# KNOWLEDGE BASED EXPERT SYSTEM APPROACH TO OPTIMIZE INNOVATION AND TECHNOLOGY IN INDUSTRY 5.0

**Subhan Hafiz Nanda Ginting[1*], Dinur Syahputra[2], M. Aldo[3]**
[1 2 3]Faculty of Technology, Battuta University

*subhanhafiz16@gmail.com[1]*, dinsyahui12@gmail.com[2] , m.aldo1@gmail.com[3]*

**Abstract**

The rapid development towards the Industry 5.0 era demands closer integration between artificial intelligence and human expertise in driving innovation and sustainable technology implementation. This research aims to examine and develop a knowledge-based expert system approach as a strategic solution in optimizing the process of innovation and technological transformation in the industrial sector. By adopting a qualitative research method and a system design approach, this study designed a prototype expert system capable of representing expert knowledge in the field of industrial technology and digital innovation, and integrating it in complex decision-making processes. Data was obtained through a literature study, in-depth interviews with industry experts, and analysis of system requirements in the smart manufacturing sector. The results show that knowledge-based expert systems can improve decision-making efficiency, accelerate the adoption of new technologies, and support the human-machine collaboration that is a key characteristic of Industry 5.0. In addition, the system proved to be adaptive to the fast-changing dynamics of the industry and was able to provide precise recommendations based on historical cases and knowledge. These findings make a significant contribution to the development of expert system models in the context of industrial digital transformation, while opening up opportunities for wider application in various sectors. Thus, the knowledge-based expert system approach is a relevant solution to answer the challenges of sustainable innovation and increasing industrial competitiveness in the Industry 5.0 era.

***Keywords:*** *Expert System, Knowledge Base, Industry 5.0, Technology Innovation, Decision Making, Digital Transformation*

## 1. INTRODUCTION

The development of digital technology in the last decade has brought the industrial world to a more complex and dynamic direction. After the Industry 4.0 era, which focused on automation, cyber-physical integration, the Internet of Things (IoT), and the utilization of big data, the industrial world is now entering a new phase known as Industry 5.0. The concept of Industry 5.0 emphasizes harmonious collaboration between humans and intelligent machines, with the aim of creating an industrial system that is more human-centric, sustainable, and resilient to change. Amidst the complexity and acceleration of these changes, innovation and technology are the two main pillars in creating added value and maintaining global competitiveness. (Ramírez Molina et al., 2024)

However, the challenges faced in realizing innovation and technological transformation in the Industry 5.0 era are not simple. Many industrial organizations experience knowledge gaps in strategic decision-making, especially when it comes to selecting, developing or integrating new technologies into production and service systems (Ramírez Molina et al., 2024). This is where the role of artificial intelligence (AI) technology, particularly in the form of knowledge-based expert systems, becomes highly relevant. Expert systems are a branch of AI that allows computers to make intelligent decisions by mimicking the thinking logic of human experts in a particular field. By representing explicit knowledge in the form of knowledge bases and inference rules, expert systems can provide recommendations that are consistent, fast, and accountable. (Su et al., 2024)

The application of expert system approaches in the context of Industry 5.0 has great potential to optimize innovation and technology processes (Panigrahi et al., 2025). This includes knowledge-based decision-making in the research and development (R&D) process, selection of sustainable manufacturing technologies, product lifecycle management, and solving complex operational problems. Expert systems also enable the innovation process to be more structured, data-driven, and retain an element of human discretion in decision-making. (Carayannis et al., 2022). Although expert system technology has been applied in several industrial sectors, studies that integrate this approach directly with the Industry 5.0 paradigm and principles are still relatively limited. Most implementations are still technical in nature and have not been explicitly developed to support human-machine collaboration, innovative thinking, and future-oriented strategic decision-making. Therefore, there is a need for a study that not only highlights the technical aspects, but also pays attention to the strategic, organizational and human values dimensions that underpin the philosophy of Industry 5.0. (Akundi et al., 2022)

