Extended Materials
From Matching Efficiency to Matching Quality: Modeling and Explaining Relational Mechanisms in Two-Sided Matching

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Contents

Appendix A: Two-sided Matching Literature Analysis

In the field of two-sided matching, prior research in management and information systems (IS) has examined matching-related problems from multiple perspectives. Based on a systematic review of representative studies (see Table 1), two-sided matching has been widely recognized as a critical issue in platform-based markets and organizational decision-making contexts (Shen et al. 2024, Liu et al. 2024). Existing studies span a variety of application domains, including online platforms, labor markets, the sharing economy, and healthcare resource allocation.

Platform Perspective: Decentralized versus Centralized Matching.

A dominant stream of the literature distinguishes two-sided matching platforms according to the locus of matching decision authority, categorizing them into decentralized and centralized mechanisms (Bojd and Yoganarasimhan 2022). In decentralized matching platforms, both sides of the market make autonomous choices among potential counterparts, typically supported by platform-provided information, recommendations, or rankings. By contrast, in centralized matching platforms, participants submit preferences, requirements, or constraints, and matching outcomes are generated centrally by the platform or an intermediary according to predefined rules. It is worth noting that some platforms may exhibit hybrid or partially centralized designs in practice; nevertheless, this distinction remains the most widely adopted analytical framework in the existing literature. In terms of research coverage, prior studies have largely focused on decentralized matching platforms, particularly in contexts such as online dating, recruitment, and short-term rentals. In comparison, relatively few studies explicitly examine centralized matching mechanisms. As a result, research that systematically integrates bilateral user characteristics to improve matching quality in centralized settings remains limited.

Methodological Perspective: Empirical and Modeling Approaches

From a methodological standpoint, the two-sided matching literature primarily adopts two broad approaches: empirical analysis and model-based analysis. Empirical studies typically investigate platform design features, institutional arrangements, and user behavioral mechanisms. For example, prior work has examined how anonymity affects matching outcomes in online dating platforms (Bapna et al. 2016), and how direct communication influences matching outcomes in rental platforms (Zhao et al. 2024). These studies provide important insights into user behavior and platform design. In contrast, model-based research—often drawing on mathematical optimization, mechanism design, or game theory—focuses on designing efficient matching mechanisms and improving platform-level performance. For instance, some studies analyze how variations in choice capacity affect matching outcomes (Jung et al. 2022), while others explore optimal product or matching designs under assumed preference structures (Aouad and Saban 2023). Despite their contributions, both empirical and modeling approaches tend to emphasize platform-level mechanisms and efficiency, while paying relatively limited attention to individual-level heterogeneity and personalized interactions between bilateral features.

Research Objectives: Matching Efficiency versus Matching Quality.

With respect to research objectives, existing studies primarily focus on two dimensions: matching efficiency and matching quality. Matching efficiency concerns whether a match is successfully formed, whereas matching quality reflects post-match satisfaction, stability, and longer-term outcomes. However, the literature has predominantly concentrated on efficiency-related outcomes, with comparatively limited attention devoted to matching quality. A small number of studies begin to examine quality-related issues—for example, by analyzing how communication features influence post-match outcomes (Zhao et al. 2024)—yet such work generally remains at the level of platform functionality rather than addressing personalized, feature-based prediction and explanation of matching quality.

Deep Learning and Matching Research.

In addition, we reviewed recent studies that employ machine learning and deep learning methods to predict matching outcomes (see Table 2). Existing research in this stream largely focuses on predicting whether a match occurs or the likelihood of a successful match, again emphasizing matching efficiency. Relatively few studies apply deep learning approaches to matching quality prediction, and more importantly, the interactive relationships between features on both sides of the match have not been systematically modeled—particularly in centralized matching contexts.

In summary, while the two-sided matching literature in management and information systems has generated substantial insights, it has largely centered on platform functionality, mechanism design, and efficiency improvement. Research that integrates bilateral user characteristics at the individual feature level to predict and explain matching quality, especially within centralized matching platforms, remains relatively scarce. This gap provides both the theoretical foundation and practical motivation for the present study, which seeks to advance the understanding and modeling of two-sided matching quality from a feature-interaction and interpretability perspective.

Table 1 Research on Two-Sided Matching in Information Systems

No.	Reference	Context	Platform Type	Method	Efficiency / Quality	Research Question
1	Bapna et al. (2016)	Online Dating Platform	Decentralized	Empirical Model	Efficiency	Impact of anonymity on matching outcomes.
2	Jung et al. (2022)	Online Dating Platform	Decentralized	Empirical Model	Efficiency	How choice capacity design affects matching outcomes.
3	Bojd and Yoganarasimhan (2022)	Online Dating Platform	Centralized	Empirical Model	Efficiency	Investigating the impact of star ratings on successful matching in online dating platforms.
4	Shi and Viswanathan (2023)	Online Dating Platform	Decentralized	Empirical Model	-	Effect of optional verification signals on matching outcomes.
5	Zhao et al. (2024)	Housing Rental Platform	Decentralized	Empirical Model	Quality	Role of direct communication in improving matching quality.
6	Shen et al. (2024)	Online Dating Platform	Decentralized	Empirical Model	-	How information asymmetry in online dating platforms affects preference matching
7	Wang et al. (2024)	Housing Rental Platform	Decentralized	Empirical Model	-	Does supplier quality differentiation improve matching efficiency in maturing P2P markets?
8	Guo et al. (2026)	Online Labor Platform	Decentralized	Empirical Model	Efficiency	Influence of employer project descriptions on matching efficiency.
9	Kanoria and Saban (2021)	Online Matching Platform	Decentralized	Mathematical Model	Efficiency	Design of search strategies for participants in matching markets.
10	Rios et al. (2023)	Online Dating Platform	Decentralized	Mathematical Model	Efficiency	How to dynamically select candidate sets to maximize match success.
11	Aouad and Saban (2023)	Online Labor Market	Decentralized	Mathematical Model	Efficiency	Optimal assortment design under assumptions about user preferences.
12	Celdir et al. (2024)	Online Dating Platform	Decentralized	Mathematical Model	Efficiency	How popularity bias affects users' chances of finding a match.
13	Shi (2023)	Online Platform	Decentralized & Centralized	Mathematical Model	Efficiency	Exploring matching strategies across different matching types to maximize matching efficiency.
14	Malgonde et al. (2020)	Online Educational Platform	Decentralized	Simulation Model	–	Co-evolutionary learning via two-sided recommender systems.
15	Arnosti et al. (2021)	Online Matching Platforms	Decentralized	Game-Theoretic Model	Efficiency	Achieving matching with minimal search effort.
16	Du and Lei (2022)	Ride-Hailing	Decentralized	Game-Theoretic Model	Efficiency	How information design improves matching quality.
17	Le et al. (2023)	Organ Transplantation	Centralized	Mathematical Model	Efficiency	Maximizing the number of successful transplants via dual-donor exchange.
18	Liu et al. (2024)	Online labor platform	Decentralized	Game Model	-	The impact of high-quality matching technologies on both sides of the match and the platform.
19	Lee and Cui (2024)	Online Labor Platform	Decentralized & Centralized	Game Model	Efficiency	A comparative analysis of the effectiveness of decentralized and centralized matching platforms in resolving platform disputes.
20	Basu et al. (2024)	Online Labor Platforms	Decentralized	Mathematical / Game Model	-	Effects of information asymmetry and preference uncertainty on user behavior and optimal pricing to maximize profit.

