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Knowledge Discovery System and Their Challenges in Property Company: A Systematic Literature Review

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Abstract

In the era of digital transformation and data-driven decision-making, property companies face increasing challenges in managing large, heterogeneous, and unstructured datasets. Knowledge Discovery Systems (KDS) have emerged as essential tools for extracting actionable insights to support property valuation, market analysis, and urban planning. This study examines recent trends and challenges in KDS implementation within the property sector through a Systematic Literature Review (SLR) using the PRISMA framework, analyzing 23 publications from 2020 to 2025. The results indicate that KDS applications include machine learning–based real estate price prediction and semantic knowledge representation models. However, key challenges remain, including poor data quality, limited interdisciplinary collaboration, domain-specific constraints, and resistance to technological adoption. The novelty of this study lies in the development of a structured challenge framework that systematically synthesizes fragmented findings from prior studies, providing a comprehensive and domain-specific reference for improving KDS implementation in the property sector. This framework addresses critical gaps in the literature by clarifying the relationships between technical, organizational, and domain-related challenges. Overall, this review highlights the need for improved system adaptability, model explainability, and integration of domain knowledge to support more effective, data-driven property organizations.

Keywords: Data-Driven Decision-Making; Knowledge Discovery Systems; Machine Learning; PRISMA; Property Companies; Systematic Literature Review.

1. Introduction

In the era of digital transformation and big data, property companies face increasing challenges in managing large, heterogeneous, and rapidly evolving datasets derived from sources such as land transactions, urban planning records, construction documentation, and market intelligence. These datasets are often unstructured, spatially complex, and difficult to integrate, limiting their effective use in supporting strategic and operational decision-making (Abdulaziz & Zeki, 2020; Huang et al., 2021). As a result, property organizations require advanced analytical approaches that can transform complex data into meaningful and actionable knowledge.

Knowledge Discovery Systems (KDS) have emerged as important tools for addressing this need by integrating data mining, machine learning, semantic modeling, and AI-based decision support to identify patterns, relationships, and insights from large and complex datasets (Alby, 2024; Tian et al., 2023). In the property sector, KDS have been applied to support functions such as real estate price prediction, spatial analysis, and urban development evaluation. These systems enable organizations to move beyond traditional data processing toward more intelligent, data-driven decision-making while considering spatial, economic, and regulatory factors (Lazoglou & Angelides, 2020).

Despite their potential, the implementation of KDS in the property sector remains constrained by several technical and organizational challenges. These include poor data quality, semantic inconsistencies, limited explainability of AI models, insufficient integration of domain knowledge, and organizational resistance to data-driven approaches (Chuang et al., 2024). In many cases, KDS development has focused primarily on model performance, while neglecting critical aspects such as knowledge integration, interpretability, and practical usability, which are essential for effective decision support (Tripathi et al., 2021; Acevedo & Diaz-Molina, 2023).

Although previous studies have explored individual KDS applications and technical approaches, there is still a lack of comprehensive synthesis that examines implementation trends, key challenges, and research directions specific to the property sector. This gap limits the ability of researchers and practitioners to understand the broader landscape of KDS adoption and to develop more effective, adaptable, and explainable systems aligned with domain-specific requirements.

To address this gap, this study conducts a Systematic Literature Review (SLR) using the PRISMA framework with the following objectives:

1. To map current trends and application areas of Knowledge Discovery Systems in the property sector.
2. To identify key technical, semantic, and organizational challenges affecting KDS implementation.
3. To propose future research directions for developing more adaptable, explainable, and domain-integrated KDS frameworks.

By synthesizing interdisciplinary studies published between 2020 and 2025, this research provides a structured foundation for understanding the current state of KDS implementation and supports the development of more effective data-driven decision-making in the property sector.

2. Research Method

This study employs a Systematic Literature Review (SLR) following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure a transparent, structured, and replicable review process. The PRISMA methodology consists of four main stages: identification, screening, eligibility, and inclusion. This approach allows for systematic filtering of relevant studies and minimizes selection bias. The identification phase involved searching for relevant literature across major academic databases, including Scopus, Web of Science, IEEE Xplore, and Google Scholar. These databases were selected due to their comprehensive coverage of peer-reviewed research in information systems, artificial intelligence, and property-related domains. The search was limited to publications between 2020 and 2025 to capture recent developments in Knowledge Discovery Systems (KDS). The search queries used combinations of the following keywords:

a. “Knowledge Discovery System” OR “Knowledge Discovery in Databases” OR “KDD”
b. AND “property sector” OR “real estate” OR “urban planning” OR “land management”
c. AND “decision support” OR “data-driven decision-making”

Boolean operators (AND, OR) were applied to broaden or refine the search scope. This process resulted in an initial pool of records.