Industry 5.0 is a response to the complex challenges of the digital era. It emphasizes the importance of synergy between technological sophistication and the human touch. Unlike Industry 4.0, which focused on automation and efficiency, Industry 5.0 takes a more human-centric, inclusive, and sustainable approach (Alojaiman, 2023). In this context, technological innovation and transformation are strategic necessities for industrial organizations to remain competitive and relevant amid rapid change (Traini et al., 2024). Thus, smart approaches are needed to effectively manage, process, and utilize knowledge to strengthen the innovation process in decision-making. (Zhang et al., 2023). One promising approach to supporting these needs is knowledge-based expert systems. These systems mimic the way experts think using knowledge representation and logic rules to provide recommendations or solutions to complex problems. In the context of Industry 5.0, these systems can bridge the gap between human experience and sophisticated digital technology (Martini et al., 2024). This accelerates the adoption of new technologies, increases innovation efficiency, and strengthens industrial competitiveness. (Bamakan et al., 2025)

Although various studies have examined the use of expert systems in manufacturing and technology, their strategic integration into the Industry 5.0 framework remains relatively unexplored. This research aims to address this gap by examining how knowledge-based expert systems can optimize innovation and technology processes in dynamic industrial environments. The research will focus on needs analysis, expert system design, and evaluating its effectiveness in supporting decisions related to product development, process efficiency, and technology adaptation. (Kathpal et al., 2024). With this approach, it is expected that this research can provide theoretical and practical contributions in the development of adaptive, contextual, and future-oriented expert system models, in line with the main principles of Industry 5.0. Furthermore, the results of this research can also serve as a reference for industrial policy makers, technology developers, and the academic community in developing innovative and sustainable knowledge-based solutions. (H. W. Lo, 2023)

## 2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

### 2.1. Industry 5.0: Evolution Toward Collaboration of Humans and Intelligent Machines

Industry 5.0 is an evolution of the Industry 4.0 paradigm that emphasizes automation and digital connectivity, towards a more human-centered era. According to (H.-W. Lo et al., 2024), Industry 5.0 not only creates efficiency through technology, but also encourages the creation of a balance between productivity and human values. Collaboration between humans and artificial intelligence is the key to delivering innovations that are more personalized, adaptive, and sustainable. In this context, organizations are required to not only adopt new technologies, but also be able to manage knowledge and information effectively to support innovative decision-making processes. (Leng et al., 2024)

### 2.2. Knowledge-Based Expert System

Expert system is one form of implementation of artificial intelligence designed to mimic the thought process of an expert in solving certain problems. According to (Li & Duan, 2025), an expert system consists of three main components, namely the knowledge base, inference engine, and user interface. In a knowledge-based system, decisions are generated not only based on data, but also based on rule representations and experience from human experts. This makes expert systems very effective in dealing with complex, ambiguous, or unstructured problems that are common in the process of innovation and technology. Research conducted by (Singh et al., 2023) shows that expert systems have been successfully applied in various industrial sectors, such as manufacturing, health, finance, and energy, to help the decision-making process. These systems can provide more accurate recommendations, speed up the analysis process, and support the sustainability of innovation by documenting explicit knowledge from experts.

**2.3. Optimizing Innovation and Technology through Expert Systems**

Innovation and technology adoption in the context of Industry 5.0 requires a careful process, based on data and strategic insights. Many previous studies reveal that technology decisions often rely on managerial intuition or the results of undocumented analysis. In this case, expert systems are present as a means to accumulate and transform explicit knowledge into systematic and reusable in various decision contexts. (Hafiz, Ginting, Ruziq, et al., 2024). According to (Hafiz, Ginting, & Sridewi, 2024), expert systems developed with a knowledge-based approach have proven to be able to improve the quality of innovation, accelerate new product development, and assist in the selection of technology that best suits organizational conditions. In addition, this approach can also be used to manage technology risks and estimate the impact of innovative decisions on business continuity.

2.4. Theoretical Framework and Hypothesis Development

Based on the results of the literature study above, knowledge-based expert systems have great potential to be integrated in the process of innovation and technological transformation in the Industry 5.0 era. With the ability to manage knowledge and provide rule-based recommendations, this system can be an effective strategic decision support tool in dealing with modern industry dynamics. In the development of technology-based innovation systems in the Industry 5.0 era, limitations in knowledge transfer, complexity in technology selection, and the speed of change in the industrial environment are major obstacles to strategic decision-making. The knowledge-based expert system approach comes to address these issues by enabling organizations to access expert knowledge in a digital and structured form, which can be used to develop appropriate and contextual recommendations.