Table 2 Machine Learning Approaches to Two-Sided Matching

No.	Reference	Context	Platform Type	Method	Efficiency / Quality	Deconfo-unding	Intra-relation	Inter-relation	Explanation	Research Question
1	Dolatsara et al. (2020)	Organ Transplantation	Centralized	Machine Learning	Quality					Predicting heart transplantation survival probabilities.
2	Chen et al. (2021)	Sharing Economy Platform	Decentralized	Topic Model	Efficiency					Predicting transaction success using bilateral reviews.
3	Wang et al. (2021)	Ride-hailing Platform	Centralized	Deep Learning	Efficiency			✓		Predicting real-time passenger-driver matching success.
4	Kwon et al. (2022)	Online Dating Platform	Decentralized	Deep Learning	Efficiency					Predicting match probability from facial visual features.
5	Yang et al. (2022)	Online Labor Platform	Decentralized	Deep Learning	Efficiency					This study proposes a dual-perspective graph representation learning approach to model directed interactions between candidates and jobs.
6	Gong et al. (2024)	Online Labor Platform	Decentralized	Deep Learning	Efficiency					This study design a model to calculate a matching score between the job seeker's resume and the job posting.
7	(Shi et al. 2025)	Online Recruitment Platform	Decentralized	Deep Learning	Efficiency					This study the dynamic feedback loops and preference adjustments inherent in two-way proactive recruitment to improve interview-through rates
8	**This Work**	Ride-Hailing & Organ Transplantation	Centralized	Deep Learning	Quality	✓	✓	✓	✓	Predicting matching quality using bilateral user features.

Note. **Context** — The specific application scenario under study; Platform Type— The type of matching platform (Decentralized or Centralized); **Method** — The methodological approach employed; **Efficiency / Quality** — Whether the research objective is to improve matching efficiency or matching quality; **Deconfounding** — Whether the research accounts for and mitigates the influence of confounding factors; **Intra-relation** — Whether the study considers dependencies among features within each participant; **Inter-relation** — Whether the study accounts for interactions between the features of the two matched parties; **Explanation** — Whether the study provides explicit explanatory outputs; **Research Question** — The central research question addressed by the study.

Appendix B: Decentralized Matching Platform and Centralized Matching Platform

Building on prior research on two-sided markets and matching systems (Ke and Zhu 2021, Bojd and Yoganarasimhan 2022, Aouad et al. 2023, Shi 2023), two-sided matching platforms can be broadly categorized as decentralized or centralized, depending on where decision authority over the final match resides. This distinction is central to understanding how matching quality is generated, perceived, and governed across different platform environments.

In decentralized matching platforms, the platform primarily functions as an information intermediary. It provides users with recommendations, rankings, or personalized information about potential counterparts, thereby reducing search costs and facilitating efficient search and discovery. However, the final matching decision remains with the participants themselves, and a match is formed only when both sides mutually agree (Kanoria and Saban 2021). As a result, matching outcomes in decentralized settings are more directly shaped by users' individual preferences and choices, even though platform design elements such as recommendation algorithms and information disclosure policies continue to influence the choice environment. Representative examples include e-commerce platforms, job-matching platforms, and short-term rental platforms, where users retain substantial autonomy in accepting or rejecting recommended matches.

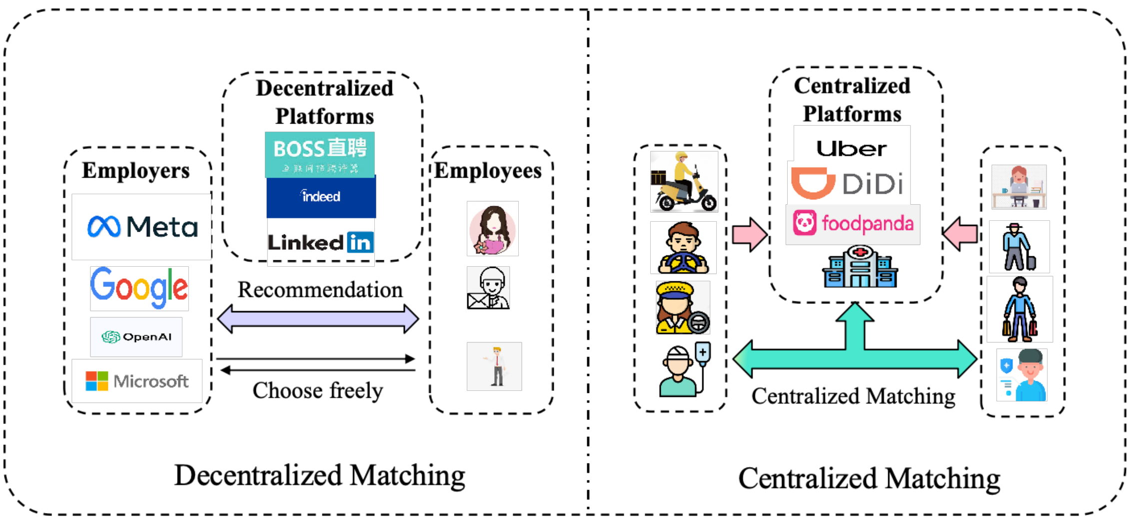

Figure 1 **Illustration of Decentralized and Centralized Matching**

In contrast, centralized matching platforms rely on a centrally coordinated decision process to determine final matching outcomes (Kanoria and Saban 2021). In these systems, participants typically submit preferences, requirements, or availability information, while the platform or a centralized intermediary allocates matches according to predefined rules or algorithmic procedures. Once the matching decision is made, users often have limited ability to influence or veto the assignment. Prominent examples include ride-hailing platforms, where drivers and passengers are algorithmically paired, as well as organ transplantation systems, in which donor and recipient information is evaluated by centralized allocation mechanisms operated by hospitals or regulatory bodies.

This distinction has important implications for matching quality and accountability. In decentralized platforms, mismatches are more likely to be perceived as the outcome of users' own choices, even when platform design substantially shapes the available options. In centralized platforms, by contrast, matching outcomes are more directly attributed to the platform or central authority. Consequently, poor matching quality in centralized settings is more likely to erode user trust, reduce participant retention, and threaten the long-term stability of the system. These concerns are particularly salient in high-stakes domains such as healthcare, where mismatches can lead to severe and irreversible consequences. In organ transplantation, for example, accurately anticipating donor–recipient compatibility is critical for managing risks such as chronic rejection and for supporting long-term graft survival.

Motivated by these considerations, this study focuses on centralized bilateral matching platforms. We aim to predict matching quality and to develop an interpretable and high-accuracy predictive framework that supports accountable decision making, enhances user trust, and promotes the long-term stability of centralized two-sided systems.

Appendix C: Holistic Matching VS. Feature-wise Matching

From the perspectives of neuroscience and cognitive psychology, human reasoning in matching tasks is commonly discussed as involving two contrasting modes of information processing: holistic matching and feature-wise matching (Navon 1977, Bruce and Young 1986). Holistic matching refers to a mode of reasoning in which the feature representations of both entities are first integrated independently, and match quality is subsequently assessed based on the overall similarity of these aggregated representations. In contrast, feature-wise matching emphasizes a more analytic process, whereby corresponding feature dimensions across the two entities are compared sequentially, and match quality is evaluated based on fine-grained differences and associations at the feature level. However, by treating features as independent dimensions, feature-wise approaches often overlook dependency structures among features within each entity, limiting their ability to capture relational mechanisms.

