



Optimizing Circular Waste Matchmaking Through Social Resource Networks Using Predictive Analytics and Resource Compatibility Modeling

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ABSTRACT :

Growing material consumption, resource scarcity, and escalating waste generation are intensifying the need for circular systems capable of retaining the economic and functional value of residual resources across industrial and community networks. However, conventional waste exchanges frequently depend on fragmented listings, predefined material categories, and manual partner searches, limiting their ability to identify viable relationships between heterogeneous waste streams and resource demands. This study proposes an optimized circular waste matchmaking framework based on Social Resource Networks (SRNs), predictive analytics, and resource compatibility modeling. The framework represents waste generators, resource users, intermediaries, and material streams as interconnected network entities while integrating information concerning material composition, quantity, quality, location, availability, processing requirements, historical exchanges, and organizational demand. Predictive models anticipate resource availability and demand patterns, whereas compatibility modeling evaluates technical suitability, spatial proximity, temporal alignment, economic feasibility, environmental value, and exchange constraints. Match scores enable candidate exchanges to be prioritized according to multidimensional compatibility. Continuous feedback from accepted, rejected, and completed transactions subsequently refines predictions and matching decisions. The framework enables proactive opportunity discovery, reduces information asymmetry, improves secondary-resource utilization, and strengthens adaptive cross-sector circular resource exchange ecosystems.

Keywords: Social Resource Networks; Circular Waste Matchmaking; Predictive Analytics; Resource Compatibility Modeling; Industrial Symbiosis; Circular Economy

1. INTRODUCTION

1.1 Waste Generation, Resource Scarcity, and the Circularity Challenge

Growing populations, industrialization, and consumption continue to increase global material demand while generating substantial volumes of industrial and commercial waste [1]. Conventional production remains predominantly structured around linear take-make-dispose systems in which extracted resources are transformed, consumed, and discarded despite retaining potentially recoverable economic and functional value [3]. This pattern intensifies pressure on finite resources, increases disposal requirements, and contributes to environmental degradation and emissions associated with primary-material extraction [5]. Circular economy strategies seek to decouple economic activity from continuous resource depletion by maintaining materials within productive use through reuse, recovery, repurposing, remanufacturing, and recycling [2]. Achieving this transition requires residual materials to be understood not merely as waste requiring treatment but as secondary resources capable of replacing primary inputs within appropriate industrial applications [6].

1.2 Fragmentation in Conventional Waste and Resource Exchange

Despite their potential value, secondary resources frequently remain underutilized because information about their availability and possible applications is fragmented across organizations and sectors [4]. Conventional waste databases and exchange platforms often operate as isolated repositories in which materials are listed using inconsistent terminology, classifications, specifications, and measurement units [7]. Organizations seeking secondary inputs may consequently struggle to compare available materials with production requirements, particularly when potential suppliers operate outside familiar industrial sectors. Manual searches further restrict the number of potential relationships that can reasonably be evaluated [3]. Limited cross-industry visibility and information asymmetry regarding composition, quality, quantities, location, availability, and processing requirements therefore prevent technically useful waste streams from being discovered by organizations capable of utilizing them productively [8].

1.3 Need for Predictive and Compatibility-Aware Waste Matchmaking

Digital listings improve resource visibility but remain predominantly reactive because they connect users with materials already declared available. Circular exchange increasingly requires intelligence capable of anticipating when resources will emerge and where corresponding demand is likely to develop [9]. Keyword matching alone cannot determine whether similarly described materials satisfy technical specifications, quality tolerances, quantity requirements, processing capabilities, or regulatory conditions [5]. Likewise, an apparently compatible resource may become impractical when transportation distance, availability timing, storage requirements, preprocessing costs, or environmental burdens are considered [7]. Predictive analytics can identify prospective supply-demand relationships from historical and contextual patterns, while multidimensional compatibility modeling can determine whether predicted opportunities are practically viable [4]. Their integration therefore enables matchmaking to progress from resource retrieval toward anticipatory, evidence-based exchange recommendations [6].

1.4 Research Aim, Scope, and Contributions

This study develops a Social Resource Network-based framework integrating predictive analytics and multidimensional compatibility modeling to optimize circular waste matchmaking. The framework represents waste generators, resource users, intermediaries, and secondary materials as interconnected network entities whose historical and current interactions provide intelligence for prospective exchange discovery [8]. Predictive models estimate future resource availability and demand, while compatibility analysis evaluates technical suitability, quantity, quality, spatial proximity, temporal alignment, economic feasibility, environmental value, regulatory requirements, and organizational trust [2]. Candidate exchanges are subsequently scored and ranked according to predicted availability and multidimensional compatibility. Transaction outcomes provide feedback for refining forecasts, compatibility weights, and future recommendations [9]. This integration supports anticipatory resource intelligence, adaptive network learning, and discovery of viable circular exchanges across traditionally disconnected industrial sectors [1].

2. SOCIAL RESOURCE NETWORKS FOR CIRCULAR WASTE EXCHANGE

2.1 From Linear Waste Management to Networked Resource Circulation

Conventional waste management has historically emphasized collection, treatment, recycling, and disposal after materials reach the end of their intended use [5]. Circular resource management extends this perspective by seeking to preserve material functionality and economic value through reuse, recovery, repurposing, refurbishment, and remanufacturing before disposal becomes necessary [7]. This transition also changes the appropriate scale of resource management. Rather than optimizing individual waste streams independently, circular systems connect organizations whose outputs and input requirements can complement one another [10]. Residual materials that lack further utility within one production process may consequently retain significant value elsewhere. Industrial symbiosis strengthens this network perspective by enabling coordinated exchanges of materials, energy, water, infrastructure, and services [6]. Circularity therefore evolves from isolated recovery activities toward interconnected systems in which resources circulate repeatedly among diverse economic actors [9].