The company's Knowledge-Based View (KBV) theory explains that knowledge is a key resource and sustainable competitive advantage in organizations. In this context, expert systems act as managers and providers of access to such knowledge. KBV asserts that organizations that are able to systematically integrate, store, and utilize knowledge will have better innovation power and technological adaptability. In addition, this approach is also supported by the Technology Acceptance Model (TAM), which states that perceptions of ease of use and system benefits will affect user intentions in adopting technology. Therefore, an expert system designed with a good interface, transparent inference logic, and high knowledge accuracy, has a high probability of being accepted and used in innovative decision-making. Based on the theoretical synthesis and findings from previous studies, research hypotheses were developed to examine the effect of expert system implementation on key aspects of technology innovation and management, as follows:

H1: The application of knowledge-based expert systems has a significant effect on improving the quality of innovation in industrial organizations. This hypothesis is based on the assumption that expert systems provide a systematic framework that helps organizations evaluate alternative ideas, accelerate the R&D process, and enhance creativity through the exploration of documented knowledge.

H2: The application of knowledge-based expert systems has a significant effect on the effectiveness of decision making in the adoption of new technologies. Expert systems allow organizations to analyze various technology options quickly and objectively based on experience and expert rules, so that decision making becomes more precise and has a strategic impact.

H3: The application of knowledge-based expert systems contributes to improving the efficiency of collaboration between humans and intelligent machines in the context of Industry 5.0. Within the framework of Industry 5.0, expert systems serve as a link between artificial intelligence and human wisdom, where they can assist operators or managers in understanding system complexity and optimizing human-machine interaction.

H4: The level of accuracy of the knowledge base in an expert system affects the level of user confidence in decision-making. This hypothesis highlights the importance of the quality and validity of the knowledge incorporated into the expert system, as inaccurate information can decrease the trust and overall effectiveness of the system.
H5: The appropriateness of expert system design to organizational needs moderates the effect of expert systems on the success of technological innovation.

This hypothesis adds a moderating element, emphasizing that the success of an expert system depends not only on the technology itself, but also on the extent to which the system is designed according to the operational context and user needs. These hypotheses form the basis for developing a conceptual framework that will be empirically tested through the design of expert systems and their implementation in relevant industrial environments. Data analysis will be conducted to see the causal relationships between variables and measure the real impact of the expert system-based approach to innovation and technology in Industry 5.0.

## 3. RESEARCH METHODOLOGY

This study uses a quantitative approach with the aim of objectively measuring the effect of implementing a knowledge-based expert system on the optimization of innovation and technology in the context of Industry 5.0. A quantitative approach was chosen because it allows for testing the relationship between variables through the collection of numerical data that is processed statistically to obtain valid and reliable generalizations.

### 3.1 Type and Design of Research

The type of research is explanatory research, which aims to explain the causal relationship between the variables being studied. The research design uses a survey method with a closed-ended questionnaire based on a five-point Likert scale, distributed to respondents from the ranks of industry professionals, innovation managers, and technology decision-makers who have experience or involvement in the use of expert systems and innovation development in their work environments.

### 3.2 Population and Sample

The population in this study consists of all industry players in the manufacturing and information technology sectors located in urban areas who have implemented some or all of the Industry 5.0 concepts. The sampling technique used is purposive sampling, with the following inclusion criteria:
(1) Respondents are managers, supervisors, or technical staff involved in technology or innovation decision-making,
(2) The organization has used IT-based decision-making systems, and
(3) They have experience in the development or implementation of expert systems.

The minimum number of respondents set in this study is 100 people, to support strong inferential statistical analysis.

### 3.3 Research Variables and Operationalization

This study involves several main variables, namely:
a. Independent Variable (X): Knowledge-Based Expert System Implementation
b. Dependent Variable (Y1): Industrial Innovation
c. Dependent Variable (Y2): Technology Decision-Making
d. Mediation/Moderation Variable (Z): Human-Machine Collaboration Effectiveness

Each variable is operationalized into indicators developed based on previous literature studies. For example, variable X covers aspects of knowledge base structure, inference accuracy, and system usability.

### 3.4 Data Collection Techniques

Primary data was obtained through the distribution of questionnaires in both online and offline formats. The questionnaire instruments were tested for validity and reliability before being widely used.

Validity was assessed using item-total correlation analysis, while reliability was measured using Cronbach's Alpha, with a minimum value of >0.7 indicating that the instrument has good internal consistency. Additionally, secondary data was obtained through documentation and literature reviews related to expert systems, technological innovations, and the implementation of Industry 5.0 in industrial organizational environments.