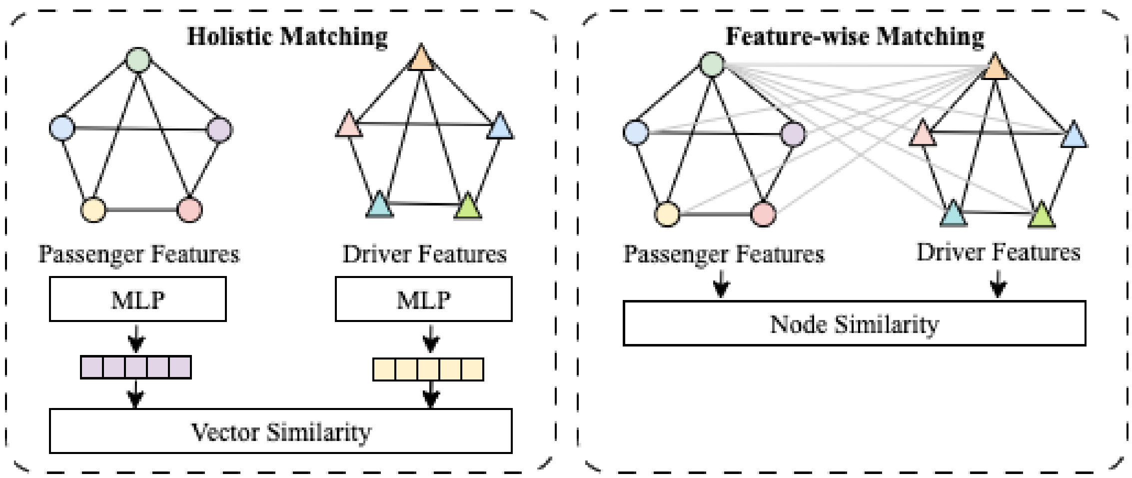

Figure 2 **Illustration of Different Matching Types.**

A similar distinction can also be observed in prior deep learning approaches to matching tasks, as illustrated in Figure 2. Holistic matching methods typically rely on learning unified representations for each side of the match and then computing similarity or compatibility scores. For example, Shi et al. (2025) study online recruitment platforms by encoding job descriptions and résumés using multilayer perceptrons (MLPs) and applying a cross-ratio function to predict match likelihood. Likewise, Kwon et al. (2022) examine online dating platforms by extracting facial representations of both parties using generative adversarial networks, followed by an MLP-based holistic prediction model to improve post-match satisfaction. These approaches share a common characteristic in that matching decisions are driven primarily by comparisons between aggregated entity-level representations. In contrast, feature-wise matching approaches explicitly compare attributes across the two sides of a match. For instance, Wang et al. (2021) focus on ride-hailing platforms and compute vector-level similarities across corresponding driver and passenger attributes to capture cross-party feature interactions. While such methods offer greater transparency at the feature level, they typically treat features as independent dimensions and do not explicitly model dependency structures among features within each entity. As a result, intra-entity feature dependencies and their potential influence on matching outcomes are not systematically captured.

Taken together, existing deep learning approaches to matching can be broadly characterized along a holistic–feature-wise spectrum. However, prior work has primarily focused on predictive performance and matching efficiency, with limited attention to how different information organization strategies affect reasoning and interpretation, particularly in the context of LLMs. With the emergence of LLMs, which process inputs in natural language form rather than fixed numerical representations, it remains an open question whether holistic or feature-wise prompting better supports interpretable and logically coherent reasoning in matching tasks.

Appendix D: Differences between Recommendation and Two-sided matching

Although personalized recommendation and two-sided matching may appear conceptually similar and are sometimes treated as closely related tasks in the literature (Tanriverdi et al. 2010), they differ in important ways with respect to their objectives, decision mechanisms, and modeling paradigms. Prior studies have already provided useful discussions distinguishing recommendation systems from matching systems (Shi and Zhang 2019, Malgonde et al. 2020). Building on this stream of work, this appendix further clarifies the boundary between the two in order to delineate the scope of the present study. Figure 3 provides a schematic comparison of personalized recommendation and two-sided matching.

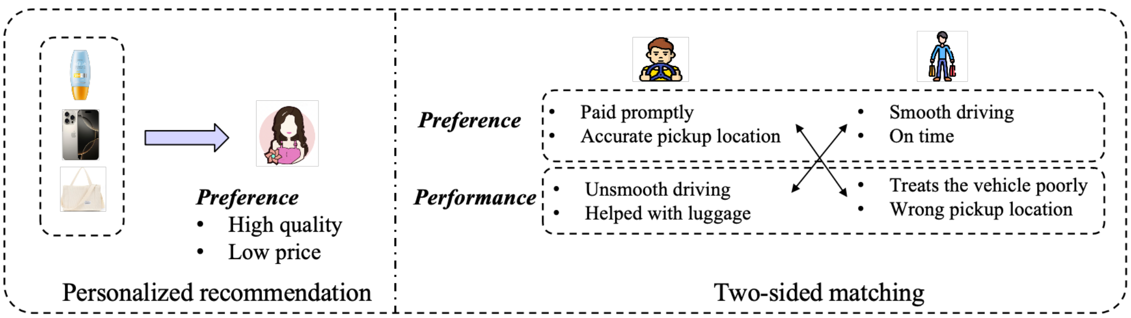

Figure 3 Illustration of Recommendation and Two-sided Matching

Definition. Two-sided matching refers to a market setting in which two distinct groups of agents (e.g., job seekers and employers, students and schools, buyers and sellers) mutually select each other based on their respective attributes, preferences, and constraints, ultimately forming pairings that satisfy both sides (Gale and Shapley 1962, Roth and Sotomayor 1992). A defining characteristic of two-sided matching is that match formation depends on the joint consideration of both parties' preferences, rather than unilateral decision-making by a single side.

In contrast, personalized recommendation systems are primarily designed to serve one side of the market, typically users, and to optimize outcomes aligned with that side's objectives, such as click-through rates, conversions, or user satisfaction (Malgonde et al. 2020). This setting is therefore best characterized as a unidirectional optimization problem. For example, in e-commerce platforms, recommendation algorithms suggest products to users without explicitly modeling whether products "prefer" particular users, as items generally lack autonomous preferences or adaptive behavioral responses. Consequently, personalized recommendation systems focus on modeling user preferences and behavior, while treating the recommended objects as passive entities.

By contrast, two-sided matching is inherently bidirectional and co-determined. In such settings, both sides of the market actively express preferences and exhibit observable behavioral patterns that influence match outcomes (Shen et al. 2024). Consider a ride-hailing platform: drivers may prefer passengers who are punctual and reliable in payment, while passengers may prefer drivers who drive safely and arrive on time. At the same time, both parties' historical behaviors—such as service quality, punctuality, or compliance with platform norms—shape future matching outcomes. Effective matching therefore requires integrating not only each side's explicit preferences, but also their past behavioral performance and the trade-offs between the two sides' objectives. More broadly, bilateral matching quality depends on complex relational structures, including intra-feature dependencies within individuals (e.g., how different behavioral attributes jointly characterize a driver or passenger) and inter-feature interactions between participants (e.g., how one party's behavior interacts with the other party's preferences). These relational characteristics distinguish two-sided matching from recommendation tasks that rely primarily on one-sided preference modeling.

For this reason, directly applying methods developed for personalized recommendation—such as user–item collaborative filtering or standard deep recommendation models—to two-sided matching quality prediction is often insufficient. Such approaches typically fail to capture the reciprocal, interdependent nature of two-sided decision-making and may lead to biased predictions or unintended imbalances across market participants (Malgonde et al. 2020). Accordingly, this study emphasizes that predicting bilateral matching quality requires a dedicated modeling framework that jointly accounts for the attributes, behaviors, and interactions of both sides, rather than adapting one-sided recommendation techniques.

Appendix E: Details of Driver-passenger Dataset

In collaboration with a leading global ride-hailing platform, we obtained data on completed ride-hailing orders from a single large metropolitan city in China, covering the period from March 1, 2024 to May 1, 2024. The dataset consists of four main categories of information: passenger features, driver features, order context information, and bilateral satisfaction evaluations.

Among these, bilateral satisfaction evaluations, specifically, the passenger's rating of the driver and the driver's rating of the passenger, are commonly used proxy measures of bilateral matching quality in ride-hailing platforms and are operationalized as the prediction targets in our analysis ($DriSatisfaction$, $PasSatisfaction$). As the focus of this study is on post-match quality rather than matching efficiency, we include only successfully matched and completed orders. This design ensures that matching efficiency is held constant across all observations and aligns with the research objective of evaluating variation in matching quality conditional on successful matches.