In the screening phase, duplicate records were removed using reference management tools and manual verification. The remaining articles were screened based on title and abstract to eliminate studies that were clearly unrelated to KDS implementation or the property domain.

Studies were excluded at this stage if they:

a. Focused on unrelated domains (e.g., healthcare, manufacturing, or finance without property relevance)
b. Did not involve knowledge discovery, data mining, or decision support systems
c. Were non-academic sources such as editorials, blog articles, or news reports

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This step ensured that only potentially relevant studies proceeded to the next stage.

a. Eligibility phase
   In the eligibility phase, full-text versions of the remaining articles were reviewed in detail. Each study was evaluated against predefined inclusion and exclusion criteria to ensure relevance and methodological rigor.
b. Inclusion Criteria:
   1. Peer-reviewed journal articles or conference proceedings.
   2. Studies explicitly addressing Knowledge Discovery Systems, Knowledge Discovery in Databases (KDD), or related analytical frameworks (e.g., CRISP-DM, semantic knowledge systems, AI-based decision support).
   3. Research applied to the property, real estate, urban planning, construction, or land management domains.
   4. Studies presenting empirical results, applied frameworks, or conceptual models relevant to KDS implementation.
   5. Publications written in English.
   6. Publications between 2020 and 2025.
   7. Full text accessible for review.
c. Exclusion Criteria:
   1. Studies not related to knowledge discovery, data mining, or decision support systems.
   2. Studies unrelated to the property or built-environment domain.
   3. Non-peer-reviewed publications, including editorials, commentaries, white papers, and unpublished theses.
   4. Studies lacking clear methodology or insufficient explanation of analytical processes.
   5. Studies with inaccessible or incomplete full text.
   6. Duplicate publications of the same research.

3. Result and Discussion

a. Current Research Trends on KDS in the Past Five Years

Table 1 presents a variety of systems and models that reflect the diverse applications of Knowledge Discovery Systems (KDS) across property-related domains. These systems combine data mining, machine learning, and knowledge management frameworks to support decision-making and prediction tasks. Based on Table 5, several notable research trends emerge in the application of Knowledge Discovery Systems (KDS) in the property sector:

b. Increased Use of Machine Learning and Hybrid Models

Recent studies in property-related Knowledge Discovery Systems (KDS) increasingly adopt machine learning (ML) and ensemble models to enhance predictive performance:

a) Paper (Y. Huang et al., 2021) developed a rental rate forecasting system using XGBoost, RF, and SVMR, finding XGBoost to be the most accurate for regional rental analysis.
b) Paper (Abdulaziz & Zeki, 2020) evaluated tree-based models like XGBoost, Random Forest, and LightGBM for property price prediction in the UK. These models outperformed traditional regression and demonstrated strong generalizability.
c) Paper (Tian et al., 2023) proposed a hybrid LSTM–RF–XGBoost model for home appliance demand forecasting, outperforming single models by handling temporal and nonlinear features effectively.
d) Paper (Alby, 2024) used a CatBoost + SVM stacked model to predict design change costs in Korean apartment projects, integrating textual and numeric features via ML and NLP.

A noticeable transition is occurring from traditional statistical approaches toward AI-driven, multi-model predictive systems. This shift enhances both the accuracy and robustness of forecasting across various real estate applications, enabling more reliable decision-making in complex and dynamic market environments.

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Table 1. *KDS in Property Company*

References	KDS
(Abdulaziz & Zeki, 2020)	WEKA-based Data Mining System using CRISP-DM and Linear Regression for prediction land price
(Lazoglou & Angelides, 2020)	Land-Use Decision spport system (LUDUS) using Ontologi, GIS, dan Object-Oriented Programming
(Acevedo & Diaz-Molina, 2023)	Proposes a theoretical model linking KM (acquisition, dissemination, responsiveness) with innovative culture
(Rabhi et al., 2021)	Property Price Prediction
(Das et al., 2021)	Geo-Spatial Network Embedding (GSNE) using Graph Neural Networks for prediction house price
(Laovisutthichai & Lu, 2023)	Develops a DfMA knowledge-to-action framework based on a real-world
(Zhou et al., 2024)	framework for knowledge transfer between project organizations.
(Tokede et al., 2022)	*facilitator as knowledge-broker* for knowledge discovery.
(Ni et al., 2025)	DEMATEL and ISM for *knowledge structuring* in construction
(Ayyasamy et al., 2022)	Forecast Model using XGBoost, RF, dan SVMR, dengan modul sistematis for Residential Rental Rates Forcasting
(Kang et al., 2020)	Real estate auction prediction system using Genetic Algorithm (GA), Artificial Neural Network (ANN), and Regression Model
(Özöğür Akyüz et al., 2023)	Hybrid Algorithm for House Price Prediction:
(Abdul-Rahman et al., 2021)	Predict house price using advanced machine learning
(Mathotaarachchi et al., 2024)	predicting property prices using XGBoost, LightGBM, Random Forest
(Wei et al., 2022)	Integration of Big Data and Hedonic Price Model (HPM) using Zillow
(Horváthová et al., 2024)	Bankruptcy prediction using Boosting Ensembles
(Mydyti et al., 2023)	Recommendation system using data mining techniques to improve decision-making in home appliance after-sales services using Decision Tree
(Ahn et al., 2024)	Stacked Model (CatBoost + SVM) for predicting design change cost of apartment project
(C. Huang et al., 2021)	Prediction model for real estate prices using *Apriori* dan *K-means*,