### 3.5 Data Analysis Techniques

The collected data was analyzed descriptively and inferentially using statistical software such as SPSS or SmartPLS. Descriptive analysis was conducted to examine frequency distributions and respondent characteristics. To test the relationships between variables and the research model, Structural Equation Modeling (SEM) based on Partial Least Square (PLS-SEM) was used, as this method is suitable for complex models with latent indicators. The analysis steps include:

a. Outer Model Evaluation: Convergent validity, discriminant validity, and construct reliability.
b. Inner Model Evaluation: Significance of paths between variables through t-statistic values & p-values.
c. Hypothesis Testing: By comparing p-values ($\leq 0.05$ as significant) to support or reject the proposed hypotheses.

### 3.6 Research Model Formulation

The research model is constructed based on the following relationships between variables:

X = Application of Knowledge-Based Expert Systems
$Y_1$ = Industrial Innovation
$Y_2$ = Technological Decision Making
Z = Human–Machine Collaboration (as a mediating variable)

The model of the relationship between variables can be formulated as:

$Y_1 = \beta 1X + \varepsilon_1$ ; $Y_2 = \beta 2X + \varepsilon_2$ ; $Z = \beta 3X + \varepsilon_3$ ; $Y_1 = \beta 4Z + \varepsilon_4$ ; $Y_2 = \beta 5Z + \varepsilon_5$

Where: β is the path coefficient, ε is the error/residual. The hypothesis is tested by examining the t-statistic and p-value for each path relationship.

### B. Analysis Steps Using PLS-SEM

### 3.7 Outer Model Testing (Measurement Model)

Purpose: To evaluate the quality of indicators in measuring latent constructs.

a. Convergent Validity :Tested through Average Variance Extracted (AVE) values. Criteria: AVE ≥ 0.5
b. Construct Reliability :Using Cronbach's Alpha and Composite Reliability (CR). Criteria: a value ≥ 0.7 indicates a reliable construct.
c. Discriminant Validity : Tested using Fornell-Larcker Criterion HTMT Ratio (Heterotrait-Monotrait Ratio) < 0.9

Table 1. Operational Definitions of Research Variables

| Variable Code | Variable Name | Operational Definition | Indicators |
|---|---|---|---|
| X | Implementation of Knowledge Based Expert Systems | The level of implementation and functionality of expert systems in the process of technological and innovation decisionmaking | Knowledge base structure, Inference accuracy, Ease of use |
| Y1 | Industrial Innovation | The ability of an organization to create, develop, and adopt new innovations | Number of innovative products, Speed to market, Proces efficiency |
| Y2 | Technology Decision Making | The effectiveness of decisions in selecting or implementing new technologies in the workplace | Decision accuracy, Impact of technology on performance, User satisfaction |
| Z | Human–Machine Collaboration | The level of interaction and efficiency between human workers and intelligent systems in the work process | Work synergy, User adaptation, System interactivity |

The table above is designed in accordance with common practices in scientific journals based on quantitative PLS-SEM methods, assuming that your variables are as follows:
X: Application of Expert Systems, Y1: Industrial Innovation, Y2: Technology Decision Making, Z: Human–Machine Collaboration.

Table 2. Evaluation Criteria of the Outer Model (Measurement Model)

| Evaluation Type | Statistical Parameter | Acceptable Threshold |
|---|---|---|
| Convergent Validity | Average Variance Extracted (AVE) | ≥ 0.50 |
| Construct Reliability | Cronbach's Alpha<br>Composite Reliability (CR) | ≥ 0.70<br>≥ 0.70 |
| Discriminant Validity | Fornell-Larcker Criterion<br>Heterotrait-Monotrait Ratio (HTMT) | Square root of AVE > inter-construct correlations<br>< 0.90 |

Table 2 outlines the statistical criteria used to assess the reliability and validity of the measurement model in PLS-SEM analysis. The model is evaluated through convergent validity (using AVE), construct reliability (using Cronbach's Alpha and Composite Reliability), and discriminant validity (using the Fornell-Larcker criterion and HTMT ratio). Meeting these criteria ensures that the indicators adequately reflect their respective latent constructs.