2.2 Industrial Symbiosis and Cross-Sector Resource Relationships

Industrial symbiosis operationalizes resource circulation by connecting organizations whose production processes generate complementary outputs and requirements [8]. A residual material produced by one organization can substitute for virgin inputs elsewhere when its composition, quality, quantity, and processing characteristics satisfy another organization's technical requirements [11]. Traditional symbiotic relationships have frequently developed within geographically concentrated industrial clusters, where proximity facilitates transportation and repeated interaction [6]. However, valuable complementarities can also exist between organizations operating in unrelated sectors and distant locations. Agricultural residues may support manufacturing or energy applications, while manufacturing by-products can become inputs for construction or material processing [9]. Expanding opportunity discovery beyond established clusters therefore increases the potential search space for secondary-resource utilization and enables circular relationships that conventional sector-specific waste systems may overlook [12].

2.3 Social Resource Networks as Socio-Technical Systems

Social Resource Networks provide an infrastructure for organizing these distributed relationships by integrating technological capabilities with human and organizational participation. Within an SRN, waste generators, resource users, recyclers, processors, logistics providers, intermediaries, communities, and regulators form interconnected actors around shared resource information and exchange opportunities [7]. The technical infrastructure can maintain resource profiles, organizational requirements, transaction histories, analytical models, communication mechanisms, and recommendations [10]. The social dimension encompasses collaboration, negotiation, trust, reputation, institutional responsibilities, and decisions concerning whether recommended exchanges should proceed [5]. Regulators and intermediaries can additionally support compliance, verification, and coordination. An SRN is therefore not simply a digital waste marketplace; it is a socio-technical environment in which data, algorithms, relationships, institutions, and physical material flows jointly shape circular-resource exchanges [11].

2.4 Network Relationships, Trust, and Resource Visibility

Network relationships provide information that conventional material listings frequently exclude. Connections among participants can reveal previous transactions, repeated collaborations, shared intermediaries, complementary requirements, and emerging resource communities [12]. Transaction histories and reputation indicators can reduce uncertainty regarding material quality, delivery reliability, organizational behavior, and fulfillment of agreed exchange conditions [8]. Information sharing simultaneously improves resource visibility by exposing secondary materials to participants beyond established supplier relationships. Trust becomes particularly important where organizations exchange heterogeneous materials whose quality or consistency cannot be evaluated from descriptions alone [6]. Consequently, connectivity and reputation complement technical resource information by influencing whether discovered opportunities become credible and actionable exchanges [10].

2.5 SRN-Enabled Intelligent Matchmaking

The SRN consequently provides the relational and informational foundation required for intelligent matchmaking. Resource profiles describe available materials and organizational requirements, while network histories reveal previous interactions and exchange outcomes [9]. Predictive analytics can use these observations to anticipate emerging supply and demand, whereas compatibility models evaluate whether prospective relationships are technically and operationally feasible [11]. Integrating these capabilities allows the network to discover, evaluate, and prioritize opportunities rather than requiring participants to search static listings manually [7].

