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MATRIX-BASED COMPUTATIONAL MODELS FOR DECISION INTELLIGENCE: A SYSTEMATIC REVIEW OF COMPLEX SYSTEMS, DATA ANALYTICS, AND MANAGERIAL DECISION-MAKING

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ABSTRACT

Linear algebra has evolved from a foundational mathematical discipline concerned with vectors, matrices, transformations, and systems of equations into a computational language underlying modern analytics, optimization, network science, artificial intelligence, and decision support. Despite this extensive diffusion, research concerning matrix-based modelling remains fragmented across mathematics, computer science, operations research, engineering, information systems, and management. This systematic review develops an integrated perspective on how matrix representations and transformations have progressed from mathematical computation toward complex-system modelling and managerial decision intelligence. The review synthesizes literature around five interconnected domains: mathematical representation, matrix transformation, complex-system modelling, optimization and decision analysis, and management analytics. Particular attention is given to matrix decomposition, eigenvalue methods, singular value decomposition, principal component analysis, adjacency and transition matrices, multi-criteria decision-making, optimization, machine learning, and business analytics. PRISMA 2020 is adopted as the reporting framework, while bibliometric and thematic techniques are proposed for mapping the intellectual structure of the field. The synthesis indicates that matrices increasingly function not merely as computational objects but as representational infrastructures through which heterogeneous organizational data, relationships, dependencies, alternatives, and constraints can be transformed into decision-relevant structures. The review further develops a Matrix-to-Decision Intelligence (MDI) framework comprising four stages: representation, transformation, optimization, and decision intelligence. The framework positions linear algebra as a connective layer between data and managerial action and identifies emerging research opportunities around explainable matrix models, dynamic and high-dimensional systems, hybrid matrix-AI architectures, uncertainty-aware decision models, and human-centred decision intelligence. The study contributes a cross-disciplinary conceptual architecture for researchers seeking to connect mathematical modelling with contemporary management analytics.

Keywords: linear algebra; matrix-based models; decision intelligence; complex systems; management analytics; optimization; network science; machine learning; systematic review; bibliometric analysis

1. INTRODUCTION

The contemporary analytical enterprise is increasingly characterized by high-dimensional data, interconnected systems, multiple decision criteria, dynamic dependencies, and rapidly changing computational environments. Organizations no longer make decisions solely from isolated variables or conventional descriptive statistics. Strategic, operational, financial, human-resource, marketing, and supply-chain decisions frequently involve relationships

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among large numbers of entities and criteria. Such relationships require representations capable of preserving structure while remaining computationally tractable. Matrix-based modelling provides one of the most established mathematical mechanisms for accomplishing this task.

At its foundation, linear algebra provides a language for representing vectors, matrices, linear transformations, systems of equations, projections, orthogonality, eigenstructures, and decompositions. The development of matrix methods has consequently extended far beyond pure mathematics. Classical elimination, factorization, least-squares approximation, eigenvalue analysis, and singular value decomposition are now integral to numerical computing, statistical learning, dimensionality reduction, optimization, network analysis, and artificial intelligence. Contemporary treatments of linear algebra explicitly connect matrix computation with data analysis and computational methods, demonstrating the discipline's transition from abstract mathematical structure toward computational problem solving (Strang, 2021). Golub and Van Loan (2013), for example, present numerical linear algebra as a field simultaneously concerned with mathematical theory and practical computational implementation, including large-scale singular value decomposition, structured eigenvalue problems, parallel algorithms, and tensor computations.

The importance of this evolution becomes particularly apparent in management analytics. Organizational phenomena can be represented through matrices in numerous ways. A customer-product matrix may encode purchasing relationships; an employee-skill matrix can represent competency structures; a supplier-location matrix can characterize supply-chain relationships; a covariance matrix can represent financial risk; an adjacency matrix can capture organizational or interorganizational networks; and a decision matrix can encode alternatives against multiple evaluation criteria. Once such phenomena are represented mathematically, transformations and optimization procedures can reveal latent structure or identify decision alternatives.

This development also creates a conceptual bridge between linear algebra and decision intelligence. Decision support systems historically focused on helping managers structure and evaluate decisions through models, information, and computational resources (Power, 2002). Contemporary analytics extends this logic by integrating descriptive, predictive, and prescriptive methods. Matrix operations increasingly sit beneath these analytical layers. Data matrices support statistical learning, covariance matrices underpin dimensionality-reduction techniques, adjacency matrices represent networks, parameter matrices drive machine-learning models, and decision matrices structure multi-criteria evaluation.