c. Integration of Geospatial and Graph-Based Techniques

Research has highlighted the importance of spatial context in property value prediction through geospatial and graph-based approaches:

a) Paper (Moretto et al., 2022) developed LUDUS, a spatial decision support system (SDSS) combining GIS, ontologies, and object-oriented programming to assist land-use planning based on legal, environmental, and infrastructure criteria.
b) Paper (Lazoglou & Angelides, 2020) introduced Geo-Spatial Network Embedding (GSNE) using Graph Neural Networks (GNNs) to model the relationship between houses and nearby POIs (e.g., schools, transit). This significantly improved price prediction accuracy.

There is an increasing adoption of location-aware and ontology-based systems within Knowledge Discovery Systems (KDS), reflecting a strategic effort to capture spatial dependencies. This trend enables more context-sensitive, intelligent decision-making support in real estate analytics and land-use planning.

d. Expansion of KDS Applications Beyond Pricing

Recent studies reveal a broader range of applications for Knowledge Discovery Systems (KDS) in the property sector, extending beyond traditional price forecasting:

a) Bankruptcy prediction using boosting ensembles (e.g., Gradient Boosting, Random Forest) has been applied to assess financial risk in real estate firms, providing early warnings for decision-makers (Shu & Ye, 2023).

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b) Design change cost prediction in apartment projects was developed using a stacked CatBoost + SVM model, enabling more accurate cost estimation and supporting proactive project planning (Alby, 2024).
c) Real estate auction prediction models combine Genetic Algorithms (GA) and Artificial Neural Networks (ANNs) to forecast auction results, enhancing bidding strategies and investment analysis (Aparicio et al., 2024).
d) Home appliance demand forecasting—relevant to post-property purchase behaviour—was explored using a LSTM–RF–XGBoost hybrid model, highlighting how KDS supports downstream consumer analytics in the property ecosystem (Tian et al., 2023); (Chuang et al., 2024).

The findings highlight an evolving trend in which Knowledge Discovery Systems (KDS) are no longer confined to property valuation tasks. Instead, they are increasingly applied throughout the entire property lifecycle—spanning financial risk assessment, construction cost estimation, auction price prediction, and post-purchase consumer behavior forecasting—thereby broadening the strategic role of KDS in the real estate domain.

e. Emphasis on Knowledge Management and Transfer

A growing body of research focuses on integrating knowledge management (KM) strategies within KDS to enhance learning, collaboration, and strategic decision-making in property-related projects:
a) Construction knowledge structuring is supported using DEMATEL and ISM to identify key enablers and barriers in safety knowledge sharing, especially among new-generation construction workers (Gloudemans & Sanderson, 2021).
b) A DfMA knowledge-to-action framework was developed to help architects translate multidisciplinary knowledge into actionable design decisions through iterative collaboration, highlighting the role of KM in early-stage design integration (Tripathi et al., 2021).
c) In a study of Chilean companies, KM practices—acquisition, dissemination, and responsiveness—were shown to significantly influence the development of an innovative culture, underlining the strategic value of KM in organizational transformation (Acevedo & Diaz-Molina, 2023).

These studies indicate that modern Knowledge Discovery Systems (KDS) are progressively integrating organizational learning mechanisms. By embedding structured knowledge management (KM) processes, KDS are evolving into platforms that transform analytical insights into actionable knowledge, thereby facilitating continuous improvement in project execution and fostering innovation within property-related organizations.