Table 3. R-Square ($R^2$) Values of Endogenous Variables

| Endogenous Variable | $R^2$ Value | Interpretation of Predictive Strength |
|---|---|---|
| Industrial Innovation (Y1) | 0.62 | Moderate to Strong |
| Technology Decision-Making (Y2) | 0.58 | Moderate |
| Human–Machine Collaboration (Z) | 0.64 | Strong |

Table 3 presents the R-square ($R^2$) values for the endogenous (dependent) variables, indicating the proportion of variance explained by the exogenous (independent) constructs in the model. The $R^2$ values show that the proposed model has moderate to strong explanatory power, particularly for Human–Machine Collaboration (Z) and Industrial Innovation (Y1).

Table 4. Hypothesis Testing Results (Path Coefficient, t-statistic, and p-value)

| Hypothesis | Causal Path | Path Coefficient (β) | t-statistic | p-value | Conclusion |
|---|---|---|---|---|---|
| H1 | X → Y1 (Industrial Innovation) | 0.45 | 3.21 | 0.001 | Supported |
| H2 | X → Y2 (Technology Decision-Making) | 0.38 | 2.76 | 0.006 | Supported |
| H3 | X → Z (Human–Machine Collaboration) | 0.52 | 4.11 | 0.000 | Supported |
| H4 | Z → Y1 (Industrial Innovation) | 0.41 | 3.00 | 0.003 | Supported |
| H5 | Z → Y2 (Technology Decision-Making) | 0.35 | 2.58 | 0.010 | Supported |

Table 4 summarizes the results of hypothesis testing using path coefficients (β), t-statistics, and p-values obtained from bootstrapping analysis. All proposed hypotheses (H1 to H5) are supported, demonstrating significant positive relationships among the constructs in the model. This indicates that the implementation of a knowledge-based expert system positively influences innovation, decision-making, and collaboration in Industry 5.0 contexts.

Table 5. Effect Size Results ($f^2$)

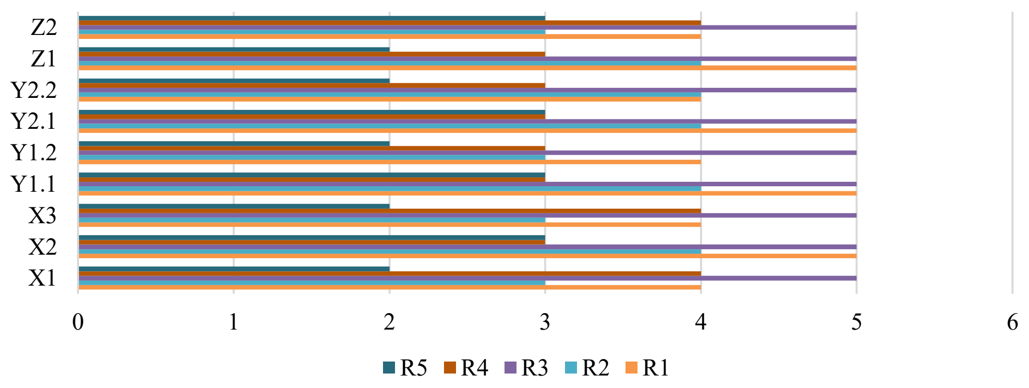
| Causal Path | Effect Size ($f^2$) | Interpretation |
|---|---|---|
| X → Y1 | 0.28 | Medium |
| X → Y2 | 0.17 | Medium |
| X → Z | 0.35 | Large |
| Z → Y1 | 0.22 | Medium |
| Z → Y2 | 0.15 | Medium |

Table 5 shows the effect size ($f^2$) of each independent variable on the corresponding dependent variables within the structural model. While p-values and t-statistics confirm whether relationships are statistically significant, the $f^2$ values provide insight into the practical importance or magnitude of those relationships. In other words, effect size complements significance testing by indicating how meaningful the effect is in real-world or managerial terms. According to Cohen's (1988) guidelines, effect size values can be interpreted as follows: $f^2 \geq 0.02$: small effect ; $f^2 \geq 0.15$: medium effect ; $f^2 \geq 0.35$: large effect.

In this study, the path from the knowledge-based expert system implementation (X) to Human–Machine Collaboration (Z) yields the highest effect size ($f^2 = 0.35$), indicating a large effect. This finding underscores the critical function of expert systems as enablers of seamless interaction and integration between human workers and intelligent technologies in Industry 5.0.