Principal component analysis illustrates this transition particularly clearly. PCA transforms correlated variables into a smaller set of orthogonal components, thereby reducing dimensionality while retaining important variation in the data. Jolliffe and Cadima (2016) describe PCA as a central multivariate technique with applications across numerous analytical settings. Similarly, machine-learning methods rely extensively on linear algebra, probability, optimization, and matrix representations. Murphy (2012) explicitly situates linear algebra and optimization among the mathematical foundations of modern machine learning. Deep learning extends this dependence through layered transformations involving parameter matrices and numerical computation (Goodfellow et al., 2016).

Network science provides another important bridge. Networks can be represented through adjacency, weighted, transition, and Laplacian matrices. Newman (2010) identifies adjacency matrices, weighted networks, directed networks, graph Laplacians, and random walks as central mathematical tools for network analysis. Such representations allow organizational

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and economic systems to be analysed in terms of connectivity, centrality, influence, diffusion, dependencies, and structural change.

The literature, however, remains fragmented. Mathematical literature frequently emphasizes computational efficiency and theoretical properties; machine-learning literature emphasizes predictive performance; operations-research literature focuses on optimization; network science emphasizes structural relationships; and management literature tends to focus on managerial applications. What is comparatively less developed is an integrated framework explaining how matrix-based mathematical representations evolve into decision intelligence across complex organizational systems.

This review addresses that gap by examining the following trajectory:

Linear Algebra → Matrix Representation → Matrix Transformation → Complex-System Modelling → Optimization → Analytics → Decision Intelligence

The purpose is not to reduce decision intelligence to linear algebra. Rather, the objective is to identify linear algebra as one of the mathematical infrastructures through which complex organizational phenomena become computationally representable, analytically tractable, and potentially actionable.

2. REVIEW OBJECTIVES

The review pursues six objectives:

- To examine the evolution of matrix-based mathematical models from foundational linear algebra to contemporary computational analytics.
- To classify the major matrix-based techniques used in complex-system modelling and management analytics.
- To examine how matrix representations support optimization, network analysis, machine learning, and multi-criteria decision-making.
- To identify the pathways through which mathematical representations are transformed into decision-support information.
- To identify theoretical, methodological, computational, and managerial gaps in existing research.
- To develop an integrated Matrix-to-Decision Intelligence (MDI) framework for future research.

3. RESEARCH QUESTIONS

The review is structured around the following research questions:

- RQ1. How has matrix-based modelling evolved from classical linear algebra toward contemporary analytics and decision intelligence?
- RQ2. Which matrix-based mathematical techniques are most relevant to complex-system and management analytics?
- RQ3. How are matrices employed to represent relationships, dependencies, alternatives, uncertainty, and optimization problems?
- RQ4. How has the integration of matrix methods with machine learning, network science, and artificial intelligence changed analytical decision-making?

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- RQ5. What theoretical and methodological gaps remain at the intersection of linear algebra, complex systems, and management analytics?
- RQ6. How can matrix-based modelling contribute to next-generation decision-intelligence architectures?

4. CONCEPTUAL FOUNDATIONS

4.1 Linear Algebra as an Analytical Language

Linear algebra can be understood not merely as a collection of mathematical procedures but as a representational language. A vector may encode an observation, employee profile, product characteristics, financial position, or feature representation. A matrix may encode observations across variables, relationships among entities, transformations between spaces, or alternatives across decision criteria.

A general data matrix can be expressed as:

$$X = [x_{ij}],\ i = 1, \ldots, n;\ j = 1, \ldots, p$$

where n represents observations and p represents variables.

This formulation is deceptively simple. The same structure can support regression, classification, dimensionality reduction, clustering, optimization, forecasting, and decision analysis. Linear algebra therefore operates as a common mathematical substrate connecting different analytical paradigms.

Strang's (2021) treatment of vectors, matrices, linear equations, vector spaces, orthogonality, projections, and factorization illustrates the conceptual foundations from which these applications emerge.

4.2 Matrix Transformation

Matrix multiplication can represent transformations between spaces:

$$y = Ax$$

where x represents an input vector, A represents a transformation matrix, and y represents the transformed output.

This structure appears repeatedly across analytical disciplines. In organizational analytics, x may represent employee characteristics and A a transformation relating competencies to job requirements. In finance, a covariance matrix may transform portfolio weights into portfolio variance. In network analysis, multiplication by an adjacency matrix can propagate information across connected entities. In machine learning, weight matrices transform feature representations between computational layers.

Thus, matrix multiplication can be interpreted more broadly as a mechanism through which relationships and transformations are operationalized mathematically.

4.3 Matrix Decomposition

Matrix decomposition provides a mechanism for revealing hidden structure. A matrix may be decomposed as:

$$A = LU$$

or, under appropriate conditions,

$$A = QR$$

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and singular value decomposition provides:

$$A = U\Sigma V^T$$

SVD is particularly important because it allows high-dimensional data to be expressed through orthogonal latent components. Golub and Van Loan (2013) provide extensive treatment of large-scale SVD and structured eigenvalue problems, illustrating the computational significance of matrix decomposition.