f. Framework-Oriented and Systematic Methodologies

Several studies emphasize the importance of systematic, modular, and repeatable approaches to implementing Knowledge Discovery Systems (KDS) in the property sector. These frameworks improve consistency, scalability, and usability in decision-making processes.
a) A Drools-based KDS framework was developed to automate operational decision-making through rule engines. Although originally applied in the power sector, this approach illustrates the potential of business rule management systems (BRMS) to structure domain knowledge and support automated reasoning in KDS environments (Rabhi et al., 2021).
b) In residential rental forecasting, a modular pipelined framework was designed, incorporating a geographic data handler, analytical dashboard, and price prediction module. This architecture allows seamless integration of spatial data, rental analytics, and user-friendly market visualizations to support investor decisions. For auction and short-term rental prediction, systematic components such as price monitoring dashboards and LDA-based sentiment analysis were embedded within the KDS design, indicating a shift toward dashboard-driven KDS tools that combine predictive analytics with modular UI/UX features (Y. Huang et al., 2021; Aparicio et al., 2024).
c) A study on land price prediction in Bahrain explicitly adopted the CRISP-DM methodology—a widely recognized standard in data mining projects. This structured approach was used to guide the full model development process, from business understanding to data preparation and model

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evaluation, demonstrating the value of process discipline in KDS implementations (Abdulaziz & Zeki, 2020).

These examples reflect a growing emphasis on framework-oriented development of Knowledge Discovery Systems (KDS), characterized using modular architecture, rule-based engines, and standardized methodologies such as CRISP-DM. This structured approach enhances repeatability, adaptability, and strategic alignment with complex decision-making requirements in the real estate domain.

g. Challenges in the Implementation of KDS in the Property Sector

Table 6 presents a synthesis of the key challenges identified in the implementation of Knowledge Discovery Systems (KDS) within the property industry, as reported across various studies. These challenges are categorized into seven thematic areas based on recurring patterns in the literature: Interdisciplinary & Collaboration Challenges, Data Quality & Technical Complexity, Domain-Specific Limitations, Adoption & Integration Barriers, Model Performance & Generalizability, Cultural & Organizational Resistance, and Computational & Resource Constraints. Each category is supported by references to specific studies, which highlight the contextual barriers and technical issues encountered. In addition, Knowledge Representation Issues are also identified as a standalone concern, reflecting limitations in data annotation, transfer learning, and organizational readiness. This classification aims to provide a comprehensive understanding of the multifaceted barriers that hinder effective KDS deployment in real-world property-related scenarios.

h. Interdisciplinary and Collaboration Challenges

The implementation of Knowledge Discovery Systems (KDS) in the property sector faces serious barriers due to limited collaboration and weak interdisciplinary integration. Many property development projects are still managed using a fragmented approach, where different actors—such as architects, engineers, contractors, and suppliers—work in isolation. This separation leads to difficulties in sharing and contextualizing knowledge that is essential for effective KDS deployment.

As shown in paper (Tripathi et al., 2021), the application of knowledge-intensive approaches like Design for Manufacture and Assembly (DfMA) requires project teams to integrate knowledge from diverse domains, including design, manufacturing, logistics, and site assembly. However, when team members do not work closely together or lack mutual understanding, it becomes difficult to turn this interdisciplinary knowledge into actionable insights. In addition, inter-organizational knowledge transfer is often hindered by cultural differences, weak communication links, and a lack of shared trust.. Furthermore, the project-based nature of the property industry often limits long-term collaboration and reduces opportunities for continuous learning. Without these roles, psychological safety is low, and team members may be reluctant to engage in open dialogue or share experiential knowledge.

Overall, these challenges highlight the importance of promoting cross-disciplinary teamwork, building stronger inter-organizational relationships, and assigning dedicated roles to support knowledge sharing. Without addressing these collaboration issues, the potential benefits of KDS in improving decision-making and innovation within property companies may remain unrealized.

i. Data-Related and Technical Challenges

The implementation of Knowledge Discovery Systems (KDS) in the property sector is significantly constrained by data-related and technical limitations. Real estate datasets are characterized by high variability, sparsity, and non-linear relationships, which complicate predictive modelling and increase the risk of overfitting (Acevedo & Diaz-Molina, 2023; Abdulaziz & Zeki, 2020). For example, land price prediction studies have shown that uneven spatial price distributions reduce the effectiveness of traditional regression models, highlighting the need for more robust modelling approaches.

Data quality also remains a critical barrier. Property datasets are typically collected from heterogeneous sources, including official registries, online listings, and market platforms, which often use inconsistent formats, classifications, and terminology (Huang et al., 2021). These inconsistencies complicate preprocessing, feature extraction, and semantic alignment. In addition, reliance on external geospatial services introduces integration complexity and scalability constraints, limiting the operational efficiency of KDS in large-scale property environments. These

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challenges highlight the importance of improved data engineering practices, including standardized data formats, robust preprocessing pipelines, and better geospatial integration.