After data preprocessing and quality checks, the final sample consists of 340,000 valid ride-hailing orders. Each observation contains 27 passenger-related features, 28 driver-related features, and two outcome variables capturing passenger satisfaction and driver satisfaction. Both outcome variables are constructed from aggregated post-trip ratings submitted by the respective parties. Descriptive statistics and variable definitions for all features are reported in Table 3.

Table 3: Descriptive Statistics of Passenger-Driver Features

Variable Name	**Descriptions**	**Type**	**Mean**	**Std**	**Min**	**Max**	**Unique**	**Count**
PasAge	Passenger age	Con	33.75	9.50	6	92	80	340,000
PasGender	Passenger gender	Cate	0.48	0.50	0	1	2	340,000
PasRole	Passenger role	Cate	1.10	0.43	1	3	2	340,000
PasAuthState	Verification status	Cate	1.68	1.04	0	6	5	340,000
PasEduType	Education level	Cate	0.12	0.49	0	4	5	340,000
PasStudentVerify	Student verified	Cate	0.02	0.15	0	1	2	340,000
PasPhonePrice	Passenger's phone price	Con	5,169.73	3,261.73	199	21,999	198	340,000
PasProvNum	Passenger's home province	Cate	18.74	8.15	0	34	34	340,000
PasCityNum	Passenger's home city	Cate	301.30	117.79	2	500	380	340,000
PasRegDays	Passenger registration days	Con	2,563.45	1,055.08	0	4,372	4,270	340,000
PasPre0	Pick-up accuracy	Con	0.003	0.05	0	1	391	340,000
PasPre1	Route reasonableness	Con	0.16	0.32	0	1	2,131	340,000
PasPre2	Driving smoothness	Con	0.22	0.36	0	1	2,077	340,000
PasPre3	Vehicle cleanliness	Con	0.22	0.37	0	1	2,006	340,000
PasPre4	Friendliness	Con	0.23	0.38	0	1	2,068	340,000
PasPre5	Service proactiveness	Con	0.17	0.33	0	1	2,072	340,000
PasBeh0	Pick-up location accuracy	Con	-0.003	0.04	-0.67	0.80	520	340,000
PasBeh1	Destination accuracy	Con	-0.009	0.06	-0.80	0.50	1,043	340,000
PasBeh2	Pick-up punctuality	Con	0.05	0.16	-0.88	0.97	1,821	340,000
PasBeh3	Friendliness	Con	0.03	0.19	-0.92	0.97	1,919	340,000
PasBeh4	Payment timeliness	Con	0.02	0.17	-0.94	0.95	1,751	340,000
PasBeh5	Vehicle carefulness	Con	0.03	0.16	-0.83	0.96	1,796	340,000
DriGrade	Driver grade	Cate	1.07	1.43	0	7	8	340,000
DriGender	Driver gender	Cate	0.94	0.23	0	1	2	340,000
DriAge	Driver age	Con	42.27	9.08	21	67	47	340,000

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Variable Name	**Descriptions**	**Type**	**Mean**	**Std**	**Min**	**Max**	**Unique**	**Count**
DrivingAge	Driving experience	Con	5,492	2,474	0	16,381	8,882	340,000
DriPowerType	Vehicle type	Cate	2.24	1.38	1	7	5	340,000
DriCarAge	Vehicle age	Con	884.34	654.38	0	2922	2,192	340,000
DriProvNum	Driver's home province	Cate	16.23	5.37	0	24	31	340,000
DriCityNum	Driver's home city	Cate	278.65	154.90	2	500	330	340,000
DriCarLevelNum	Vehicle Level	Cate	9.98	1.51	0	15	15	340,000
DriCheckLevelNum	Driver Level	Cate	0.023	0.214	0	3	4	340,000
DriPhonePrice	Driver's phone price	Con	2,031.38	401.08	1,999	6,999	2	340,000
DriPre0	Pick-up location accuracy	Con	0.013	0.08	0	1	10,195	340,000
DriPre1	Destination accuracy	Con	0.04	0.12	0	1	14,508	340,000
DriPre2	Pick-up punctuality	Con	0.12	0.25	0	1	23,894	340,000
DriPre3	Friendliness	Con	0.19	0.28	0	1	26,881	340,000
DriPre4	Payment timeliness	Con	0.16	0.30	0	1	25,162	340,000
DriPre5	Vehicle carefulness	Con	0.13	0.25	0	1	24,333	340,000
DriBeh0	Pick-up accuracy	Con	0.002	0.03	-0.67	0.89	409	340,000
DriBeh1	Route reasonableness	Con	0.11	0.23	-0.67	1.00	2,356	340,000
DriBeh2	Driving smoothness	Con	0.15	0.25	-0.75	1.00	2,344	340,000
DriBeh3	Vehicle cleanliness	Con	0.15	0.26	-0.75	1.00	2,247	340,000
DriBeh4	Friendliness	Con	0.15	0.26	-0.80	1.00	2,359	340,000
DriBeh5	Service proactiveness	Con	0.11	0.23	-0.75	1.00	2,320	340,000
EstDis	Estimated distance	Con	9.00	10.79	0	1,312.52	36,866	340,000
EstPri	Estimated price	Con	30.37	32.50	0	3,619.43	14,722	340,000
EstDur	Estimated duration	Con	1,103.85	891.39	2	41,144	5,827	340,000
SceneNum	Order context	Cate	6.11	3.75	0	13	14	340,000
IsHoliday	Holiday	Cate	0.28	0.45	0	1	2	340,000
DriSatisfaction	Driver satisfaction rating	Cate	0.03	0.84	-1	1	3	340,000
PasSatisfaction	Passenger satisfaction rating	Cate	0.07	0.83	-1	1	3	340,000

Note. **Variable Name** denotes the name of the variable used in this study; **Description** provides its meaning; **Type** indicates the variable type, where 'cate' stands for categorical and 'con' for continuous. Summary statistics include: **Mean** (average), **Std** (standard deviation), **Min** (minimum), **Max** (maximum), **Unique** (number of unique values), and **Count** (number of observations).

Appendix F: Details of Donor-recipient Dataset

For the organ transplantation analysis, we use donor–recipient matching data obtained from the Organ Procurement and Transplantation Network (OPTN). The OPTN datasets are publicly available and de-identified, and thus suitable for research purposes without access to personally identifiable information. We analyze two transplantation contexts: liver transplantation and kidney transplantation. In the liver transplant dataset, both donors and recipients are characterized by 34 clinical and demographic features. In the kidney transplant dataset, donors are described by 104 features and recipients by 100 features, reflecting the greater clinical complexity and heterogeneity associated with kidney transplantation. The definitions, explanations, and descriptive statistics of all variables in the kidney transplant dataset are summarized in Table 4, while corresponding information for the liver transplant dataset is provided in Table 5. These datasets enable the examination of bilateral feature interactions between donors and recipients and support the analysis of post-match outcomes in a centralized, high-stakes matching environment.