In management analytics, decomposition can support:

- dimensionality reduction
- latent-factor identification
- customer segmentation
- recommendation systems
- document analysis
- financial risk modelling
- organizational similarity analysis

The conceptual significance is that decomposition transforms a large and potentially opaque structure into a set of interpretable mathematical components.

5. METHODOLOGY

5.1 Review Design

The study adopts a systematic literature review design supplemented by conceptual synthesis and bibliometric mapping. PRISMA 2020 is used as the principal reporting framework because it emphasizes transparent reporting of the rationale, search process, selection process, synthesis, and findings (Page et al., 2021). The PRISMA 2020 statement includes a 27-item checklist and revised flow diagrams.

Because the present manuscript does not incorporate a supplied database export, numerical counts of records retrieved, duplicates removed, screened papers, or included studies are intentionally not fabricated. For a camera-ready empirical systematic review, these fields should be populated from the actual Scopus/Web of Science/IEEE data-extraction process before submission.

5.2 Proposed Databases

A comprehensive search should cover:

- Scopus
- Web of Science Core Collection
- ScienceDirect
- IEEE Xplore
- SpringerLink
- ACM Digital Library
- Google Scholar for supplementary citation chasing

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Scopus and Web of Science should serve as the principal bibliometric sources where institutional access is available.

5.3 Search Strategy

The search strategy should combine four conceptual blocks.

Block A: Mathematical foundation

“linear algebra” OR matrix OR matrices OR “matrix model” OR “matrix-based”

Block B: Computational techniques

“matrix factorization” OR “singular value decomposition” OR eigenvalue OR “principal component analysis” OR optimization OR “matrix decomposition”

Block C: Complex systems

“complex system*” OR network* OR “network science” OR “system dynamics” OR “organizational network*”

Block D: Management and decision applications

“management analytics” OR “business analytics” OR “decision intelligence” OR “decision support” OR “multi-criteria decision” OR “strategic decision*”

A representative Scopus formulation is provided below (TITLE-ABS-KEY field):

TITLE-ABS-KEY(("linear algebra" OR matrix OR matrices OR "matrix-based model*") AND ("matrix factorization" OR "singular value decomposition" OR eigenvalue* OR "principal component analysis" OR optimization OR "matrix decomposition") AND ("complex system*" OR network* OR "network science" OR "system dynamics") AND ("management analytics" OR "business analytics" OR "decision intelligence" OR "decision support" OR "multi-criteria decision*" OR "strategic decision*"))

The exact search expression should be adapted to each database because controlled vocabulary, wildcard behaviour, and field codes differ.

5.4 Inclusion Criteria

Studies should be included when they:

- explicitly employ a matrix-based or closely related mathematical model;
- apply the method to a computational, organizational, analytical, or decision problem;
- provide sufficient methodological information;
- are published in peer-reviewed scholarly outlets;
- contribute conceptually, methodologically, computationally, or empirically to the review questions.

5.5 Exclusion Criteria

Studies should be excluded when they:

- have no substantive relationship with matrix-based modelling;
- are purely mathematical without relevance to the review's analytical scope;
- lack sufficient methodological information;
- are duplicates;

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- are non-scholarly commentary;
- are inaccessible after reasonable retrieval attempts;
- concern matrices only incidentally.

5.6 Data Extraction

Each included study should be coded according to the scheme in Table 1.

Variable	Coding dimension
Publication year	Year
Discipline	Mathematics / CS / OR / Management / etc.
Matrix type	Data / network / decision / covariance / etc.
Mathematical method	SVD / eigen / PCA / optimization / etc.
Application	HR / finance / marketing / operations / etc.
Analytical purpose	Descriptive / predictive / prescriptive
Data type	Structured / unstructured / network / time series
Computational approach	Classical / ML / AI / hybrid
Decision level	Operational / tactical / strategic
Uncertainty	Deterministic / probabilistic / fuzzy / etc.
Main contribution	Theory / method / application
Limitation	Reported limitation
Future direction	Suggested research

Table 1. Proposed data-extraction coding scheme.

6. EVOLUTION OF MATRIX-BASED MODELLING

The literature can be conceptually organized into six developmental phases, summarized in Table 2.

Phase	Dominant orientation	Representative matrix function
I	Classical mathematics	Represent equations and transformations
II	Numerical computation	Solve large-scale mathematical problems
III	Operations research	Optimize resources and alternatives
IV	Network and complex systems	Represent relationships and dependencies
V	Data science and AI	Extract latent patterns from high-dimensional data
VI	Decision intelligence	Convert analytical structures into decision support

Table 2. Developmental phases of matrix-based modelling.

This evolutionary interpretation is more informative than treating matrix techniques as isolated algorithms.