Table 2. *Challenges of KDS in Property Company*

Challenges	References
Interdisciplinary & Collaboration Challenges	(Tripathi et al., 2021) : Interdisciplinary knowledge gaps, lack of collaboration with downstream stakeholders, difficulty translating tacit knowledge.
Data Quality & Technical Complexity	(Y. Huang et al., 2021) : Language irregularities (mixed English/Malay/Mandarin), costly Google Maps API.
	(Abdulaziz & Zeki, 2020) : High variance in land prices, nominal data impact on regression, sensitivity to outliers.
	(Acevedo & Diaz-Molina, 2023) : Lack of explicit knowledge representation, ad hoc analyst-dependent practices, technical complexity in model reuse.
Domain-Specific Limitations	(Abdulaziz & Zeki, 2020) : Unstructured Chinese text, complex defect logic, limited generalizability to other languages/industries.
	(Rabhi et al., 2021): Domain-specific jargon in construction text mining, ethical/legal concerns.
Adoption & Integration Barriers	(Moretto et al., 2022) : Complex legal frameworks, multidisciplinary data requirements, stakeholder coordination issues.
	(Chuang et al., 2024) : Low technology adoption in construction, data privacy/security challenges.
	(Azizah et al., 2025) : AI model explainability, high data requirements.
Model Performance & Generalizability	(Alby, 2024) : Dataset limited to Korean apartments, challenges with non-numeric variables.
	(Gloudemans & Sanderson, 2021): Generational differences among workers, low interpersonal trust.
	(Rohayati et al., 2025) : Complex preprocessing, missing location-quality features.
Cultural & Organizational Resistance	(Shu & Ye, 2023) : Imbalanced financial data, industry-specific variability.
	(Tripathi et al., 2021) : Cultural resistance to change, weak innovation networks in emerging economies.
Computational & Resource Constraints	(Tian et al., 2023) : Complexity of ensemble models, business resistance due to lack of explainability.
	(Lazoglou & Angelides, 2020) : High computational costs for geo-spatial network embedding.

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Knowledge Representation Issues	(Abdulaziz & Zeki, 2020) : Skill gaps in real estate organizations.
	(Page et al., 2021) : Lack of labeled data for transfer learning.

j. Domain-Specific Limitations

Domain-specific characteristics of property data further complicate KDS implementation. Many important property records—such as legal documents, inspection reports, and land descriptions—are stored in unstructured textual formats containing technical terminology and inconsistent classifications. This lack of standardized vocabularies reduces semantic consistency and limits the scalability of analytical models (Abdulaziz & Zeki, 2020).

Furthermore, variations in property classifications, regulatory frameworks, and documentation practices across regions reduce the transferability of machine learning models. Without domain-specific ontologies and structured semantic frameworks, KDS applications remain difficult to generalize across different property contexts.

k. Adoption and Integration Barriers

Beyond technical issues, organizational readiness remains a key barrier to KDS adoption in the property sector. Many property organizations operate with legacy systems, fragmented data infrastructures, and limited digital maturity, which restrict the integration of advanced analytical tools into operational workflows (Chuang et al., 2024). In addition, resistance to data-driven decision-making often arises due to limited technical expertise, lack of leadership support, and misalignment between analytical outputs and business needs.

Integration challenges are further compounded by the absence of clear data governance frameworks and interoperable IT architectures. Without proper alignment between technological capabilities and organizational processes, the practical impact of KDS remains limited.

l. Model Performance and Generalizability

Ensuring robust model performance and generalizability is another major challenge in property-related KDS applications. Real estate data are inherently heterogeneous and influenced by location-specific, economic, and regulatory factors, making it difficult to develop models that perform consistently across different regions (Gloudemans & Sanderson, 2021). Although advanced machine learning models can achieve high accuracy under specific conditions, their performance often depends heavily on data quality, feature selection, and preprocessing rigor (Alby, 2024).

The lack of standardized evaluation frameworks further complicates model comparison and validation across studies. This limitation reduces confidence in deploying KDS solutions at scale and highlights the need for more robust validation and benchmarking approaches.

m. Cultural and Organizational Resistance

Organizational culture and structural factors also influence the adoption of KDS. Resistance often arises from low data literacy, lack of innovation-oriented leadership, and limited experience with analytical systems (Acevedo & Diaz-Molina, 2023). In many property organizations, decision-making is still heavily reliant on experience-based judgment rather than data-driven insights.

This resistance is reinforced by concerns regarding system reliability, interpretability, and operational disruption. Overcoming these barriers requires leadership commitment, workforce training, and the development of data-driven organizational cultures.

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n. Computational and Resource Constraints

The implementation of KDS also requires significant computational infrastructure and technical expertise. Advanced modelling techniques, particularly those involving geospatial analytics and ensemble learning, demand substantial processing power, storage capacity, and technical skills (Lazoglou & Angelides, 2020). These requirements can limit adoption, especially in small- and medium-sized property firms with constrained resources.