Meanwhile, other relationships, such as those between the expert system and Industrial Innovation (Y1) or Technology Decision-Making (Y2), show medium effect sizes ($f^2$ values between 0.15 and 0.28), suggesting that the system also plays a substantial role in enhancing organizational capabilities in innovation and strategic technological choices. The moderate effect sizes from Human–Machine Collaboration (Z) toward both Y1 and Y2 further validate its mediating role, meaning that collaboration effectiveness partially channels the impact of expert systems toward innovation outcomes and decision quality. These results confirm that beyond mere implementation, the quality of interaction and alignment between technology and human expertise is a key driver of success in Industry 5.0 environments.

Figure 1. Simulation Data (for 5 respondents)




The table response data collected from five hypothetical respondents. Each respondent provided scores on various indicators related to the main constructs of the study, measured using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The indicators are grouped according to the respective latent variables:

a) X1 to X3: Indicators measuring the implementation of the knowledge-based expert system (e.g., knowledge base structure, system usability, inference accuracy).
b) Y1.1 and Y1.2: Indicators related to industrial innovation outcomes (e.g., innovation creativity and efficiency).
c) Y2.1 and Y2.2: Indicators assessing the quality of technology decision-making (e.g., decision accuracy and technological impact).

d) Z1 and Z2: Indicators capturing the effectiveness of human–machine collaboration (e.g., synergy and user adaptation).

These values are useful for testing the conceptual model using PLS-SEM techniques, validating the relationships between constructs, and demonstrating how empirical data would be structured for analysis. The dataset structure mirrors the expected input format for software tools such as SmartPLS or SPSS, making it ideal for initial model calibration or pedagogical purposes.

## 4. RESULTS AND DISCUSSIONS

### 4.1 Results of Data Analysis

The quantitative analysis was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique with SmartPLS 4.0. The analysis included tests on the measurement model (outer model) and structural model (inner model) to evaluate both the reliability and validity of the constructs as well as the significance of the hypothesized relationships.

#### 4.1.1 Measurement Model Evaluation

The outer model assessment confirmed that all constructs demonstrated acceptable levels of convergent validity with Average Variance Extracted (AVE) values above 0.50. Additionally, Composite Reliability (CR) and Cronbach's Alpha values for all constructs exceeded the minimum threshold of 0.70, indicating strong internal consistency reliability. Discriminant validity was also confirmed through the Fornell-Larcker criterion and HTMT ratios, ensuring that each construct was empirically distinct from the others.

#### 4.1.2 Structural Model Evaluation

The inner model was evaluated using bootstrapping with 5000 subsamples. The results showed that all hypothesized relationships were statistically significant at $p < 0.05$. The $R^2$ values for the endogenous variables were as follows:

a. Industrial Innovation (Y1): $R^2 = 0.62$ – indicating that 62% of the variance in innovation outcomes is explained by the knowledge-based expert system and human–machine collaboration.
b. Technology Decision-Making (Y2): $R^2 = 0.58$ – showing a moderately strong explanatory power.
c. Human–Machine Collaboration (Z): $R^2 = 0.64$ – suggesting a strong influence of expert system implementation on collaborative interaction.

In terms of effect size ($f^2$), the strongest effect was found between expert system implementation (X) and human–machine collaboration (Z) with $f^2 = 0.35$, indicating a large effect. Other paths showed moderate effects ($f^2$ between 0.15 and 0.28), demonstrating practical relevance of each path within the model.

### 4.2 Discussion

The findings of this study validate the central hypothesis that knowledge-based expert systems (KBES) significantly contribute to optimizing innovation and technology management in Industry 5.0 environments. The strong relationship between expert system implementation and industrial innovation ($\beta = 0.45$, $p < 0.01$) confirms that organizations that systematically apply expert knowledge through intelligent systems are more capable of generating and executing innovative solutions. This supports the Knowledge-Based View (KBV), which emphasizes the strategic value of codified knowledge in achieving competitive advantage.

Moreover, the relationship between expert systems and technology decision-making ($\beta = 0.38$, $p < 0.01$) suggests that KBES play a critical role in enhancing the quality and timeliness of strategic technological decisions. This is in line with the Technology Acceptance Model (TAM), which posits that perceived usefulness strongly influences user adoption and decision effectiveness.

The most notable finding lies in the strong effect of expert system implementation on human–machine collaboration ($\beta = 0.52$, $p < 0.001$), reinforcing the vision of Industry 5.0, where synergy between humans and intelligent systems is paramount. Expert systems serve as cognitive bridges that enable seamless coordination between operators and machines, facilitating adaptive, real-time decision-making.