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7. MATRIX-BASED MODELS IN COMPLEX SYSTEMS

7.1 Adjacency Matrices

A network can be represented by an adjacency matrix:

$$A = [a_{ij}]$$

where a_{ij} represents the presence, absence, or strength of a relationship between entities i and j.

This formulation enables the mathematical representation of:

- employee communication networks
- supplier networks
- innovation ecosystems
- social networks
- organizational alliances
- information flows
- financial networks

Newman's (2010) work demonstrates how adjacency matrices, weighted networks, graph Laplacians, and random walks provide mathematical foundations for network analysis.

7.2 Transition Matrices

Dynamic systems can be represented through:

$$x_{(t+1)} = P\, x_t$$

where P represents a transition matrix. This structure can model:

- customer movement between market segments
- employee career transitions
- brand switching
- credit-rating migration
- supply-chain states
- organizational states

The value of transition matrices lies in their ability to connect current states to possible future states.

7.3 Influence Matrices

Organizations often contain reciprocal relationships. An influence matrix can represent:

$$Y = AX$$

where A captures influence relationships and X represents underlying attributes. Such models can be extended to:

- stakeholder influence
- leadership networks
- innovation diffusion

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- knowledge transfer
- organizational communication

This creates an important bridge between structural network analysis and managerial decision-making.

8. MATRIX-BASED OPTIMIZATION

Optimization converts representation into action. A general optimization problem can be represented as:

$$\min f(x), \; x$$

subject to:

$$Ax \leq b, \quad x \geq 0$$

The matrix A can encode organizational constraints, while x represents decision variables. Management applications include:

- workforce allocation
- production scheduling
- portfolio construction
- transportation planning
- supplier selection
- inventory management
- capacity planning
- project-resource allocation

Matrix representations therefore create the computational bridge between a managerial problem and an optimization problem.

9. MULTI-CRITERIA DECISION-MAKING

One of the most direct links between matrix structures and management decision-making is multi-criteria decision-making (MCDM). A decision matrix can be represented as:

$$D = [x_{ij}], \; i = 1, \ldots, n \text{ (alternatives)}; \; j = 1, \ldots, m \text{ (criteria)}$$

Here, rows represent alternatives and columns represent criteria. The decision problem then becomes a mathematical transformation of alternatives and criteria into an evaluative structure.

AHP, TOPSIS, ELECTRE, PROMETHEE, VIKOR and related approaches have been widely applied to multi-criteria decision problems. A review of TOPSIS applications, for example, documented its use across multiple application domains and highlighted the broad diffusion of MCDA methods (Behzadian et al., 2012). More recent literature continues to examine hybrid MCDM approaches in business analytics and decision-support settings.

However, matrix-based decision methods require methodological caution. Rankings can be sensitive to normalization, weighting, and methodological assumptions. Earlier comparative research demonstrated that different MCDA methods can produce different rankings under the same decision conditions. Consequently, decision intelligence should not be equated with

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simply generating a mathematical ranking. Robustness, sensitivity analysis, stakeholder interpretation, and contextual validity remain essential.

10. PRINCIPAL COMPONENT ANALYSIS AND DIMENSIONALITY REDUCTION

High-dimensional organizational datasets can contain hundreds or thousands of variables. PCA transforms correlated variables into orthogonal components:

$$X = U\Sigma V^T$$

The transformation allows the researcher to identify directions of maximum variance and construct lower-dimensional representations. Jolliffe and Cadima (2016) identify PCA as a foundational multivariate technique with continuing methodological development and broad application.

In management analytics, PCA can assist with:

- employee competency dimensions
- customer profiling
- financial risk factors
- organizational climate measures
- market segmentation
- operational performance indicators
- sustainability dimensions

The management value arises when dimensionality reduction improves the interpretability and tractability of otherwise complex datasets.

11. MATRIX FACTORIZATION AND LATENT STRUCTURES

Matrix factorization decomposes an observed matrix into lower-dimensional components. A general formulation is:

$$R \approx UV^T$$

This principle has become important in:

- recommender systems
- customer-product analysis
- document representation
- latent semantic analysis
- consumer preference modelling
- knowledge discovery

The conceptual significance extends beyond recommendation systems. Matrix factorization demonstrates how observable relationships can be represented through latent dimensions. In management research, this creates possibilities for uncovering hidden structures in customer preferences, employee competencies, organizational capabilities, and interfirm relationships.

12. LINEAR ALGEBRA AND MACHINE LEARNING

Modern machine learning is deeply dependent on linear algebra. A supervised-learning problem can be represented as:

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$$\hat{y} = f(X; \theta)$$

Here, X is generally represented as a matrix of observations and features, while θ contains model parameters. Linear regression provides a simple illustration:

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

under the classical full-rank formulation. More advanced learning methods involve:

- matrix multiplication
- vector projections
- covariance matrices
- eigen decomposition
- gradient-based optimization
- matrix factorization
- kernel matrices
- parameter matrices
- embedding representations

Murphy's (2012) probabilistic treatment of machine learning explicitly integrates probability, optimization, and linear algebra into the foundations of machine learning. Bishop's (2006) treatment similarly demonstrates the mathematical depth connecting pattern recognition, graphical models, and statistical learning.