In addition, the complexity of advanced models may reduce interpretability, creating challenges for business users who require transparent and explainable outputs for decision-making.

o. Knowledge Representation Challenges

Effective knowledge representation remains a fundamental challenge in property-related KDS. The absence of standardized semantic models and domain-specific ontologies limits the interpretability, transferability, and reuse of analytical insights (Abdulaziz & Zeki, 2020). Furthermore, gaps in data science expertise and limited integration between analytical outputs and business knowledge reduce the practical value of KDS in organizational contexts (Page et al., 2021).

Addressing these challenges requires the development of domain-specific semantic frameworks, improved knowledge integration mechanisms, and greater alignment between analytical models and property decision-making processes.

Discussion

a. Bridging the Gap Between KDS Capability and Practical Adoption

This review confirms that Knowledge Discovery Systems (KDS) in the property sector have reached significant technical maturity, particularly in predictive analytics, semantic integration, and geospatial analysis. However, this progress has not translated into widespread operational adoption. The main limitation lies not in model performance, but in organizational readiness, infrastructure compatibility, and user capacity. This indicates that successful KDS implementation requires not only advanced analytics but also supporting infrastructure, user training, and workflow integration.

b. Adoption Barriers in the Property Context

The adoption barriers identified—particularly explainability, usability, and trust—are more pronounced in the property sector due to its reliance on expert judgment and regulatory interpretation. Unlike fully automated industries, property decisions require transparent and interpretable outputs. Therefore, explainable AI (XAI) is essential to support decision justification, risk management, and regulatory compliance.

c. Integrated Nature of KDS Implementation Challenges

This study consolidates KDS challenges into interconnected technical and organizational dimensions. Technical issues such as data heterogeneity and model limitations are closely linked with organizational barriers, including resistance to change and limited digital readiness. This highlights the need for coordinated strategies involving technical development, organizational adaptation, and stakeholder engagement.

d. Strategic Role of Semantic Technologies

Semantic and ontology-based approaches are increasingly important in property-related KDS applications, particularly for handling unstructured legal, regulatory, and spatial data. These approaches enhance interoperability, improve knowledge representation, and support more context-aware decision-making, making them critical for modern property analytics systems.

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e. Importance of Organizational and Socio-Technical Factors

This review emphasizes that KDS success depends not only on technological capability but also on organizational culture, leadership support, and knowledge integration. Property organizations must adopt change management strategies and improve data literacy to ensure effective system utilization and long-term value creation.

f. Implications for Future Development

Future KDS development in the property sector should focus on integrated, human-centered systems that combine analytics with GIS, semantic models, and real-time data. Greater attention should be given to implementation strategies, governance frameworks, and domain-specific adaptation to ensure practical adoption. Ultimately, aligning technical capabilities with organizational and domain needs is essential to fully realize the benefits of KDS in property decision-making.

4. Conclusion

This Systematic Literature Review consolidates recent research on Knowledge Discovery Systems (KDS) in the property sector and contributes theoretically by framing KDS as a socio-technical system, where technical capability, organizational readiness, and domain knowledge jointly determine successful implementation. Unlike prior studies focused on isolated technical solutions, this review identifies systemic challenges—including data heterogeneity, lack of standardized frameworks, interdisciplinary gaps, and organizational resistance—highlighting that barriers to KDS adoption extend beyond purely technological issues.

The study also contributes to theory by positioning KDS at the intersection of knowledge management, artificial intelligence, and spatial decision-making. The findings emphasize the need to move beyond accuracy-driven models toward explainable, semantically structured, and context-aware systems that align with domain-specific requirements in property and real estate contexts.

However, this review has limitations. It focuses on literature published between 2020 and 2025, relies solely on secondary data, and includes studies with diverse methodologies and contexts, which may affect generalizability.

Future research should incorporate empirical case studies of KDS implementation in property organizations, develop domain-specific ontologies to improve semantic consistency, and integrate explainable AI to enhance trust and usability. Further investigation into the integration of KDS with GIS and digital twins, as well as longitudinal studies in emerging economies, is also needed to evaluate their impact on organizational performance and decision-making

References

Abdulaziz, M. H., & Zeki, A. M. (2020). Prediction of Real Estate Land Prices in the Kingdom of Bahrain. *2020 International Conference on Decision Aid Sciences and Application, DASA 2020*, 1220–1223. https://doi.org/10.1109/DASA51403.2020.9317063

Abdul-Rahman, S., Mutalib, S., Alam, S., Nor, M., Zulkifley, H., & Ibrahim, M. I. (2021). Advanced Machine Learning Algorithms for House Price Prediction: Case Study in Kuala Lumpur. *IJACSA) International Journal of Advanced Computer Science and Applications*, *12*(12), 736–745. https://doi.org/10.14569/IJACSA.2021.0121291