Table 4: Descriptive Statistics of Kidney Recipient-Donor Features

Variable Name	Description	Type	Mean	Std	Min	Max	Unique	Count
CmvIgg	Recipient-cmv by igg test result	cate	0.61	0.76	0	3	4	585,831
CmvIgm	Recipient-cmv by igm test result	cate	0.97	1.20	0	3	4	585,831
CmvStatus	Recipient cmv status	cate	1.04	0.73	0	3	4	585,831
ColdIschKi	Kidney cold ischemic time (H)	con	12.91	11.28	0	187	5,013	585,831
CreatTrr	Recipient serum creatinine at time of tx	con	6.11	4.55	0	36.70	2,489	585,831
DialTrr	Recipient pretransplant dialysis @ registration	cate	1.78	0.47	0	2	3	585,831
FinResistTx	Final restsistance @ transplant	con	0.01	0.05	0	2	142	585,831
FuncStatTrr	Recipient functional status @transplant	con	1,396.93	1,024.09	0	4,100	26	585,831
GrfPlacem	Recipient graft placement procedure @ tx	con	0.05	0.26	0	3	4	585,831
Hashbvvaccination	Did recipient receive hepatitis b vaccines prior to transplant?		0.06	0.32	0	2	3	585,831
HbvCore	Recipient hepatitis b-core antibody	cate	1.71	0.83	0	3	4	585,831
HbvNat	Trr hbv nat result	cate	0.64	1.18	0	3	4	585,831
HbvSurAntigen	Recipient hep b surface antigen	cate	1.90	0.46	0	3	4	585,831
HbvSurfTotal	Recipient hbv surface antibody total @ transplant	cate	0.44	0.75	0	3	4	585,831
HcvNat	Trr hcv nat result	cate	0.59	1.11	0	3	4	585,831
HcvSerostatus	Recipient hep c status	cate	1.70	0.73	0	3	4	585,831
HivNat	Trr hiv nat result	cate	0.63	1.18	0	3	4	585,831
HivSerostatus	Recipient hiv serostatus @ transplant	cate	1.85	0.91	0	3	4	585,831
LFinFlowRateTx	Left kidney final flow rate @ transplant	con	4.15	23.29	0	250	274	585,831
LFinResistTx	Left kidney final resistance @ transplant	con	0.01	0.05	0	2	140	585,831
MaligTrr	Recipient any known malignancies since listing @ transplant	cate	0.75	0.45	0	2	3	585,831

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Variable Name	Descriptions	Type	Mean	Std	Min	Max	Unique	Count
MaligTyTrr	Type of malignancy between listing and transplant	con	2.83	57.66	0	3,072	41	585,831
MedCondTrr	Recipient medical condition pre-transplant @ transplant	con	1.99	1.41	0	3	4	585,831
OrgRecOn	Kidney received on ice or pump	con	0.86	0.78	0	3	4	585,831
PreAvgInsulinUsedOldTrr	Recipient old average daily insulin units pre transplant @ transplant	con	0.52	5.83	0	1,000	228	585,831
PreAvgInsulinUsedTrr	Recipient average daily insulin units pre transplant @ transplant	con	0.00	0.18	0	10	175	585,831
PreTxTxfus	Recipient of pre-transplant transfusions-ki @ transplant	cate	0.78	0.75	0	2	3	585,831
PrevPreg	Recipient number of previous pregnancies-ki @ transplant	con	37.20	182.10	0	998	5	585,831
RFinFlowRateTx	Right kidney final flow rate at transplant	con	4.27	23.66	0	250	276	585,831
RFinResistTx	Right kidney final resistance at transplant	con	0.01	0.05	0	2	141	585,831
Reasonnohbvvaccinationid	Reason not vaccinated against hepatitis b		2.08	45.45	0	999	7	585,831
RecOnIce	Kidney received on ice	con	0.52	0.56	0	2	3	585,831
RecOnPump	Kidney received on pump	con	0.17	0.47	0	2	3	585,831
TxProcedurTyKi	Kidney transplant procedure type	con	111.24	44.21	101	319	17	585,831
Abo	Recipient blood group @ registration	cate	2.01	1.33	0	8	9	585,831
AgeDiab	Recipient age of diabetes onset @ registration-ki	con	8.30	16.30	0	96	83	585,831
BmiTcr	Bmi at listing	con	32.68	1,335.93	0	430,226.07	67,678	585,831
DgnTcr	Primary diagnosis at time of listing	con	2,332.92	1,207.66	0	5,002	77	585,831
Diab	Recipient diabetes @ registration	con	8.25	81.18	0	998	7	585,831
DrugtrtCopd	Recipient drug treated copd @ registration	cate	0.60	0.50	0	2	3	585,831
Education	Recipient highest educational level @ registration	con	98.04	292.11	0	998	9	585,831
Ethnicity	Recipient ethnicity	con	0.15	0.36	0	1	2	585,831
ExhPeritAccess	Recipient exhausted vascular access @ registration	cate	0.71	0.46	0	2	3	585,831
ExhVascAccess	Recipient exhausted peritoneal access @ registration	cate	0.71	0.46	0	2	3	585,831
FuncStatTcr	Recipient functional status @ registration	con	1,317.99	1,055.79	0	4,100	26	585,831
GENDER	Recipient gender	cate	1.61	0.49	1	2	2	585,831
Hba1cPaTcr	Hba1c at listing (pa kp only)	con	0.05	0.69	0	96	117	585,831
HgtCmTcr	Recipient height @ registration	con	160.72	38.60	0	225	2,643	585,831
MaligTcrKi	Recipient previous malig. @ registration (kidney)	cate	0.90	0.44	0	2	3	585,831
PeripVasc	Recipient peripheral vascular disease @ registration	cate	0.89	0.46	0	2	3	585,831
PrevMaligTy	Any previous maligancy type @ registration	con	22.84	154.13	0	3,200	120	585,831
TotSerumAlbum	Recipient total serum albumin @ registration	con	2.59	1.91	0	9.90	128	585,831

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Variable Name	Descriptions	Type	Mean	Std	Min	Max	Unique	Count
WgtKgTcr	Recipient weight (kg) @ registration	con	75.18	25.62	0	284.99	14,554	585,831
Ra1	Recipient a1 antigen	con	22.59	207.48	0	6,802	59	585,831
Ra2	Recipient a2 antigen	con	74.49	430.59	0	6,802	61	585,831
Rb1	Recipient b1 antigen	con	66.68	350.01	0	8,201	126	585,831
Rb2	Recipient b2 antigen	con	106.29	495.21	0	8,201	121	585,831
Rdr1	Recipient dr1 antigen	con	20.54	220.83	0	10,300	67	585,831
Rdr2	Recipient dr2 antigen	con	36.88	163.80	0	10,300	65	585,831
Age	Recipient age (yrs)	con	47.28	15.66	0	96	93	585,831
InitWgtKg	Candidate weight in kg at listing	con	70.19	31.51	0	284.40	11,406	585,831
Ethcat	Recipient ethnicity category	con	2.05	7.83	1	998	8	585,831
AntibodyTested	Candidate tested for anti hla antibodies	cate	0.53	0.79	0	3	4	585,831
A1	Candidate a1 antigen from waiting list	con	16.61	164.93	0	6,802	57	585,831
A2	Candidate a2 antigen from waiting list	con	47.42	345.94	0	6,802	59	585,831
A2A2B	Wl blood type b candidate eligibility for a2/a2b kidneys at removal/current time	con	0.01	0.09	0	1	2	585,831
B1	Candidate b1 antigen from waiting list	con	51.19	285.34	0	8,201	120	585,831
B2	Candidate b2 antigen from waiting list	con	78.72	420.65	0	8,201	116	585,831
Bw4	Candidate most recent/at removal bw4 antigen from waiting list	con	60.40	46.04	0	998	5	585,831
Bw6	Candidate most recent/at removal bw6 antigen from waiting list	con	60.28	45.93	0	998	5	585,831
C1	Candidate most recent/at removal c1 antigen from waiting list	con	6.64	52.59	0	1,802	56	585,831
C2	Candidate most recent/at removal c2 antigen from waiting list	con	11.59	96.55	0	1,802	56	585,831
CreatClear	Candidate measured creatinine clearance (ml/min)	con	0.67	3.42	0	200	377	585,831
CurrentPra	Candidate most recent ”current” pra from waiting list/allocation	con	3.58	14.58	0	100	101	585,831
Dq1	Candidate most recent/at removal dqb1 antigen from waiting list	con	5.33	33.62	0	609	26	585,831
Dq2	Candidate most recent/at removal dqb2 antigen from waiting list	con	7.26	48.92	0	609	27	585,831
Dr1	Candidate dr1 antigen from waiting list	con	15.93	209.97	0	10,300	73	585,831
Dr2	Candidate dr2 antigen from waiting list	con	19.69	134.63	0	10,300	65	585,831
Dr51	Candidate most recent/at removal dr51 antigen from waiting list	con	41.56	48.54	0	998	10	585,831
Dr51_2	Candidate most recent/at removal dr51 antigen from waiting list	con	6.13	23.45	0	99	9	585,831
Dr52	Candidate most recent/at removal dr52 antigen from waiting list	con	42.42	47.97	0	998	12	585,831
Dr52_2	Candidate most recent/at removal dr52 antigen from waiting list	con	5.98	23.13	0	99	11	585,831