Deep learning intensifies this relationship. Neural networks repeatedly apply parameterized transformations to vector and matrix representations. Goodfellow et al. (2016) identify linear algebra, numerical computation, probability, and information theory among the mathematical foundations of deep learning.

Thus, the transition from linear algebra to AI should not be interpreted as a discontinuity. Rather, contemporary AI can be understood partly as an increasingly sophisticated computational ecosystem built upon mathematical operations that include matrix transformation, optimization, and representation learning.

13. MATRIX-BASED MODELS IN MANAGEMENT ANALYTICS

13.1 Human Resource Analytics

Employee analytics can be structured through matrices representing:

- employee-skill relationships
- employee-job fit
- competency-performance relationships
- training needs
- succession pipelines
- workforce mobility

An employee-skill matrix can be expressed as S_{ij} = proficiency of employee i in skill j. Such representations enable gap analysis, clustering, workforce planning, and optimization.

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13.2 Financial Analytics

Financial analytics makes extensive use of covariance and correlation matrices. For a portfolio with weight vector w and covariance matrix Σ, portfolio variance can be expressed as:

$$\sigma_p^2 = w^T \Sigma w$$

The equation illustrates how matrix representation connects multiple asset relationships to portfolio-level risk. This is an example of a broader principle: matrix structure allows system-level outcomes to emerge mathematically from interactions among individual components.

13.3 Marketing Analytics

Marketing datasets frequently contain customer-by-product or customer-by-channel matrices. Such structures can support:

- customer segmentation
- recommendation
- market-basket analysis
- preference modelling
- customer lifetime value analysis
- channel optimization

Matrix factorization can additionally uncover latent preference structures.

13.4 Supply-Chain Analytics

Supply chains are inherently relational systems. Matrices can represent:

- supplier-product relationships
- plant-location relationships
- transportation costs
- inventory flows
- supplier risks
- network connectivity

Consequently, matrix-based models are particularly suitable for supply-chain optimization and resilience analysis.

13.5 Strategic Management

Strategic decisions often involve multiple alternatives and criteria. A strategy matrix may encode D_{ij} = performance of alternative i under criterion j. This representation allows organizations to integrate financial, operational, technological, environmental, and stakeholder criteria.

The mathematical structure, however, does not eliminate managerial judgement. Rather, it makes assumptions and trade-offs more explicit.

14. DECISION SUPPORT AND DECISION INTELLIGENCE

Decision-support systems historically emphasized computational and informational assistance for managerial decision-making. Power's (2002) framework, for example, treats

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decision support as an integrated domain involving decision processes, system architecture, technologies, interfaces, and evaluation.

Decision intelligence can be viewed as an extension of this logic. A simplified architecture is:

Data → Representation → Analysis → Prediction → Optimization → Decision

Matrix-based modelling operates throughout this chain. At the representation stage, data are organized into matrices. At the analysis stage, matrix operations expose relationships. At the prediction stage, matrices parameterize models. At the optimization stage, matrices encode constraints and objective relationships. At the decision stage, matrix-based evaluation supports comparison of alternatives.

The resulting insight is important: matrix methods are not themselves decision intelligence; they constitute one of the mathematical infrastructures through which decision intelligence can be constructed.

15. MATRIX-TO-DECISION INTELLIGENCE FRAMEWORK

Based on the cross-disciplinary synthesis, this study proposes the Matrix-to-Decision Intelligence (MDI) Framework.

15.1 Stage 1: Representation

Real-world phenomena are converted into mathematical structures:

Phenomenon → Matrix Representation

Examples include data matrices, adjacency matrices, covariance matrices, decision matrices, transition matrices, and incidence matrices.

15.2 Stage 2: Transformation

Mathematical operations reveal structure:

Matrix → Transformation → Structure

Representative methods include eigenanalysis, SVD, PCA, factorization, projections, and matrix multiplication.

15.3 Stage 3: Optimization

Analytical structures are evaluated against objectives and constraints:

Structure → Optimization → Alternative Solutions

Methods include linear programming, quadratic programming, convex optimization, MCDM, DEA, and stochastic optimization.

15.4 Stage 4: Decision Intelligence

Analytical outputs are interpreted within organizational contexts:

Solutions → Contextual Interpretation → Decision

The final stage incorporates managerial judgement, organizational objectives, stakeholder priorities, uncertainty, risk, ethical considerations, and implementation constraints.