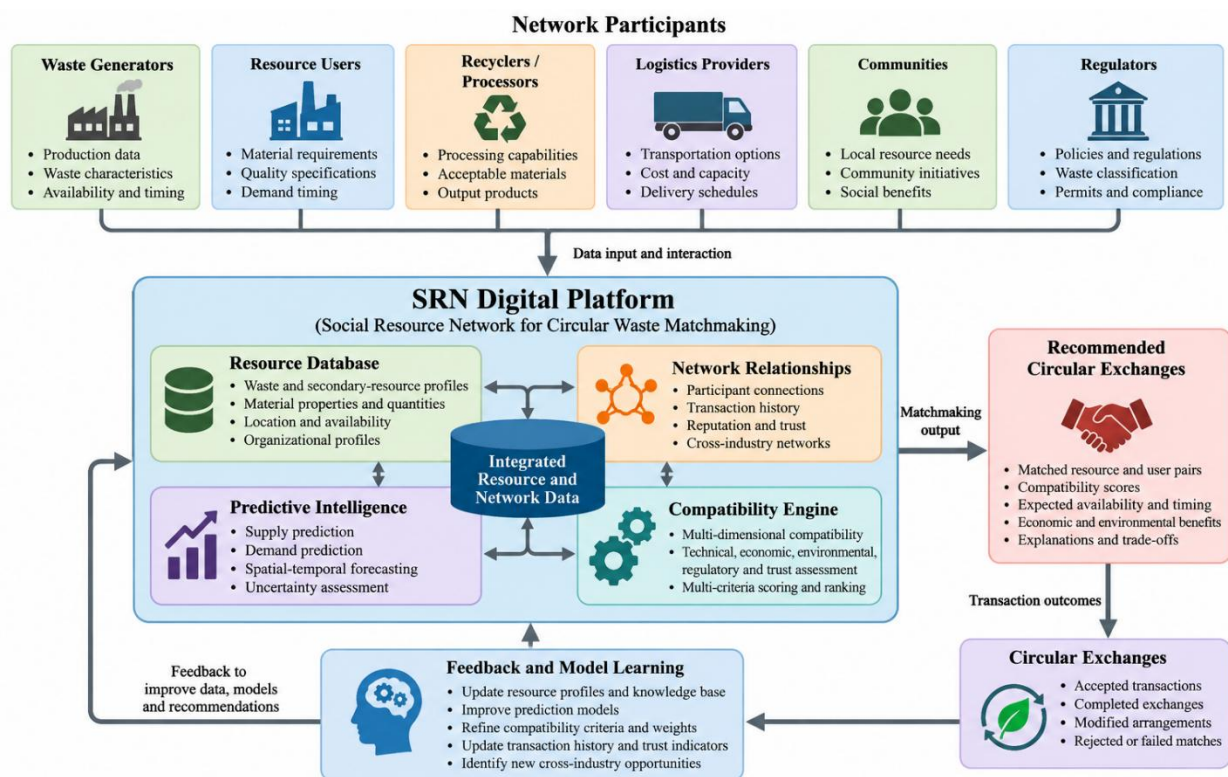


Figure 1. Conceptual Architecture of a Predictive Social Resource Network for Circular Waste Matchmaking.

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3. RESOURCE DATA REPRESENTATION AND MATCHMAKING INTELLIGENCE

3.1 Waste and Secondary-Resource Profiling

Effective matchmaking requires waste streams to be represented as structured resource profiles rather than loosely described disposal categories. Each profile should identify material type alongside chemical composition, physical properties, quality grade, contamination level, quantity, condition, and location [11]. Temporal attributes should specify whether the resource is continuously generated, periodically available, seasonal, or limited to a single batch [14]. Additional information concerning storage conditions, required preprocessing, hazardous characteristics, and potential applications can further determine whether the material is practically reusable [16]. Representing these attributes consistently allows materials originating from different production processes to be compared according to functional characteristics rather than industrial origin alone [12]. Such profiles transform heterogeneous waste descriptions into machine-readable resource representations suitable for predictive analysis and compatibility assessment [17].

3.2 Resource Demand and Organizational Requirement Profiles

Matchmaking must simultaneously represent what potential users require. Demand profiles can specify desired material composition, physical characteristics, quality tolerances, acceptable contamination levels, minimum and maximum quantities, and required delivery frequency [13]. Organizational information should describe processing capabilities, storage capacity, geographical location, production schedules, and ability to transform secondary materials before utilization [15]. Procurement constraints may additionally establish acceptable prices, transportation distances, contractual requirements, supplier qualifications, or minimum supply continuity. Distinguishing mandatory specifications from preferred characteristics is particularly important because some requirements determine technical feasibility while others influence relative attractiveness [18]. Structured demand profiles therefore provide the reference against which available and predicted secondary resources can be systematically evaluated.

3.3 Semantic Standardization and Resource Classification

Cross-industry matching is complicated by differences in how organizations describe technically similar materials. A manufacturer may classify an output according to its production origin, while another organization searches according to composition, function, or performance characteristics [12]. Standardized taxonomies can provide common material categories, but rigid classifications may overlook alternative applications [16]. Semantic representations and ontologies can instead describe relationships among materials, properties, processes, functions, and potential uses [14]. Natural-language descriptions can be mapped to standardized attributes so that terminology differences do not prevent potentially compatible resources from being compared [17]. Classification mechanisms can then organize heterogeneous records while preserving sufficient technical detail for cross-sector discovery, enabling the matchmaking system to recognize functional similarities beyond exact keyword correspondence [11].

3.4 Historical Transaction and Contextual Data

Resource and demand profiles become more informative when combined with evidence from previous network activity. Completed transactions reveal combinations of materials, users, prices, quantities, transportation distances, and processing conditions that produced viable exchanges [15]. Rejected recommendations can identify unacceptable specifications, excessive costs, timing conflicts, or trust concerns [18]. Seasonal generation patterns and market conditions provide additional context for predicting future availability and demand. Organizational relationships can indicate repeated partnerships, while regulatory information establishes constraints governing material movement or utilization [13]. Historical and contextual data therefore convert individual exchange events into accumulated network knowledge that can inform forecasts, compatibility assessments, and subsequent recommendations [16].

3.5 Integrated Matchmaking Data Model

An integrated matchmaking model should connect these heterogeneous data rather than analyzing each category independently. Resource records describe what is available, demand profiles establish what is required, and organizational data identify capabilities and constraints [17]. Transaction histories provide evidence about previous exchange outcomes, while spatial data represent geographical relationships and transportation implications. Temporal attributes capture availability and demand windows, and environmental indicators characterize potential circularity benefits [14]. Network data additionally represent trust, reputation, collaboration histories, and relationships among participants [11]. Linking these dimensions within a unified analytical representation enables algorithms to evaluate both direct resource characteristics and contextual feasibility. The resulting data architecture provides the foundation for forecasting prospective opportunities and subsequently determining which predicted exchanges warrant recommendation [18].

Table 1. Data Architecture for Predictive Circular Waste Matchmaking

Data category	Representative variables	Data source	Matchmaking function	Analytical application
Resource characteristics	Material type, composition, physical properties, quality, contamination, condition	Waste generators, laboratory analysis, material records	Establishes resource identity and technical characteristics	Classification and technical compatibility
Resource availability	Quantity, generation rate, frequency, availability window, seasonality	Production systems, inventories, historical records	Determines current and prospective supply	Supply forecasting and temporal matching
Demand requirements	Required material, specifications, quality tolerance, quantity, delivery frequency	Resource users, procurement systems, production plans	Defines desired secondary-resource characteristics	Demand prediction and requirement matching
Organizational capabilities	Processing capacity, storage, equipment, location, accepted materials	Organizational profiles, operational systems	Determines ability to receive and utilize resources	Feasibility screening and partner selection
Transaction history	Accepted/rejected matches, quantities, prices, completion status, reasons for rejection	SRN transaction records	Provides evidence from previous exchanges	Predictive learning and recommendation refinement
Spatial-logistics data	Location, distance, transport mode,	Logistics providers,	Determines movement	Spatial optimization and