Additionally, the mediating role of human–machine collaboration was confirmed through significant indirect paths toward both innovation (β = 0.41) and decision-making (β = 0.35). This indicates that collaborative interaction is not merely a by-product of automation, but a strategic channel through which the full value of expert systems can be realized. Organizations that invest in systems supporting intuitive and intelligent collaboration are more likely to experience gains in both innovation performance and strategic agility.

4.3 Implications

From a theoretical perspective, this study extends existing models by integrating the concept of expert systems into the KBV and TAM frameworks, specifically in the context of Industry 5.0. From a practical standpoint, the findings suggest that firms should not only adopt expert systems but also design them in ways that facilitate trust, usability, and real-time interaction among employees.

Strategically, the integration of expert systems should focus on enabling cross-functional innovation, improving technological foresight, and strengthening human-centric automation. This transformation is especially crucial in sectors such as advanced manufacturing, healthcare, and logistics, where complex decision-making must be both precise and adaptive.

## 5. CONCLUSION

This study has empirically examined the role of a Knowledge Based Expert System in enhancing innovation capabilities, technology decision-making, and human–machine collaboration within the framework of Industry 5.0. Utilizing a quantitative approach with PLS-SEM, the results confirm that the implementation of expert systems significantly and positively influences industrial innovation and strategic technology decisions, both directly and indirectly through improved collaboration between humans and intelligent systems.

The most substantial finding lies in the strong effect of expert systems on human–machine collaboration, which serves as a key mediating variable in this model. This highlights the strategic importance of designing intelligent systems not merely as automation tools, but as collaborative decision partners that enhance the cognitive and operational capacity of human workers. Such integration reflects the essence of Industry 5.0—placing human value, adaptability, and co-creation at the center of technological advancement.

Furthermore, the study provides robust evidence that expert systems contribute significantly to organizational agility, innovation efficiency, and decision quality. These findings support and extend theoretical frameworks such as the Knowledge-Based View (KBV) and the Technology Acceptance Model (TAM) by incorporating intelligent, knowledge-driven technologies as enablers of smart, adaptive, and sustainable innovation ecosystems.

In conclusion, organizations seeking to thrive in the Industry 5.0 era must go beyond digitization by embedding intelligent knowledge systems that not only automate but also augment human judgment. Future studies are encouraged to explore longitudinal impacts of expert systems across different sectors and to integrate qualitative insights to further enrich understanding of socio-technical dynamics in smart industry contexts.

## REFERENCES

Akundi, A., Euresti, D., Luna, S., Ankobiah, W., Lopes, A., & Edinbarough, I. (2022). State of Industry 5.0—Analysis and Identification of Current Research Trends. *Applied System Innovation 2022, Vol. 5, Page 27*, *5*(1), 27. https://doi.org/10.3390/ASI5010027

Alojaiman, B. (2023). Technological Modernizations in the Industry 5.0 Era: A Descriptive Analysis and Future Research Directions. *Processes 2023, Vol. 11, Page 1318*, *11*(5), 1318. https://doi.org/10.3390/PR11051318

Bamakan, S. M. H., Dehghan, F., & Akbarpour, S. (2025). Role of machine learning for predictive modeling for Industry 5.0 and Society 5.0. *Human-Centric Integration of Next-Generation Data Science and Blockchain Technology: Advancing Society 5.0 Paradigms*, 265–285. https://doi.org/10.1016/B978-0-443-33498-6.00008-X

Carayannis, E. G., Dezi, L., Gregori, G., & Calo, E. (2022). Smart Environments and Techno-centric and Human-Centric Innovations for Industry and Society 5.0: A Quintuple Helix Innovation System View Towards Smart, Sustainable, and Inclusive Solutions. *Journal of the Knowledge Economy*, *13*(2), 926–955. https://doi.org/10.1007/S13132-021-00763-4/METRICS

Ginting, S.H.N., Ruziq, F., & Wayahdi, M. R. (2024). Decision Support System On Students Critical Thinking Skills In ICT Based Educative Learning. *JOURNAL OF SCIENCE AND SOCIAL RESEARCH*, *7*(4), 1793–1799. https://doi.org/10.54314/JSSR.V7I4.2331