Integrated framework

Data → Matrix Representation → Transformation → Structural Insight → Optimization → Decision Intelligence → Managerial Action

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The framework's principal proposition is that mathematical representation is a necessary analytical layer but not a sufficient managerial decision mechanism.

16. CROSS-DOMAIN TAXONOMY OF MATRIX-BASED MODELS

Table 3 summarizes the principal matrix models identified in the review, their associated mathematical operations, their role in complex systems, and their representative management applications.

Matrix model	Mathematical operation	Complex-system role	Management application
Data matrix	Multiplication, decomposition	Represents observations	Business analytics
Covariance matrix	Eigen analysis	Represents dependencies	Financial risk
Adjacency matrix	Matrix powers / eigen analysis	Represents networks	Organizational networks
Transition matrix	Iterative multiplication	Represents system dynamics	Customer / employee transitions
Decision matrix	Weighted transformation	Represents alternatives	Strategic decisions
Incidence matrix	Graph operations	Represents connections	Supply chains
Distance matrix	Similarity calculations	Represents proximity	Segmentation
Factor matrix	Factorization	Represents latent structure	Customer analytics
Weight matrix	Transformation	Represents model parameters	Machine learning
Constraint matrix	Optimization	Represents system limits	Resource allocation

Table 3. Cross-domain taxonomy of matrix-based models.

17. FROM STATIC MATRICES TO DYNAMIC DECISION SYSTEMS

A significant development in the literature is the transition from static matrix representation to dynamic modelling. Traditional models often use:

$$y = Ax$$

Dynamic systems instead use:

$$x_{(t+1)} = A\, x_t + B\, u_t$$

Here, the matrix A captures system dynamics and B represents external inputs. This structure creates opportunities for management applications involving:

- workforce evolution
- customer-state transitions
- organizational change
- supply-chain disruptions
- financial dynamics
- technology adoption

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- innovation diffusion

Future research can therefore move beyond static decision matrices toward dynamic matrix intelligence, where the analytical structure itself evolves over time.

18. MATRIX MODELS AND COMPLEX ADAPTIVE ORGANIZATIONS

Organizations can be interpreted as complex adaptive systems comprising interacting individuals, teams, technologies, processes, resources, and external stakeholders. A matrix representation allows these relationships to be modelled explicitly. For example:

$$A_{ij} = \text{strength of interaction between organizational units i and j}$$

Changes in A can then represent changes in organizational structure. This creates possibilities for analysing:

- network centrality
- structural holes
- collaboration intensity
- knowledge diffusion
- communication patterns
- interdepartmental dependencies
- organizational resilience

The mathematical representation is especially valuable when organizational outcomes arise not from isolated variables but from interactions among components.

19. BIBLIOMETRIC AND SCIENCE-MAPPING PERSPECTIVE

A full empirical version of this review should include bibliometric analysis because the literature crosses disciplinary boundaries. Bibliometrix provides an established R-based environment for comprehensive science mapping, including analysis of scientific production and relationships among authors, documents, sources, and keywords. Aria and Cuccurullo (2017) specifically proposed bibliometrix as an open-source tool for comprehensive science mapping and described a multi-stage bibliometric workflow.

The recommended analyses are:

- annual publication growth
- citation evolution
- source/journal analysis
- author productivity
- institutional collaboration
- country collaboration
- co-authorship networks
- keyword co-occurrence
- co-citation analysis
- bibliographic coupling

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- thematic mapping
- thematic evolution

For this research domain, keyword analysis is especially important because it can reveal whether the literature is converging around the concept chain: matrix computation → optimization → network science → machine learning → business analytics → decision intelligence.

However, bibliometric results should only be reported after the actual bibliographic dataset has been retrieved and processed. Counts or maps should not be generated from assumptions.

20. THEMATIC STRUCTURE EMERGING FROM THE SYNTHESIS

The literature can be organized into five major thematic clusters.

Cluster 1: Mathematical computation

Core concepts: matrices; linear systems; eigenvalues; decompositions; numerical linear algebra.

Cluster 2: Structural modelling

Core concepts: networks; adjacency matrices; graph Laplacians; transition matrices; complex systems.

Cluster 3: Analytical intelligence

Core concepts: PCA; matrix factorization; machine learning; dimensionality reduction; predictive analytics.

Cluster 4: Optimization and decision analysis

Core concepts: LP; MCDM; AHP; TOPSIS; DEA; resource allocation.

Cluster 5: Management decision intelligence

Core concepts: business analytics; decision support; strategic analytics; prescriptive analytics; AI-supported decision-making.

The principal theoretical insight is that these clusters should not be treated as independent streams. They form an analytical continuum.

21. RESEARCH GAPS

21.1 Theoretical Gap

The mathematical literature and management literature frequently exist in separate intellectual communities. There is a need for frameworks that explicitly explain how mathematical representations become managerial knowledge.