Data category	Representative variables	Data source	Matchmaking function	Analytical application
	route, storage requirements	organizational records	feasibility	logistics assessment
Temporal data	Supply timing, demand window, production schedule, frequency	Production and procurement records	Synchronizes resource generation with utilization	Temporal prediction and coordination
Economic/environmental data	Resource value, processing cost, disposal savings, transport cost, waste diversion	Transactions, operational records, environmental assessments	Evaluates exchange benefits and trade-offs	Economic and environmental compatibility
Network and trust data	Reputation, previous collaborations, reliability, relationship strength	SRN profiles and transaction histories	Reduces organizational uncertainty	Trust-aware recommendation and ranking
Regulatory data	Material classification, handling rules, permits, traceability requirements	Regulatory records, compliance documentation	Establishes permissible exchange conditions	Compliance screening and risk assessment

4. PREDICTIVE ANALYTICS FOR RESOURCE AVAILABILITY AND DEMAND

4.1 Predictive Waste Matchmaking as a Forecasting Problem

Conventional waste matchmaking is predominantly reactive because recommendations can only be generated after organizations declare resources available or submit explicit requirements. This approach restricts coordination time and may cause potentially valuable exchanges to be missed when supply and demand occur within narrow availability windows [20]. Predictive matchmaking reframes resource exchange as a forecasting problem by estimating what materials are likely to become available, in what quantities, where, and when, alongside corresponding future demand [23]. Historical production, transaction, and resource-use patterns can therefore support prospective rather than retrospective opportunity discovery. By identifying likely supply-demand relationships before materials physically enter the exchange network, predictive intelligence provides organizations with additional time for technical evaluation, logistics planning, negotiation, and processing preparation [21].

4.2 Predicting Waste and Secondary-Resource Availability

Resource-supply forecasting begins by learning relationships between historical production activity and resulting residual-material generation. Previous waste quantities, production volumes, operating schedules, process characteristics, maintenance cycles, and seasonal patterns can reveal recurring relationships between organizational activity and secondary-resource availability [22]. Predictive models can estimate not only the expected quantity of a resource but also its generation frequency and likely availability period. Quality characteristics may additionally vary with feedstock, production settings, operating conditions, or process changes and should therefore be incorporated where historical observations permit [24]. Location is another important attribute, particularly for organizations operating multiple production facilities, because geographically dispersed waste generation creates different exchange possibilities and transportation requirements. Combining these dimensions allows the SRN to forecast a multidimensional supply profile describing anticipated material characteristics, quantity, quality, timing, frequency, and geographical origin rather than predicting waste volume alone [20].

4.3 Predicting Resource Demand and User Requirements

Demand forecasting estimates which organizations are likely to require secondary resources and how those requirements may change over time. Historical procurement records can reveal recurring material requirements, preferred quantities, quality specifications, purchasing intervals, and acceptable supply conditions [23]. Production schedules provide additional evidence because anticipated output levels influence future input requirements, while previous SRN transactions indicate whether organizations repeatedly acquire particular secondary materials [25]. Seasonal production cycles can create predictable demand peaks, whereas market conditions may alter manufacturing activity and resource consumption [21]. Organizational requirements should also distinguish stable technical specifications from variable attributes such as quantity, price tolerance, or delivery timing. Integrating these signals allows predictive models to estimate probable demand windows and requirement profiles, enabling potential suppliers to be identified before formal procurement requests or resource searches are initiated [24].

4.4 Predictive Analytical Techniques

Different predictive methods can be selected according to data volume, temporal structure, nonlinear relationships, and required interpretability. Regression models can estimate continuous outcomes such as future resource quantities using relationships between production variables and historical waste generation [20]. Time-series methods are appropriate where supply or demand exhibits trends, seasonality, or recurring temporal patterns. Decision trees provide interpretable rules linking operational conditions with predicted outcomes, whereas random forests aggregate multiple trees to improve robustness and represent nonlinear interactions among variables [22]. Neural models can capture more complex relationships within large datasets involving production, transactions, material characteristics, and contextual variables [25]. Classification approaches may alternatively estimate the probability that a specific resource or demand condition will occur within a defined period. Model selection should therefore reflect forecasting

purpose, available evidence, computational requirements, uncertainty, and the need for transparent predictions [23].

4.5 Spatial and Temporal Prediction

Effective circular exchange depends not only on whether supply and demand will occur but also on their spatial and temporal alignment. Forecasts should identify where resources are expected to emerge and compare these locations with prospective users [21]. Geographical concentration can reveal regional exchange opportunities, while distance influences transportation cost and environmental performance. Temporal prediction determines whether generation schedules overlap with demand windows or whether storage is required to bridge timing differences [24]. Frequent generation may support continuous exchange, whereas intermittent outputs require flexible collection and inventory arrangements. Integrating spatial and temporal predictions therefore identifies opportunities whose expected timing and geographical configuration make coordinated exchange practically achievable [22].