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Variable Name	Descriptions	Type	Mean	Std	Min	Max	Unique	Count
Dr53	Candidate most recent/at removal dr53 antigen from waiting list	con	41.91	48.27	0	998	8	585,831
Dr53_2	Candidate most recent/at removal dr53 antigen from waiting list	con	6.06	23.32	0	99	7	585,831
EndStatKi	Kidney status at time of transplant	con	3,742.75	1,121.09	0	5,999	11	585,831
Gfr	Candidate gfr score	con	3.39	6.34	0	140	334	585,831
InactReasonCd	Reason for inactive status	con	0.34	1.92	0	16	15	585,831
InitCurrentPra	Candidate first current pra	con	2.05	10.96	0	100	101	585,831
InitEpts	Initial calculated epts	con	0.10	0.22	0	1	101	585,831
InitPeakPra	Recipient peak pra at listing	con	2.57	12.37	0	100	101	585,831
InitStat	Initial waiting list status code	con	3,744.88	1,151.73	0	8,999	12	585,831
OnDialysis	Wl candidate has had regularly administered dialysis for esrd (y/n)	cate	1.42	0.71	0	2	3	585,831
PeakPra	Candidate most recent "peak" pra from waiting list/allocation	con	5.84	18.73	0	100	101	585,831
UseWhichPra	Use peak or current pra for allocation scoring	cate	1.31	2.05	0	5	3	585,831
BmiCalc	Calculated recipient bmi	con	26.20	6.99	0	74.20	533	585,831
AgeGroup	Recipient age group a=adult p=peds	cate	1.04	0.21	0	2	3	585,831
EbvSerostatus	Recipient epstein barr virus status at transplant-adults only	cate	1.06	0.88	0	3	4	585,831
EndBmiCalc	Calculated candidate bmi at removal/current time	con	24.43	9.67	0	74.20	536	585,831
EndCpra	Candidate most recent calculated pra	con	10.16	25.87	0	100.00	60,658	585,831
EndCpraDetail	Candidate detailed value of most recent calculated pra	con	0.10	0.26	0	1.00	68,110	585,831
AntihypeDon	Deceased donor-antihypertensives w/in 24 hrs pre-cross clamp	cate	0.74	0.68	0	2	3	585,831
BloodInfDon	Deceased donor-blood as infection source	con	0.06	0.23	0	1	2	585,831
BunDon	Deceased donor-terminal blood urea nitrogen	con	11.33	15.03	0	250	488	585,831
CancerSiteDon	Deceased donor-cancer site	con	9.46	91.74	0	999	35	585,831
CardarrestNeuro	Deceased donor-cardiac arrest post brain death	cate	0.50	0.56	0	2	3	585,831
CdcRiskHivDon	Deceased donor - per phs, does the donor have risk factors for blood-borne disease transmission?	cate	0.53	0.64	0	2	3	585,831
ClinInfectDon	Deceased donor-clinical infection (y,n)	cate	0.92	0.85	0	2	3	585,831
CodCadDon	Deceased donor-cause of death	con	42.79	198.82	0	999	6	585,831
ContinCigDon	Deceased donor-history of cigarettes in past@ ¿20pack yrs+recent 6mo use	cate	0.32	0.69	0	2	3	585,831
ContinCocaineDon	Deceased donor-history of cocaine use+recent 6mo use	cate	0.13	0.45	0	2	3	585,831
ContinOthDrug Don	Deceased donor-history of other drugs in past+recent 6mo use	cate	0.42	0.75	0	2	3	585,831

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Variable Name	Descriptions	Type	Mean	Std	Min	Max	Unique	Count
ControlledDon	Deceased donor controlled non-heart beating (y/n)	cate	0.17	0.56	0	2	3	585,831
CoreCoolDon	Deceased donor-core cooling for controlled non-hrt beating	cate	0.15	0.49	0	2	3	585,831
CreatDon	Deceased donor-terminal lab creatinine	con	0.72	1.10	0	50	988	585,831
DdavpDon	Deceased donor-synthetic anti diuretic hormone (ddavp)	cate	0.64	0.66	0	2	3	585,831
DeathCircumDon	Deceased donor-circumstance of death	con	185.64	385.71	0	997	8	585,831
DeathMechDon	Deceased donor-mechanism of death	con	70.10	244.69	0	997	15	585,831
DiabdurDon	Deceased donor-diabetes duration	con	0.11	0.59	0	5	5	585,831
DiabetesDon	Deceased donor-history of diabetes	cate	0.83	0.46	0	2	3	585,831
DietDon	Deceased donor-hypertension diet controlled	cate	0.08	0.33	0	2	3	585,831
DiureticsDon	Deceased donor-hypertension diuretic controlled	cate	0.11	0.36	0	2	3	585,831
ExtracranialCancerDon	Deceased donor-extracranial cancer at procurement	cate	0.60	0.49	0	2	3	585,831
HepCAntiDon	Deceased donor-antibody to hep c virus result	cate	1.19	0.97	0	6	7	585,831
HeparinDon	Deceased donor management - heparin	cate	1.08	0.98	0	2	3	585,831
HistCancerDon	Deceased donor-history of cancer	cate	0.82	0.43	0	2	3	585,831
HistCigDon	Deceased donor-history of cigarettes in past @ ¿20pack yrs	cate	0.98	0.64	0	2	3	585,831
HistCocaineDon	Deceased donor-history of cocaine use in past	cate	0.61	0.65	0	2	3	585,831
HistDiabetesDon	Deceased donor-history of diabetes, incl. duration of disease	con	5.07	66.03	0	998	7	585,831
HistHypertensDon	Deceased donor-history of hypertension	cate	0.95	0.59	0	2	3	585,831
HistInsulinDepDon	Deceased donor-insulin dependent diabetes	cate	0.04	0.26	0	2	3	585,831
HistOthDrugDon	Deceased donor-history of other drug use in past	cate	0.82	0.77	0	2	3	585,831
Htlv1OldDon	Deceased donor-antibody to htlv i result	cate	0.32	0.74	0	5	6	585,831
Htlv2OldDon	Deceased donor-antibody to htlv ii result	cate	0.36	0.86	0	5	6	585,831
HypertensDurDon	Deceased donor-hypertension duration	con	0.45	1.16	0	5	5	585,831
InoProcureAgent1	Deceased donor-inotropic medication agent 1	con	12.68	109.00	0	999	8	585,831
InoProcureAgent2	Deceased donor-inotropic medication agent 2	con	11.18	104.26	0	999	8	585,831
InoProcureAgent3	Deceased donor-inotropic medication agent 3	con	3.23	56.55	0	999	8	585,831
InotropAgents	Deceased donor-inotropic agent support	cate	0.46	0.52	0	2	3	585,831

