nature Switzerland.
6. Obradović Posinković, T., & Vlahov Golomejić, R. D. (2024). The Relevance of Artificial Intelligence in Project Management. In The International Conference on Artificial Intelligence and Applied Mathematics in Engineering (pp. 88-99). Springer, Cham.
7. Bodea, C. N., Mitea, C., & Stanciu, O. (2020, October). Artificial intelligence adoption in project management: main drivers, barriers and estimated impact. *In Proceedings of the 3rd International Conference on Economics and Social Sciences* (pp. 758-767).
8. Wang, L., Liu, Z., Liu, A., & Tao, F. (2021). Artificial intelligence in product lifecycle management. *The International Journal of Advanced Manufacturing Technology,* 114, 771-796.
9. Wang, Q. (2019). How to apply AI technology in Project Management 1, 2.
10. Lahmann, M. (2018, September 7). AI will transform project management. PwC Switzerland.
11. Cooper, R. G. (2023). The artificial intelligence revolution in new-product development. *IEEE Engineering Management Review.*
12. Feyzioglu, O., & Buyukozkan, G. (2006). Evaluation of new product development projects using artificial intelligence and fuzzy logic. *In International conference on knowledge mining and computer science* (Vol. 11, pp. 183-189).
13. Ahmed, M. R., & Ahmed, B. (2023). Artificial Intelligence and Product Development. Ahmed, MR, & Ahmed, BE (2023). *Artificial Intelligence and Product Development, American Academy of Business Journal,*(27), 2.
14. Chai, T. Y., & Nizam, I. (2021). Impact of artificial intelligence in automotive industries transformation. ResearchGate.
15. Hofmann, M., Neukart, F., & Bäck, T. (2017). Artificial intelligence and data science in the automotive industry. *arXiv preprint arXiv*:1709.01989.
16. Madrid, J. A. (2023). The Role of Artificial Intelligence in Automotive Manufacturing and Design. *International Journal of Advanced Research in Science*. Tongxin Jishu.
17. Sanjay. C. P, Sam .R. (2022). Artificial Intelligence In Automobiles: An Overview, *International Journal of Engineering Applied Sciences and Technology.*
18. Despot, K., Srebrenkoska, S., & Sandeva, V. (2023). The role of artificial intelligence in automotive design. *KNOWLEDGE-International Journal, 61*(3), 423-429.
19. Manimuthu, A., Venkatesh, V. G., Shi, Y., Sreedharan, V. R., & Koh, S. L. (2022). Design and development of automobile assembly model using federated artificial intelligence with smart contract. *International Journal of Production Research, 60*(1), 111-135.
20. Regenwetter, L., Nobari, A. H., & Ahmed, F. (2022). Deep generative models in engineering design: *A review. Journal of Mechanical Design, 144*(7), 071704.
21. Bressoud, T., & White, D. (2020). Introduction to Data Systems: Building from Python. Springer.