4.6 Prediction Uncertainty and Dynamic Updating

Forecasts remain uncertain because production schedules change, demand fluctuates, resource quality varies, and historical records may be incomplete [25]. Predictions should therefore communicate confidence rather than representing future availability or demand as certain. Prediction intervals, probability estimates, or confidence categories can indicate the reliability of prospective opportunities and support risk-aware planning [23]. Forecast errors should subsequently become learning signals when actual supply or demand differs from predicted conditions. As new production records, transactions, rejected recommendations, and market observations enter the SRN, models can be recalibrated to reflect changing patterns [20]. Dynamic updating consequently allows predictive intelligence to evolve alongside network activity rather than remaining dependent on static historical relationships [24].

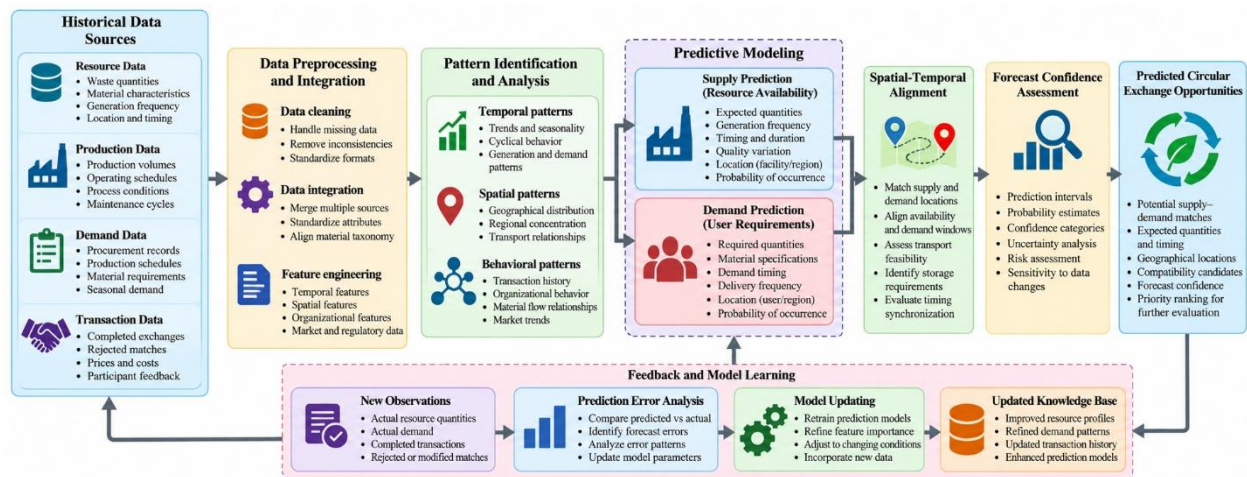


Figure 2. Predictive Analytics Workflow for Circular Resource Supply and Demand Forecasting.

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5. RESOURCE COMPATIBILITY MODELING AND MATCHMAKING OPTIMIZATION

5.1 Resource Compatibility as a Multi-Dimensional Decision Problem

Predictive analytics can reveal prospective relationships between resource supply and demand, but prediction alone cannot establish whether an exchange should occur. Compatibility is inherently multidimensional because materials that appear similar by name may differ substantially in composition, quality, quantity, location, availability, processing requirements, or regulatory status [24]. Matchmaking must therefore evaluate technical and material suitability alongside quantitative, spatial, temporal, economic, environmental, operational, regulatory, and relational conditions [27]. Some dimensions represent mandatory feasibility constraints, whereas others determine the comparative attractiveness of otherwise feasible alternatives. Resource compatibility can consequently be formulated as a multi-criteria decision problem in which heterogeneous evidence is integrated to distinguish theoretically possible relationships from practically executable circular exchanges [29].

5.2 Technical and Material Compatibility

Technical compatibility establishes whether a secondary resource can perform the function required by a prospective user. Evaluation should begin with chemical composition and relevant physical properties, including dimensions, density, moisture content, particle characteristics, mechanical behavior, thermal properties, or other application-specific parameters [25]. Quality grade, contamination level, degradation, and physical condition further determine whether a resource can enter another production process directly or requires preprocessing [28]. Matchmaking should consequently

distinguish intrinsic material suitability from suitability achievable through sorting, cleaning, separation, treatment, blending, or transformation. The resulting processing requirements affect both technical feasibility and subsequent economic performance. Performance specifications should additionally establish whether the secondary material can satisfy functional requirements when partially or completely substituting a virgin input [30]. Technical compatibility therefore represents a structured comparison between resource characteristics, transformation possibilities, and the receiving organization's minimum performance requirements [26].

5.3 Quantity, Spatial, and Temporal Compatibility

A technically suitable material may still be incompatible when supply volume, geographical separation, or timing does not correspond with user requirements. Quantity compatibility compares available or predicted volumes with minimum, maximum, and recurring demand [27]. Spatial compatibility considers distance between organizations, transportation infrastructure, consolidation opportunities, and whether movement requirements remain operationally practical [31]. Temporal compatibility evaluates whether resource-generation periods coincide with demand windows, delivery schedules, and production cycles [24]. Where timing differs, storage may bridge temporary mismatches, although capacity limitations and material deterioration can restrict this option. Generation frequency and continuity are particularly important for users requiring stable inputs. Consequently, quantity, space, and time collectively determine whether technically compatible resources can be supplied at the required scale, location, and operational moment [29].

5.4 Economic and Environmental Compatibility

Circular exchange must also provide sufficient economic and environmental value to justify implementation. Economic assessment should compare secondary-resource value with transportation, storage, sorting, preprocessing, quality verification, and transaction costs [28]. Avoided disposal expenditure and reduced virgin-material procurement can improve exchange attractiveness even when additional processing is required [30]. Environmental compatibility should examine whether the proposed relationship increases waste diversion and substitutes primary materials while considering transportation, processing energy, and associated emissions [25]. A distant exchange that requires energy-intensive treatment may offer less environmental benefit than its material-recovery rate initially suggests. Economic and environmental criteria should therefore be evaluated jointly rather than assuming every recovered-material exchange is inherently advantageous. This approach prioritizes exchanges that preserve resource value without transferring disproportionate costs or environmental burdens elsewhere [31].