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Variable Name	Descriptions	Type	Mean	Std	Min	Max	Unique	Count
InotropSupportDon	Deceased donor inotropic medication at procurement	cate	0.90	0.74	0	2	3	585,831
InsulinDepDon	Deceased donor-insulin dependent diabetes, incl. duration of dependence	con	2.93	53.41	0	998	7	585,831
InsulinDurDon	Deceased donor-insulin dependent diabetes duration	con	0.04	0.36	0	5	5	585,831
IntracranialCancerDon	Deceased donor-intracranial cancer at procurement	cate	0.59	0.50	0	2	3	585,831
LtKiBiopsy	Deceased donor-left kidney biopsy at recovery	cate	0.91	0.72	0	2	3	585,831
LtKiGlomerul	Deceased donor-left kidney %glomerulosclerosis at recovery	con	0.32	0.78	0	6	7	585,831
NonHrtDon	Deceased donor-non-heart beating donor	cate	0.70	0.62	0	2	3	585,831
OtherHypertensMedDon	Deceased donor-hypertension controlled by non-diuretic meds	cate	0.20	0.56	0	2	3	585,831
OtherInfConfDon	Deceased donor infection other source-confirmed	cate	0.04	0.27	0	2	3	585,831
OtherInfDon	Deceased donor infection other source	con	0.04	0.19	0	1	2	585,831
ProteinUrine	Deceased donor protein in urine	cate	0.75	0.80	0	2	3	585,831
PtDiureticsDon	Deceased donor-diuretics b/n brain death w/in 24 hrs of procurement	cate	0.91	0.85	0	2	3	585,831
PtSteroidsDon	Deceased donor-steroids b/n brain death w/in 24 hrs of procurement	cate	0.97	0.89	0	2	3	585,831
PtT3Don	Deceased donor-triiodothyronine-t3 b/n brain death w/in 24 hrs of procurement	cate	0.52	0.51	0	2	3	585,831
PtT4Don	Deceased donor-thyroxine-t4 b/n brain death w/in 24 hrs of procurement	cate	0.86	0.82	0	2	3	585,831
PulmInfDon	Deceased donor-infection pulmonary source	con	0.27	0.45	0	1	2	585,831
RtKiBiopsy	Deceased donor-right kidney biopsy at recovery	cate	0.91	0.72	0	2	3	585,831
RtKiGlomerul	Deceased donor-right kidney %glomerulosclerosis at recovery	con	0.33	0.78	0	6	7	585,831
SgotDon	Deceased donor-terminal sgot/ast	con	70.96	355.49	0	36,000	2,738	585,831
SgptDon	Deceased donor-terminal sgpt/alt	con	62.15	279.34	0	44,117	2,675	585,831
SkinCancerDon	Deceased donor-skin cancer at procurement	cate	0.60	0.49	0	2	3	585,831
Tattoos	Deceased donor-tatoos	cate	0.73	0.77	0	2	3	585,831
TbiliDon	Deceased donor-terminal total bilirubin	con	0.63	1.40	0	87	555	585,831
UrineInfConfDon	Deceased donor-infection urine source-confirmed	cate	0.05	0.32	0	2	3	585,831
UrineInfDon	Deceased donor-infection urine source	con	0.06	0.25	0	1	2	585,831

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Variable Name	Descriptions	Type	Mean	Std	Min	Max	Unique	Count
VasodilDon	Deceased donor-vasodilators w/in 24hrs pre-cross clamp	cate	0.68	0.61	0	2	3	585,831
VdrlDon	Deceased donor-rpr-vdrl result	cate	1.39	0.93	0	5	6	585,831
WarmIschTmDon	Deceased donor non-heart beating estimated warm ischemic time	con	0.56	4.09	0	180	114	585,831
CmvIggDon	Living donor-cmv by igg test result	cate	0.35	0.68	0	3	4	585,831
CmvIgmDon	Living donor-cmv by igm test result	cate	0.54	1.04	0	3	4	585,831
CmvNucleicDon	Donor cmv by nucleic acid	cate	0.66	1.23	0	3	4	585,831
CmvTestDon	Liv donor cmv tested?	cate	0.41	0.81	0	2	3	585,831
EbvDnaDon	Living donor-epstein barr virus by dna test result	cate	0.28	0.85	0	3	4	585,831
EbvIggDon	Living donor epstein barr virus by igg test result	cate	0.22	0.47	0	3	4	585,831
EbvIgmDon	Living donor epstein barr virus by igm test result	cate	0.42	0.91	0	3	4	585,831
EbvTestDon	Living donor epstein barr virus tested?	cate	0.26	0.64	0	2	3	585,831
HbvDnaDon	Living donor hbv dna	cate	0.59	1.13	0	3	4	585,831
HbvTestDon	Living donor hbv test done	cate	0.41	0.81	0	2	3	585,831
HcvAntibodyDon	Living donor hep c antibody	cate	0.53	0.89	0	3	4	585,831
HcvRibaDon	Living donor hep c-riba test	cate	0.74	1.28	0	3	4	585,831
HcvRnaDon	Living donor hep c rna	cate	0.57	1.10	0	3	4	585,831
HcvTestDon	Living donor hep c test done?	cate	0.37	0.77	0	2	3	585,831
KiCreatPreop	Living kidney donor preoperative creatinine	con	0.21	0.40	0	25	269	585,831
KiProcTy	Living donor kidney procedure type	con	0.89	1.61	0	6	7	585,831
Rda1	Donor retpyed a1 antigen	con	10.90	139.86	0	6,802	57	585,831
Rda2	Donor retpyed a2 antigen	con	36.88	321.64	0	6,802	59	585,831
Rdb1	Donor retpyed b1 antigen	con	35.65	280.41	0	8,201	117	585,831
Rdb2	Donor retpyed b2 antigen	con	61.00	429.22	0	8,201	119	585,831
Rddr1	Donor retpyed dr1 antigen	con	12.78	200.56	0	10,300	62	585,831
Rddr2	Donor retpyed dr2 antigen	con	21.25	166.92	0	10,300	63	585,831
DonRetyp	Deceased donor-retyped at tx center	cate	1.40	0.51	0	2	3	585,831
AboDon	Donor blood type	cate	1.98	1.33	0	8	9	585,831
CmvDon	Donor serology anti cmv	cate	0.97	0.78	0	6	7	585,831
GenderDon	Donor gender	cate	1.55	0.50	0	2	3	585,831
HbvCoreDon	Donor hbv core antibody	cate	1.74	0.72	0	6	7	585,831
HbvSurAntigenDon	Donor hep b surface antigen	cate	1.96	0.32	0	5	6	585,831
AgeDon	Donor age (yrs)	con	37.58	15.17	0	88	87	585,831
EthcatDon	Donor ethnicity category	con	2.52	28.77	1	998	8	585,831
BmiDonCalc	Donor bmi - pre/at donation calculated	con	23.29	10.70	0	74.60	74,508	585,831
Da1	Donor a1 antigen	con	13.04	123.32	0	6,802	57	585,831
Da2	Donor a2 antigen	con	54.98	313.45	0	6,802	57	585,831
Db1	Donor b1 antigen	con	49.11	256.85	0	5,703	113	585,831
Db2	Donor b2 antigen	con	86.50	397.64	0	8,201	113	585,831
Ddr1	Donor dr1 antigen	con	21.16	304.63	0	10,300	62	585,831

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Variable Name	Descriptions	Type	Mean	Std	Min	Max	Unique	Count
Ddr2	Donor dr2 antigen	con	31.12	181.66	0	10,300	61	585,831
DonTy	Donor type - deceased or living	cate	2.31	0.46	1	3	3	585,831
GstatusKi	Graft failed (1=yes)-kidney	con	0.00	0.00	0	1	2	585,831