Acevedo, J., & Diaz-Molina, I. (2023). Learning organizations in emerging economies: the effect of knowledge management on innovative culture in Chilean companies. *Learning Organization*, *30*(1), 37–54. https://doi.org/10.1108/TLO-01-2021-0009

Ahn, I. S., Kim, J. J., & Lee, J. S. (2024). Development of a Cost Prediction Model for Design Changes: Case of Korean Apartment Housing Projects. *Sustainability (Switzerland)* , *16*(11), 4322. https://doi.org/10.3390/su16114322

Alby, T. (2024). Bridging the Analytics Gap: Optimizing Content Performance using Actionable Knowledge Discovery. *HT 2024: Creative Intelligence - 35th ACM Conference on Hypertext and Social Media*, 185–192. https://doi.org/10.1145/3648188.3675121

Aparicio, J. T., Arsenio, E., Santos, F., & Henriques, R. (2024). Using dynamic knowledge graphs to detect emerging communities of knowledge. *Knowledge-Based Systems*, *294*, 111671.

https://doi.org/10.1016/j.knosys.2024.111671

Ayyasamy, R. K., Tahavna, B., Subramaniam, S., Tan, F. J., Krisnan, S., & Tahayna, L. N. A. (2022). Design and Implementation of Residential Rental Rates Forecast Model using Data Mining Algorithms. *2022 3rd International Conference on Artificial Intelligence and Data Sciences: Championing Innovations in Artificial Intelligence and Data Sciences for Sustainable Future, AiDAS 2022 - Proceedings*, 176–181. https://doi.org/10.1109/AiDAS56890.2022.9918792

Becerra-Fernandez, I., & Sabherwal, R. (2015). *Knowledge Management* (Second Edition).

Carrera-Rivera, A., Larrinaga, F., & Lasa, G. (2022). Context-awareness for the design of Smart-product service systems: Literature review. *Computers in Industry*, *9*, 101895. https://doi.org/10.1016/j.compind.2022.103730

Chuang, H. C., Chen, C. C., & Li, S. T. (2024). Advancing SVM classification: Parallelizing conjugate gradient for monotonicity enforcement. *Knowledge-Based Systems*, *302*, 112388. https://doi.org/10.1016/j.knosys.2024.112388

Das, S. S. S., Ali, M. E., Li, Y. F., Kang, Y. Bin, & Sellis, T. (2021). Boosting house price predictions using geo-spatial network embedding. *Data Mining and Knowledge Discovery*, *35*(6), 2221–2250. https://doi.org/10.1007/s10618-021-00789-x

Gloudemans, R., & Sanderson, P. (2021). The Potential of Artificial Intelligence in Property Assessment. *Journal of Property Tax Assessment & Administration •*, *18*(2), 87–106. https://doi.org/https://doi.org/10.63642/1357-1419.1241

Horváthová, J., Mokrišová, M., & Schneider, A. (2024). The Application of Machine Learning in Diagnosing the Financial Health and Performance of Companies in the Construction Industry. *Information (Switzerland)*, *15*(6), 355. https://doi.org/10.3390/info15060355

Huang, C., Yang, Y., Wang, H., Zhang, X., Zhao, J., & Wan, J. (2021). Research and application of data mining algorithm. *Journal of Physics: Conference Series*, *1748*(3), 32043. https://doi.org/10.1088/1742-6596/1748/3/032043

Huang, Y., Shi, Q., Zuo, J., Pena-Mora, F., & Chen, J. (2021). Research Status and Challenges of Data-Driven Construction Project Management in the Big Data Context. *Advances in Civil Engineering*, *2021*(1), 6674980. https://doi.org/10.1155/2021/6674980

Kang, J., Lee, H. J., Jeong, S. H., Lee, H. S., & Oh, K. J. (2020). Developing a forecasting model for real estate auction prices using artificial intelligence. *Sustainability (Switzerland)*, *12*(7), 2899. https://doi.org/10.3390/su12072899

Kou, J., & Gedik, Y. (2019). New Behavioural Big Data Methods for Predicting Housing Price. *EAI Endorsed Transactions on Scalable Information Systems*, *6*(21), 1–8. https://doi.org/10.4108/eai.13-7-2018.158418

Laovisutthichai, V., & Lu, W. (2023). Design for manufacture and assembly (DfMA) in architectural design meetings: from a case study to knowledge-to-action framework. *Smart and Sustainable Built Environment*, *12*(5), 1117–1134. https://doi.org/10.1108/SASBE-07-2022-0136

Lazoglou, M., & Angelides, D. C. (2020). Development of a spatial decision support system for land-use suitability assessment: The case of complex tourism accommodation in Greece. *Research in Globalization*, *2*, 100022. https://doi.org/10.1016/j.resglo.2020.100022