5.5 Regulatory, Operational, and Trust Compatibility

Implementation further depends on whether organizations are legally and operationally capable of completing an exchange. Waste classification, hazardous-material requirements, transportation rules, permits, documentation, and traceability obligations can impose mandatory eligibility conditions [26]. Operational compatibility concerns receiving capacity, storage infrastructure, processing equipment, quality-control capabilities, and ability to integrate secondary materials into existing processes [29]. Relational considerations become important where resource characteristics or delivery reliability cannot be guaranteed exclusively through digital information. Previous transactions, fulfillment records, disputes, verification outcomes, and reputation indicators can provide evidence of organizational reliability [27]. Trust-aware assessment therefore complements technical compatibility by considering whether counterparties have demonstrated the capacity and reliability necessary to sustain the proposed exchange relationship [30].

5.6 Multi-Criteria Compatibility Scoring and Match Ranking

After mandatory constraints eliminate infeasible candidates, remaining opportunities can be compared through multi-criteria compatibility scoring. Each criterion can be normalized to a common scale and assigned a weight reflecting its importance to the particular resource, user, or application [28]. Technical suitability and regulatory compliance may operate as minimum thresholds, while distance, timing, economic value, environmental benefit, and trust differentiate feasible alternatives [31]. The conceptual relationship can be represented as $\text{Compatibility Score} = f(\text{Technical Fit, Quantity, Quality, Distance, Timing, Economic Value, Environmental Benefit, Compliance, Trust})$. Rather than applying identical weights universally, the SRN can adjust priorities according to material characteristics and stakeholder requirements [25]. Ranked recommendations should also expose component scores, failed thresholds, and important trade-offs so participants understand why particular exchanges received higher priority, strengthening transparency and informed decision-making [29].

5.7 Predictive-Compatibility Integration and Match Optimization

Optimization occurs when compatibility evidence is combined with the probability that predicted supply and demand will actually materialize. A highly compatible relationship provides limited planning value when forecast confidence is extremely low, while highly probable availability should not compensate for technical or regulatory infeasibility [30]. The SRN can therefore integrate forecast probabilities with compatibility scores after enforcing mandatory constraints, prioritizing opportunities that are simultaneously probable, feasible, and beneficial [27]. This integration directs organizational attention toward exchange relationships offering stronger combinations of expected availability, practical compatibility, and circular-resource value [31].

Table 2. Multi-Dimensional Resource Compatibility Criteria and Matchmaking Indicators

Compatibility dimension	Key variables	Assessment criterion	Potential constraint	Matchmaking contribution
Technical/material	Composition, physical properties, condition, contamination	Conformity with required material and performance specifications	Incompatible composition or unacceptable contamination	Establishes fundamental technical feasibility
Quality	Grade, purity, consistency, degradation, tolerance limits	Degree to which quality falls within acceptable user range	Quality below minimum specification	Prevents unsuitable secondary-resource substitution
Quantity	Available volume, required volume, generation rate, batch size	Alignment between supply quantity and user demand	Insufficient supply or excessive unusable surplus	Determines volumetric feasibility
Spatial/logistics	Distance, transport mode, infrastructure, consolidation potential	Practicality of moving material between participants	Excessive distance, cost, or logistical complexity	Identifies geographically viable exchanges
Temporal	Availability window, demand period, frequency, delivery schedule	Synchronization of generation and consumption	Timing mismatch or inadequate storage	Supports timely and continuous resource utilization
Economic	Resource value, transport, preprocessing, storage, avoided disposal cost	Net economic attractiveness of the exchange	Costs exceeding recoverable value or savings	Prioritizes financially viable relationships
Environmental	Waste diversion, virgin-material displacement, processing energy, emissions	Net circularity and environmental benefit	Transport or processing burdens outweighing benefits	Prioritizes environmentally beneficial exchanges
Regulatory	Waste classification, permits, safety rules, documentation, traceability	Compliance with applicable exchange requirements	Prohibited movement or missing authorization	Filters legally infeasible exchanges
Operational	Processing capacity, storage, equipment, quality-control capability	Ability to receive, transform, and utilize the resource	Insufficient infrastructure or processing capacity	Confirms implementation readiness
Trust/relational	Reputation, transaction history, reliability, disputes, verification	Confidence in counterparty performance	Poor reliability or insufficient transaction evidence	Reduces relational and transaction uncertainty

6. OPTIMIZED CIRCULAR WASTE MATCHMAKING AND NETWORK LEARNING

6.1 Candidate Resource Discovery and Initial Filtering

The operational matchmaking process begins by comparing predicted resource availability with anticipated organizational demand across the SRN. Candidate discovery identifies relationships in which material characteristics and expected availability indicate a plausible correspondence with future requirements [29]. Because exhaustive evaluation of every network combination is inefficient, initial filtering removes clearly infeasible candidates before detailed compatibility assessment [32]. Mandatory constraints can include material category, minimum quantity, prohibited contamination, regulatory eligibility, maximum geographical distance, and essential technical specifications. Applying these exclusion rules reduces the candidate space while preserving potentially valuable cross-sector relationships that may not be apparent from conventional industry classifications or keyword-based searches [30].