Table 5: Descriptive Statistics of Liver Recipient-Donor Features

Variable Name	Description	Type	Mean	Std	Min	Max	Unique	Count
Age	Recipient age (YRS)	Con	52.06	11.59	18.00	79.00	62	23,048
AlbuminTx	Recipient serum albumin @ transplant	Con	2.92	0.85	0.50	23.00	81	23,048
AscitesTx	Recipient ascites @ transplant	Cate	1.05	0.60	0.00	2.00	3	23,048
BmiCalc	Calculated recipient BMI	Con	28.03	5.96	11.94	65.10	10944	23,048
CmvIgg	Recipient-CMV by IgG test result @ transplant	Cate	0.87	0.34	0.00	1.00	2	23,048
CmvIgm	Recipient-CMV by IgM test result @ transplant	Cate	0.03	0.17	0.00	1.00	2	23,048
CreatTx	Recipient serum creatinine at time of TX	Con	1.97	3.83	0.00	40.00	729	23,048
Diab	Recipient diabetes @ registration	Cate	0.15	0.35	0.00	1.00	2	23,048
Diag	Recipient primary diagnosis	Cate	2.76	2.81	0.00	10.00	11	23,048
DialTx	Dialysis prior week to transplant?	Cate	0.13	0.33	0.00	1.00	2	23,048
EbvSerostatus	Recipient EBV status @ transplant	Cate	0.93	0.25	0.00	1.00	2	23,048
Ethcat	Recipient ethnicity category	Cate	0.73	1.18	0.00	6.00	7	23,048
FinalSerumSodium	Most recent waiting list serum sodium or at removal if removed	Con	124.32	14.65	100.00	169.00	59	23,048
FuncStatTcr	Recipient functional status @ registration	Con	42.91	30.72	10.00	100.00	12	23,048
HbvCore	Recipient hepatitis B-core antibody	Cate	0.14	0.35	0.00	1.00	2	23,048
HbvSurAntigen	Recipient HEP B surface antigen	Cate	0.05	0.22	0.00	1.00	2	23,048
HccDiag	Has recipient ever had a diagnosis of HCC?	Cate	0.11	0.31	0.00	1.00	2	23,048
HcvSerostatus	Recipient HEP C status	Cate	0.27	0.44	0.00	1.00	2	23,048
HgtCmCalc	Calculated recipient height (cm)	Con	171.54	10.37	124.50	213.00	290	23,048
HivSerostatus	Recipient HIV serostatus at transplant	Cate	0.00	0.07	0.00	1.00	2	23,048
InrTx	Recipient INR at transplant	Con	11.90	14.98	0.57	99.00	458	23,048
Malig	Any previous malignancy?	Cate	0.14	0.35	0.00	1.00	2	23,048
MedCondTrr	Recipient medical condition pre-transplant @ transplant	Cate	1.32	0.84	0.00	2.00	3	23,048
MeldPeldLabScore	MELD/PELD lab score at time of transplant	Con	22.66	8.32	6.00	40.00	35	23,048
NumPrevTx	The number of previous transplants	Con	0.30	1.35	0.00	10.00	11	23,048
OnVentTrr	Recipient on ventilator @ transplant	Cate	0.13	0.34	0.00	1.00	2	23,048
PortalVeinTrr	Recipient portal vein thrombosis @ transplant	Cate	0.09	0.28	0.00	1.00	2	23,048

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Variable Name	Descriptions	Type	Mean	Std	Min	Max	Unique	Count
PrevAbSurgTrr	Recipient previous upper abdominal surgery @ transplant	Cate	0.41	0.49	0.00	1.00	2	23,048
PrevTx	History of a previous transplant involving exact same organ as current TX	Cate	0.13	0.34	0.00	1.00	2	23,048
PrevTxAny	Calculated previous transplant of any organ type	Cate	0.12	0.32	0.00	1.00	2	23,048
TbiliTx	Recipient total bilirubin @ transplant	Con	10.48	14.69	0.00	97.00	792	23,048
TipssTcr	Recipient transjugular intrahepatic portacaval stint shunt (TIPSS) @ registration	Cate	0.05	0.22	0.00	1.00	2	23,048
TxProcedurTy	Recipient liver organ type (Whole/Reduced/Split)	Cate	0.06	0.28	0.00	3.00	4	23,048
WgtKgCalc	Calculated recipient weight (kg)	Con	82.72	20.22	34.00	200.00	1072	23,048
AgeDon	Donor age (YRS)	Con	39.76	16.83	1.00	90.00	91	23,048
AntihypeDon	Deceased donor-antihypertensives w/in 24 hrs pre-cross clamp	Cate	0.19	0.39	0.00	1.00	2	23,048
BloodInfDon	Deceased donor-blood as infection source	Cate	0.07	0.26	0.00	1.00	2	23,048
BmiDonCalc	Donor BMI - pre/at donation calculated	Con	26.73	5.84	9.17	73.23	9901	23,048
BunDon	Deceased donor-terminal blood urea nitrogen	Con	21.51	17.05	0.50	250.00	241	23,048
CardarrestNeuro	Deceased donor-cardiac arrest post brain death	Cate	0.04	0.20	0.00	1.00	2	23,048
ClinInfectDon	Deceased donor-clinical infection (Y,N)	Cate	0.59	0.49	0.00	1.00	2	23,048
CmvDon	Donor serology anti CMV (for living donor, pre UNET data only)	Cate	0.65	0.48	0.00	1.00	2	23,048
CodCadDon	Deceased donor-cause of death	Cate	1.04	1.01	0.00	4.00	5	23,048
ColdIsch	Total cold ischemic time (hours)	Con	7.69	4.22	0.00	70.42	1476	23,048
CreatDon	Deceased donor-terminal lab creatinine	Con	1.56	1.64	0.04	30.00	716	23,048
DeathCircumDon	Deceased donor-circumstance of death	Cate	2.41	2.04	0.00	6.00	7	23,048
DeathMechDon	Deceased donor-mechanism of death	Cate	2.16	2.65	0.00	13.00	14	23,048
DiabdurDon	Deceased donor-diabetes duration	Cate	0.08	0.27	0.00	1.00	2	23,048
DonTy	Donor type - deceased, living	Cate	0.04	0.19	0.00	1.00	2	23,048
EthcatDon	Donor ethnicity category	Cate	0.73	1.18	0.00	6.00	7	23,048
HbvCoreDon	Donor HBV core antibody	Cate	0.04	0.20	0.00	1.00	2	23,048
HbvSurAntigenDon	Donor HEP B surface antigen	Cate	0.00	0.03	0.00	1.00	2	23,048
HematocritDon	DDR: Hematocrit	Con	30.12	4.42	3.00	75.00	409	23,048
HepCAntiDon	Deceased donor-antibody to HEP C virus result	Cate	0.03	0.18	0.00	1.00	2	23,048
HgtCmDonCalc	Calculated donor height (cm)	Con	170.90	10.99	86.00	211.00	213	23,048
HistCancerDon	Deceased donor-history of cancer (Y/N)	Cate	0.00	0.00	0.00	0.00	1	23,048
HistCocaineDon	Deceased donor-history of cocaine use in past	Cate	0.00	0.00	0.00	0.00	1	23,048

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Variable Name	**Descriptions**	**Type**	**Mean**	**Std**	**Min**	**Max**	**Unique**	**Count**
HistHypertensDon	Deceased donor-history of hypertension	Cate	0.00	0.00	0.00	0.00	1	23,048
InotropSupportDon	Deceased donor inotropic medication at procurement (Y/N)	Cate	0.00	0.00	0.00	0.00	1	23,048
LiBiopsy	Cadaver donor liver biopsy	Cate	0.26	0.44	0.00	1.00	2	23,048
NonHrtDon	Deceased donor-non-heart beating donor	Cate	0.04	0.21	0.00	1.00	2	23,048
PhDon	DDR: Blood pH	Con	7.40	0.08	5.00	7.82	88	23,048
SgotDon	Deceased donor-terminal SGOT/AST	Con	79.96	140.70	0.20	7526.00	718	23,048
SgptDon	Deceased donor-terminal SGPT/ALT	Con	70.83	142.82	0.40	5838.00	720	23,048
ShareTy	Allocation type	Cate	0.51	0.72	0.00	3.00	4	23,048
TbiliDon	Deceased donor-terminal total bilirubin	Con	0.95	1.31	0.00	68.00	196	23,048
VdrlDon	Deceased donor-RPR-VDRL result	Cate	0.01	0.09	0.00	1.00	2	23,048
WgtKgDonCalc	Donor weight (kg)	Con	78.02	19.73	14.00	199.60	1109	23,048

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