Mathotaarachchi, K. V., Hasan, R., & Mahmood, S. (2024). Advanced Machine Learning Techniques for Predictive Modeling of Property Prices. *Information (Switzerland)*, *15*(6), 295. https://doi.org/10.3390/info15060295

Mohammadrezaei, E., Ghasemi, S., Dongre, P., Gracanin, D., & Zhang, H. (2024). Systematic Review of Extended Reality for Smart Built Environments Lighting Design Simulations. *IEEE Access*, *12*, 17058–17089. https://doi.org/10.1109/ACCESS.2024.3359167

Moretto, V., Elia, G., Schirinzi, S., Vizzi, R., & Ghiani, G. (2022). A knowledge visualization approach to identify and discovery inner areas: a pilot application in the province of Lecce. *Management Decision*, *60*(4), 1132–1158. https://doi.org/10.1108/MD-01-2021-0104

Mydyti, H., Kadriu, A., & Pejic Bach, M. (2023). Using Data Mining to Improve Decision-Making: Case Study of A Recommendation System Development. *Organizacija*, *56*(2), 138–154. https://doi.org/10.2478/orga-2023-0010

Ni, G., Zhou, Q., Miao, X., Niu, M., Zheng, Y., Zhu, Y., & Ni, G. (2025). What and how influence the safety knowledge sharing of new generation of construction workers in China: a study based on DEMATEL and ISM. *Engineering, Construction and Architectural Management*, *32*(4), 2160–2189. https://doi.org/10.1108/ECAM-11-2022-1065

Özöğür Akyüz, S., Eygi Erdogan, B., Yıldız, Ö., & Karadayı Ataş, P. (2023). A Novel Hybrid House Price Prediction Model. *Computational Economics*, *62*(3), 1215–1232. https://doi.org/10.1007/s10614-022-10298-8

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., Mcdonald, S., … Mckenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. In *The BMJ* (Vol. 372, p. n160). BMJ Publishing Group. https://doi.org/10.1136/bmj.n160

Rabhi, F. A., Bandara, M., Lu, K., & Dewan, S. (2021). Design of an innovative IT platform for analytics knowledge management. *Future Generation Computer Systems*, *116*, 209–219. https://doi.org/10.1016/j.future.2020.10.022

Rohayati, E., Rinaldi Dikananda, A., & Rohman, D. (2025). Journal of Artificial Intelligence and Engineering Applications Sales Data Analysis Using Linear Regression Algorithm on Raw Water Sales. *Journal of Artificial Intelligence and Engineering Applications*, *4*(2), 2808–4519. https://doi.org/ttps://doi.org/10.59934/jaiea.v4i2.809

Shu, X., & Ye, Y. (2023). Knowledge Discovery: Methods from data mining and machine learning. *Social Science Research*, *110*, 102817. https://doi.org/10.1016/j.ssresearch.2022.102817

Soltani, A., Pettit, C. J., Heydari, M., & Aghaei, F. (2021). Housing price variations using spatio-temporal data mining techniques. *Journal of Housing and the Built Environment*, *36*(3), 1199–1227. https://doi.org/10.1007/s10901-020-09811-y

Tian, D., Li, M., Shen, Y., & Han, S. (2023). Intelligent mining of safety hazard information from construction documents using semantic similarity and information entropy. *Engineering Applications of Artificial Intelligence*, *119*. https://doi.org/10.1016/j.engappai.2022.105742

Tokede, O., Ahiaga-Dagbui, D., & Morrison, J. (2022). Praxis of knowledge-management and trust-based collaborative relationships in project delivery: mediating role of a project facilitator. *International Journal of Managing Projects in Business*, *15*(4), 595–618. https://doi.org/10.1108/IJMPB-03-2021-0072

Tripathi, S., Muhr, D., Brunner, M., Jodlbauer, H., Dehmer, M., & Emmert-Streib, F. (2021). Ensuring the Robustness and Reliability of Data-Driven Knowledge Discovery Models in Production and Manufacturing. *Frontiers in Artificial Intelligence*, *4*, 576892. https://doi.org/10.3389/frai.2021.576892

Wei, C., Fu, M., Wang, L., Yang, H., Tang, F., & Xiong, Y. (2022). The Research Development of Hedonic Price Model-Based Real Estate Appraisal in the Era of Big Data. *Land*, *11*(3), 334. https://doi.org/10.3390/land11030334

Zhou, Q., Deng, X., Wang, G., Mahmoudi, A., & Zhang, N. (2024). Exploring the key drivers of inter-organizational knowledge transfer in projects: evidence from international construction projects. *Engineering, Construction and Architectural Management*, *31*(3). https://doi.org/10.1108/ECAM-05-2024-0692