6.2 Compatibility-Based Recommendation and Ranking

Candidates surviving initial filtering undergo multidimensional compatibility assessment using the technical, qualitative, quantitative, spatial, temporal, economic, environmental, regulatory, operational, and trust criteria established previously [31]. Individual criterion scores can be combined with stakeholder-specific weights to generate an overall compatibility measure, while mandatory thresholds prevent high performance in one dimension from compensating for critical infeasibility elsewhere [33]. Feasible candidates are subsequently ranked according to their combined forecast confidence and compatibility performance. Recommendations presented to participants should include overall ranking alongside relevant component scores, predicted availability, anticipated benefits, identified constraints, and significant trade-offs, enabling users to understand both the attractiveness and limitations of each proposed relationship [35].

6.3 Stakeholder Decision and Exchange Coordination

Algorithmic recommendation does not itself constitute an exchange; participating organizations retain responsibility for evaluating and accepting proposed relationships. Interested parties can verify material information, request samples, negotiate quantities and prices, and establish quality-assurance requirements [30]. Coordination subsequently addresses transportation arrangements, delivery schedules, storage, preprocessing responsibilities, contractual terms, regulatory documentation, and traceability requirements [34]. Where conditions cannot be reconciled, participants may modify or reject the recommendation. This human decision stage converts computational compatibility into negotiated operational arrangements and ensures that organizational priorities and practical constraints remain incorporated within final transaction decisions [32].

6.4 Transaction Feedback and Match Outcome Learning

Every recommendation generates potentially valuable learning evidence regardless of whether an exchange is completed. The SRN should therefore record recommendations as accepted, rejected, modified, completed, interrupted, or failed and associate these outcomes with explanatory information [33]. Rejection reasons may include unsuitable quality, insufficient quantity, excessive distance, unfavorable economics, timing conflicts, regulatory restrictions, or organizational concerns. Completed exchanges can provide actual transportation costs, processing expenditure, delivered quantities, material performance, environmental outcomes, and participant ratings [31]. Differences between predicted and observed conditions are particularly valuable because they reveal systematic forecasting or compatibility errors. Transaction outcomes consequently transform matchmaking from a one-directional recommendation process into an evidence-generating cycle through which operational experience continuously enriches network intelligence [35].

6.5 Adaptive Network and Model Improvement

Accumulated outcome evidence enables both predictive and compatibility models to evolve as network conditions change. Differences between forecast and actual resource availability can recalibrate supply and demand models, while repeated acceptance or rejection patterns can indicate whether compatibility criteria are weighted appropriately [34]. Verified transaction outcomes can update resource profiles, processing requirements, application knowledge, and organizational trust indicators [29]. Successful cross-sector exchanges may additionally reveal previously unknown relationships between materials and applications, expanding the future candidate search space. Through periodic retraining and parameter adjustment, the SRN progressively incorporates operational evidence into subsequent predictions and recommendations, creating an adaptive matchmaking environment rather than a static rule-based exchange platform [32].

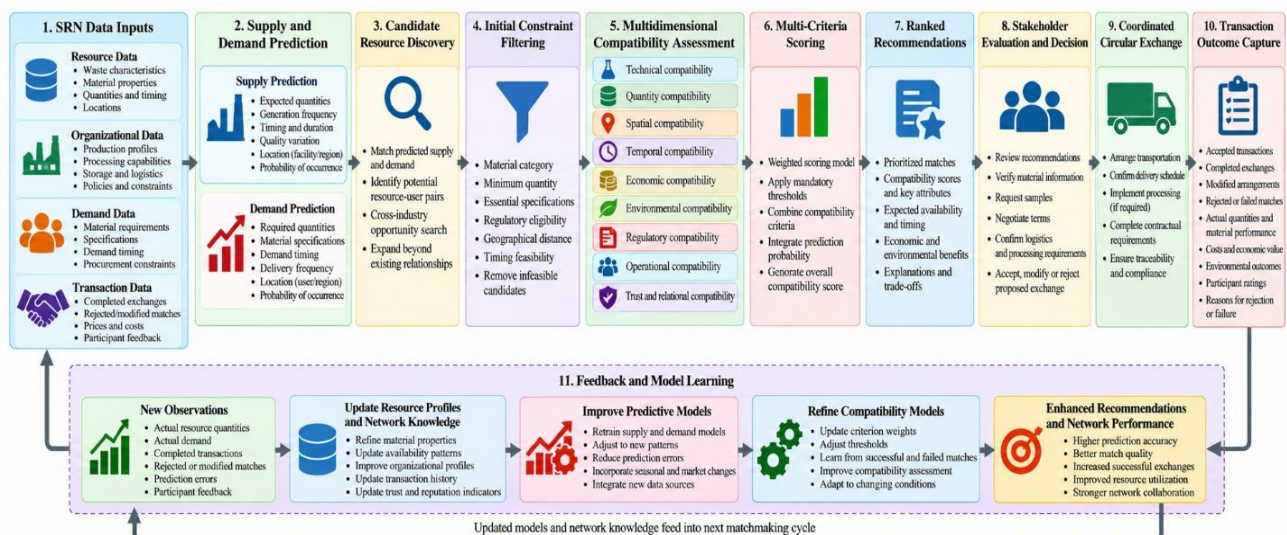


Figure 3. Integrated Predictive-Compatibility Waste Matchmaking and Continuous Learning Framework.