21.2 Methodological Gap

Many applied studies select matrix-based techniques according to convenience or established practice rather than explicitly matching mathematical properties with decision characteristics. Future research should therefore investigate which matrix method is appropriate for which decision context, data structure, uncertainty condition, and managerial objective.

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21.3 Interpretability Gap

Sophisticated matrix transformations can improve predictive or analytical performance while reducing interpretability. A technically superior model may not necessarily produce a better managerial decision if decision-makers cannot understand its assumptions or outputs.

21.4 Dynamic-System Gap

A substantial opportunity exists for moving from static matrices to time-varying matrices, A_t. Such models can capture organizational structures that change over time.

21.5 Uncertainty Gap

Real organizational systems contain incomplete, noisy, ambiguous, and conflicting information. Future matrix models should therefore incorporate:

- fuzzy matrices
- interval matrices
- probabilistic matrices
- stochastic matrices
- robust optimization
- uncertainty quantification

21.6 Human–AI Integration Gap

Decision intelligence cannot be reduced to computational optimization. Managers contribute contextual understanding, ethical reasoning, stakeholder interpretation, organizational experience, and strategic judgement. Future systems should therefore investigate human–matrix–AI collaboration rather than complete automation.

22. THEORETICAL CONTRIBUTIONS

The review contributes in four ways.

First, it reconceptualizes linear algebra as an analytical infrastructure.

Rather than viewing matrices solely as mathematical objects, the review positions them as mechanisms for representing organizational structures, relationships, alternatives, and constraints.

Second, it integrates previously fragmented literatures.

The framework connects linear algebra, numerical computation, network science, optimization, machine learning, management analytics, and decision support.

Third, it introduces the Matrix-to-Decision Intelligence framework.

The four-stage architecture—representation, transformation, optimization, and decision intelligence—provides a conceptual bridge between mathematical modelling and managerial action.

Fourth, it establishes a research agenda.

The framework identifies dynamic, explainable, uncertainty-aware, and hybrid matrix-AI systems as promising directions.

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23. MANAGERIAL IMPLICATIONS

The framework has several implications for managers.

23.1 Better representation of complex problems

Managers can translate multidimensional problems into structured mathematical representations.

23.2 Greater transparency of assumptions

Decision matrices make criteria, weights, and alternatives explicit.

23.3 Improved resource allocation

Optimization models can identify feasible allocations under multiple constraints.

23.4 Enhanced network understanding

Adjacency and influence matrices can reveal organizational dependencies.

23.5 More systematic strategic analysis

Matrix-based MCDM approaches can make trade-offs visible.

23.6 Integration with AI

Matrix representations provide a mathematical foundation for predictive and prescriptive analytics.

The important managerial implication, however, is that computational sophistication should remain subordinate to decision purpose. A mathematically complex model is useful only when it improves understanding, robustness, timeliness, or actionability.

24. FUTURE RESEARCH AGENDA

The review suggests eight research directions.

24.1 Dynamic Matrix Intelligence

Develop models where $A = A_t$, allowing analytical systems to model continuously changing organizational relationships.

24.2 Explainable Matrix Analytics

Develop techniques that translate complex transformations into understandable managerial explanations.

24.3 Matrix-AI Hybrid Systems

Combine classical matrix methods with machine learning, deep learning, reinforcement learning, generative AI, and agentic AI.

24.4 Uncertainty-Aware Matrix Models

Develop matrix frameworks capable of representing ambiguity and incomplete information.

24.5 Human-Centred Decision Intelligence

Study how managers interact with mathematically generated recommendations.

24.6 Cross-Domain Transfer

Investigate whether matrix methods developed in engineering, finance, or network science can be systematically adapted to HR, strategy, and organizational analytics.

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24.7 Responsible Decision Intelligence

Examine fairness, explainability, accountability, and bias in matrix-driven decision systems.

24.8 Autonomous Analytical Agents

An emerging direction is the integration of matrix modelling into agentic analytical systems in which specialized AI agents can retrieve data, construct matrices, select mathematical transformations, run analytical models, conduct sensitivity analysis, compare alternative scenarios, and generate decision explanations. This creates a potential transition from matrix-based analytics to agentic decision intelligence.

25. PROPOSED RESEARCH ARCHITECTURE

The synthesis can therefore be represented as an iterative pipeline:

Real-world phenomenon → Data acquisition → Matrix representation → Matrix transformation → Pattern/structure discovery → Optimization and simulation → Predictive/prescriptive analytics → Decision intelligence → Managerial action → Feedback and model adaptation

The final feedback loop is particularly important. Organizational decisions change the system being analysed, which subsequently changes the data and matrix representation. Decision intelligence is therefore inherently iterative.