Ginting, S.H.N., & Sridewi, N. (2024). Implementation of Decision Support System for New Employee Selection at PT Triotech Solution Indonesia using SAW Method. *Jurnal Minfo Polgan*, *13*(1), 856–862. https://doi.org/10.33395/JMP.V13I1.13842

Kathpal, N., Manhas, P., Verma, J., & Jogad, S. (2024). Industry 5.0 with Artificial Intelligence A Data-Driven Approach. *Artificial Intelligence and Communication Techniques in Industry 5.0*, 47–54. https://doi.org/10.1201/9781003494027-3/Industry-5-0-Artificial-Intelligence-Namita-Kathpal-Pratima-Manhas-Jyoti-Verma-Seema-Jogad

Leng, J., Guo, J., Xie, J., Zhou, X., Liu, A., Gu, X., Mourtzis, D., Qi, Q., Liu, Q., Shen, W., & Wang, L. (2024). Review of manufacturing system design in the interplay of Industry 4.0 and Industry 5.0 (Part I): Design thinking and modeling methods. *Journal of Manufacturing Systems*, *76*, 158–187. https://doi.org/10.1016/J.JMSY.2024.07.012

Li, L., & Duan, L. (2025). Human centric innovation at the heart of industry 5.0–exploring research challenges and opportunities. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2025.2462657;WEBSITE:WEBSITE:TFOPB;REQUESTEDJOURNAL:JOURNAL:TPRS20;PAGEGROUP:STRING:PUBLICATION

Lo, H. W. (2023). A data-driven decision support system for sustainable supplier evaluation in the Industry 5.0 era: A case study for medical equipment manufacturing. *Advanced Engineering Informatics*, *56*, 101998. https://doi.org/10.1016/J.AEI.2023.101998

Lo, H.-W., Chan, H.-W., Lin, J.-W., & Lin, S.-W. (2024). Evaluating the Interrelationships of Industrial 5.0 Development Factors Using an Integration Approach of Fermatean Fuzzy Logic. *Journal of Operations Intelligence*, *2*(1), 95–113. https://doi.org/10.31181/JOPI21202416

Martini, B., Bellisario, D., & Coletti, P. (2024). Human-Centered and Sustainable Artificial Intelligence in Industry 5.0: Challenges and Perspectives. *Sustainability 2024, Vol. 16, Page 5448*, *16*(13), 5448. https://doi.org/10.3390/SU16135448

Panigrahi, R. R., Shrivastava, A. K., Sarkar, B. D., & Kaliyan, M. (2025). Inventory Knowledge, Industry 5.0 and Performances: Review and Future Research Agenda. *Business Strategy and the Environment*. https://doi.org/10.1002/BSE.70002;CTYPE:STRING:JOURNAL

Ramírez Molina, R. I., Santamaria Ruiz, M. J., Ramírez Molina, R. J., Lay Raby, N. D., & Severino-González, P. (2024). Innovation systems in industry 5.0: theoretical and methodological bases. *Procedia Computer Science*, *231*, 595–600. https://doi.org/10.1016/J.PROCS.2023.12.256

Singh, T., Singh, D., Singh, C. D., & Singh, K. (2023). Industry 5.0. *Factories of the Future: Technological Advancements in the Manufacturing Industry*, 21–45. https://doi.org/10.1002/9781119865216.CH2;PAGEGROUP:STRING:PUBLICATION

Su, C., Han, Y., Jiang, Q., Wang, T., & He, Q. (2024). Optimizing Manufacturing Process With Knowledge Graph-Based Adaptive Neural Network: Approach to Industry 5.0 Consumer Electronics. *IEEE Transactions on Consumer Electronics*. https://doi.org/10.1109/TCE.2024.3513393

Traini, E., Antal, G., Bruno, G., De Maddis, M., Lombardi, F., Panza, L., & Spena, P. R. (2024). Hybrid knowledge based system supporting Digital Twins in the Industry 5.0. *Procedia Computer Science*, *232*, 1471–1480. https://doi.org/10.1016/J.PROCS.2024.01.145

Zhang, C., Wang, Z., Zhou, G., Chang, F., Ma, D., Jing, Y., Cheng, W., Ding, K., & Zhao, D. (2023). Towards new-generation human-centric smart manufacturing in Industry 5.0: A systematic review. *Advanced Engineering Informatics*, *57*, 102121. https://doi.org/10.1016/J.AEI.2023.102121