Figure 3: Integrated Predictive-Compatibility Waste Matchmaking and Continuous Learning Framework

7. PERFORMANCE EVALUATION, IMPLEMENTATION CHALLENGES, AND RESEARCH IMPLICATIONS

7.1 Matchmaking and Predictive Performance

Evaluation should first determine whether predictive matchmaking identifies relevant opportunities accurately and efficiently. Supply and demand prediction accuracy can be measured by comparing forecast quantities, timing, and occurrence probabilities with observed network conditions [28]. Recommendation precision indicates the proportion of suggested matches that prove relevant, whereas recall measures the system's ability to retrieve viable opportunities from the available candidate space [31]. Successful-match rate captures recommendations progressing to completed exchanges,

while false-match rate reveals unsuitable opportunities surviving compatibility assessment [29]. Ranking quality should determine whether highly feasible exchanges consistently appear above weaker alternatives. Evaluation should additionally measure the time required to discover suitable partners, particularly relative to manual searches or conventional listing-based resource exchanges [33].

7.2 Circularity, Economic, and Environmental Performance

Algorithmic accuracy is meaningful only when improved recommendations generate measurable resource outcomes. Circularity performance can therefore assess quantities diverted from disposal, secondary-resource utilization, recovery rates, and displacement of virgin-material consumption [30]. Economic indicators should include transaction value, avoided waste-management expenditure, procurement savings, preprocessing costs, and transportation expenditure. Environmental evaluation can examine avoided disposal, reduced primary-resource extraction, transportation effects, processing energy, and associated emissions [32]. These indicators should be considered jointly because increasing material recovery does not automatically produce positive economic or environmental outcomes. Multi-dimensional evaluation consequently determines whether successful matches translate into resource conservation and demonstrable system-level value [28].

7.3 Network and Socio-Technical Performance

The SRN should additionally be evaluated as an evolving socio-technical network rather than exclusively as an algorithmic system. Participant growth, network density, cross-industry connections, repeated exchanges, and diversity of resource relationships can indicate whether the platform strengthens circular collaboration [33]. Recommendation acceptance rates provide evidence of perceived relevance, while participant retention can indicate continuing utility. Repeated successful transactions may strengthen organizational trust and reduce uncertainty surrounding future exchanges [29]. Evaluation should therefore examine whether intelligent matchmaking expands collaboration beyond existing partnerships and progressively creates durable resource-sharing relationships across otherwise disconnected industrial communities [31].

7.4 Data Quality, Interoperability, and Prediction Uncertainty

Performance nevertheless depends strongly on the completeness and consistency of underlying data. Missing material properties, inaccurate quantities, inconsistent terminology, incompatible classification standards, and outdated organizational profiles can distort both predictions and compatibility scores [30]. Limited transaction histories can further restrict model learning, particularly for newly participating organizations or uncommon materials. Forecast uncertainty also increases when production schedules, market conditions, or resource demand change rapidly [32]. Interoperability therefore requires common data structures, semantic mappings, validation procedures, and mechanisms for communicating uncertainty so that recommendations distinguish well-supported opportunities from those derived from incomplete or volatile evidence [28].

7.5 Governance, Privacy, Trust, and Scalability

Large-scale implementation introduces governance challenges because organizations may consider production volumes, waste composition, procurement requirements, prices, and supplier relationships commercially sensitive [31]. Clear rules are required for data ownership, access permissions, sharing, retention, and regulatory responsibility. Algorithmic transparency is similarly important when recommendations influence economically significant decisions [33]. Platform governance should establish responsibilities for data verification, disputes, compliance, and model oversight while preserving organizational autonomy. As the SRN expands across sectors and regions, scalable data infrastructures and interoperable standards must accommodate increasing participant diversity without weakening privacy, trust, recommendation quality, or accountability [29].

7.6 Future Research Directions

Future research can extend the framework through graph-based models that learn complex relationships among organizations, materials, processes, and previous exchanges [32]. Explainable AI could improve recommendation transparency, while federated learning may enable collaborative model development without centralized disclosure of sensitive organizational data [30]. Additional opportunities include dynamic resource pricing, digital twins for evaluating prospective exchanges, lifecycle-assessment integration, Internet-of-Things-enabled resource tracking, uncertainty-aware recommendations, and adaptive compatibility weighting that learns stakeholder priorities and changing network conditions from accumulated transaction evidence [33].

8. CONCLUSION

This study advances circular waste exchange from fragmented, reactive resource discovery toward intelligent, network-based coordination of secondary-resource flows. Conventional waste matching largely responds to materials already declared available, whereas predictive circular matchmaking anticipates future supply and demand, creating opportunities for earlier cross-industry coordination. Prediction alone, however, cannot establish whether an anticipated exchange is viable, while compatibility assessment without forecasting remains constrained by resources already visible within the network.

Integrating Social Resource Networks, structured resource representation, predictive analytics, multidimensional compatibility modeling, multi-criteria ranking, and transaction feedback addresses these complementary limitations. The resulting framework can identify prospective cross-industry

relationships before critical supply and demand windows are missed and determine whether candidate exchanges satisfy technical, quantitative, spatial, temporal, economic, environmental, regulatory, operational, and trust requirements. Continuous feedback from accepted, rejected, completed, and failed transactions further enables predictions, compatibility weights, resource profiles, and recommendations to improve progressively.

Collectively, these capabilities can reduce information asymmetry, increase secondary-resource utilization, strengthen industrial symbiosis, and support greater waste diversion within adaptive circular-resource ecosystems. Realizing these benefits nevertheless requires reliable data standardization, interoperability, transparent models, organizational trust, effective governance, scalable infrastructure, and rigorous real-world validation across diverse industries and resource conditions.

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