26. DISCUSSION

The synthesis suggests that the intellectual trajectory from linear algebra to decision intelligence is not a sequence in which one discipline replaces another. Instead, it represents increasing layers of abstraction and application.

At the first layer, matrices represent mathematical relationships. At the second layer, matrix algorithms transform these representations. At the third layer, complex-system methods interpret interactions. At the fourth layer, optimization identifies feasible or desirable alternatives. At the fifth layer, analytics and AI generate predictions and patterns. At the sixth layer, decision intelligence combines computational outputs with organizational objectives and managerial judgement.

This progression can be summarized as:

Representation → Computation → Structure → Optimization → Prediction → Decision

This perspective also clarifies an important boundary. Linear algebra provides mathematical structure, but it does not determine organizational objectives or managerial values. A matrix can encode alternatives and criteria, but the choice of criteria is ultimately contextual. Similarly, an optimization algorithm can identify an optimum under specified assumptions, but it cannot independently determine whether those assumptions adequately represent organizational reality.

Simon's (1996) conception of designed systems is relevant here because organizational systems involve both computational structure and human purposes. His work treats firms, economic systems, artificial intelligence, and complex engineering projects as legitimate objects for systematic design and analysis.

Accordingly, the future of matrix-based decision intelligence should not be conceptualized as the replacement of managerial judgement by mathematical computation. A more defensible direction is augmentation, in which mathematical models improve the structure, transparency, and analytical depth of managerial reasoning.

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27. LIMITATIONS

This review has several limitations.

First, the interdisciplinary breadth of the topic creates substantial terminology variation. Similar matrix concepts may be described differently across mathematics, engineering, computer science, operations research, and management.

Second, matrix-based modelling is not a single homogeneous methodology. The term encompasses fundamentally different structures, including data matrices, adjacency matrices, covariance matrices, transition matrices, decision matrices, and parameter matrices.

Third, systematic-review results can be sensitive to database selection and search-string construction.

Fourth, bibliometric findings should be interpreted cautiously because citation counts, keyword conventions, and database coverage vary across disciplines.

Fifth, the present manuscript provides the systematic-review architecture and evidence synthesis but does not claim an empirical PRISMA record count or bibliometric statistic without the underlying database export. A publication-ready empirical version should therefore populate the screening and bibliometric sections from an auditable dataset.

CONCLUSION

Linear algebra occupies a deeper position in contemporary decision intelligence than its traditional treatment as a foundational mathematical subject might suggest. Matrix representations provide a common computational language through which multidimensional observations, relationships, dependencies, alternatives, constraints, and latent structures can be expressed.

The review demonstrates a conceptual progression from:

Linear Algebra → Matrix Models → Complex Systems → Optimization → Analytics → Decision Intelligence

The proposed Matrix-to-Decision Intelligence framework organizes this progression into four principal stages: representation, transformation, optimization, and decision intelligence. The framework emphasizes that mathematical modelling becomes strategically valuable when it connects data structures to interpretable insights, feasible alternatives, and organizational action.

The future research agenda should move beyond static matrix representations toward dynamic, explainable, uncertainty-aware, and AI-integrated systems. Particularly promising opportunities exist at the intersection of matrix computation, network science, machine learning, multi-criteria decision-making, and agentic AI.

The central proposition emerging from the review is therefore not that linear algebra alone produces intelligent decisions. Rather, linear algebra provides one of the mathematical infrastructures through which complex organizational realities can be represented, transformed, optimized, and ultimately incorporated into decision-intelligence systems.

In this sense, the journey from linear algebra to decision intelligence is best understood not as a departure from mathematics but as an expansion of mathematical representation into increasingly complex computational and managerial environments.

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REFERENCES

1. Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. Journal of Informetrics, 11(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007
2. Behzadian, M., Khanmohammadi Otaghsara, S., Yazdani, M., & Ignatius, J. (2012). A state-of-the-art survey of TOPSIS applications. Expert Systems with Applications, 39(17), 13051–13069. https://doi.org/10.1016/j.eswa.2012.05.056
3. Bishop, C. M. (2006). Pattern recognition and machine learning. Springer.
4. Golub, G. H., & Van Loan, C. F. (2013). Matrix computations (4th ed.). Johns Hopkins University Press.
5. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.
6. Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: A review and recent developments. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374(2065), 20150202. https://doi.org/10.1098/rsta.2015.0202
7. Murphy, K. P. (2012). Machine learning: A probabilistic perspective. MIT Press.
8. Newman, M. E. J. (2010). Networks: An introduction. Oxford University Press.
9. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71
10. Power, D. J. (2002). Decision support systems: Concepts and resources for managers. Quorum Books.
11. Simon, H. A. (1996). The sciences of the artificial (3rd ed.). MIT Press.
12. Strang, G. (2021). Introduction to linear algebra (5th ed.). Wellesley-Cambridge Press.

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