Objective Criteria Formulation for Two-Sided Matching Problems Using Environment-Based Design and Natural Language Processing

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Abstract

Objective Criteria Formulation for Two-Sided Matching Problems Using Environment-Based Design and Natural Language Processing

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Every day, people and organizations make decisions that involve multiple, often conflicting, criteria. The complexity of these decision-making problems arises from the need to balance competing factors such as fairness, efficiency, and individual preferences. This thesis focuses on two-sided matching (TSM), a particular multi-criteria decision-making (MCDM) problem central to fields like operations research and market design. In TSM systems, two distinct sets of agents—such as employers and job seekers, schools and students, or donors and recipients—seek to be matched with members of the other set. While most research addresses how to match agents, this thesis focuses on the underlying decision criteria by examining how the criteria can be defined in a way that is fair, complete, and free from bias considering all human factors in effect.

Traditionally criteria have been determined by expert opinions, surveys, or historical data. However, these methods may be biased, cannot escape from past inequalities and fail to capture the complete criteria. To address this limitation, this thesis proposes a novel interdisciplinary methodology that integrates Natural Language Processing (NLP), optimization theory, and engineering design science to discover criteria from human-centered problem descriptions. This approach extracts objective decision criteria from natural language descriptions of the matching problem in a systematic and inclusive way using environment-based design (EBD), environment-based life cycle analysis (eLCA), and recursive object model (ROM). The utilization of these engineering design methodologies allows for adaptive, domain-independent, and data-driven criteria formulation, eliminating the need for subjective inputs.

To demonstrate the effectiveness of the proposed method, the methodology is applied in both static and dynamic matching scenarios. Static matching refers to problems involving fixed sets of participants, while dynamic matching accounts for changing sets, such as time-based arrivals. For

the static case, an assignment-based optimization model is used to generate matches based on the identified criteria. For the dynamic case, a perishable capacity management optimization model is adopted, allowing the system to handle uncertainty and last-minute changes effectively.

Key contributions of this research include: a domain-independent, adaptable, and automated methodology for discovering decision criteria in two-sided matching (TSM) problems—eliminating reliance on subjective bias; an original application of design science principles to TSM, framing decision-making as a contextualized, iterative process grounded in stakeholder needs and environmental understanding; a systematic, algorithmic approach for defining input parameters in multi-criteria decision-making (MCDM) optimization models, bridging natural language understanding and mathematical formulation; a significant advancement in fairness and transparency within TSM systems by ensuring that matching decisions are based on objective, inclusive, and human-centered criteria. By redefining how matching problems are formulated and solved, this research lays the foundation for more equitable, adaptive, and human-centered decision-making systems.

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This thesis is for everyone who stood by me—and for all those who have ever felt like they do not quite fit in. Please do not lose hope. You belong, your voice matters, and your perspective holds the power to change the world.

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1. Introduction

1.1. Background and Motivation

Every day, individuals and organizations make decisions involving multiple criteria for the complex problems they face. Most of the real-world problem decisions are influenced by various constraints such as time, cost, and limited resources. Multi-criteria decision making (MCDM) allows us to consider and balance all factors simultaneously instead of tackling them one by one. By evaluating a range of criteria, decision-makers can make better choices which align with their priorities. MCDM can provide a structured and systematic approach in evaluating alternatives while ensuring no critical aspect is overlooked. MCDM allows organizations to reduce bias and enhance transparency in decision-making at times facing diverse, conflicting and complex factors.

This thesis focuses on one MCDM problem called two-sided matching (TSM). TSM problems are where two groups need to be matched with each other based on preferences and qualifications. TSM is a systematic approach that ensures the resources are allocated to maximize satisfaction while adhering to constraints. TSM markets are at the center of many economic systems such as labor markets, school admissions, and organ donation systems. Optimizing TSM ensures the mutually beneficial outcome for both parties. For instance, in labour market matching, the jobs need to be fulfilled by skillful workers, while the candidates look for the best fit for their career goals. To achieve stability in the position, the best possible candidate should be offered the job. The best possible candidate can be discovered using the decision-making criteria. The position has its requirements, and the candidate has their preferences. All these pieces of information are called criteria in the MCDM problem. Because there are many jobs and candidates at the same time, the size of the problem increases. Taking various criteria into account and finding the best possible solution for many commodities at the same time is possible with optimization.

Solving two-sided matching problems enables organizations to optimize resource allocation, improve efficiency, and ensure fairness in pairing individuals or groups with opportunities, services, or goods. Solving two-sided matching problems optimally ensures the stability of the systems built. Getting the ‘right’ matches can have massive real-world consequences on not only

people's lives but also system performance. While getting stable matches in human-based systems, bias in a matching mechanism can be subtle but very influential. The evaluation of alternatives should be carried out carefully to ensure fairness.

As TSM is an MCDM, defining criteria clearly, completely and inclusively helps the matching process in a great way. The challenge is that the criteria used for matching can be biased. Any bias in decision criteria can affect fairness and stability. Biased criteria can systematically disadvantage certain groups. If the criteria are unfair, preferences may be misrepresented, resulting in unstable outcomes. Many matching systems rely on domain experts to define the criteria, but unfortunately, expert opinions can reflect institutional biases, personal preferences, or limited points. Some methods use historical data to generate criteria, but these lack correcting any bias that might have been carried out in the past. Through human decision-makers, some important criteria might be overlooked because it is hard to measure them or simply because they did not have an effect in the past. Biased criteria may ignore the real drivers of match quality, leading to poor matches. Therefore, identifying matching criteria in a way that is adaptive, systematic and unbiased is a critical challenge in two-sided matching systems - one that this research aims to address. While MCDM provides a structured approach, its effectiveness in TSM hinges on the quality of the criteria used. The next section outlines the specific gap this thesis aims to address.

1.2. Problem Statement

This thesis addresses a key limitation in TSM problems: the reliance on biased and incomplete criteria during matching. Existing two-sided matching problems often rely on subjective or biased criteria for generating matches. In current literature, there is a lack of systematic, unbiased methods for criteria identification. The existing methods where criteria are traditionally determined through expert opinion or surveys often fail to provide complete and full information. To overcome bias and incomplete information in two-sided matching, this research aims to advance the theory by addressing unbiased criteria identification. We propose a method to systematically identify criteria in an unbiased way, improving fairness and effectiveness in matching systems. Our approach can be adopted for any kind of two-sided matching problem and applied in any domain. It is a data-driven approach that can be carried out by anyone. We also show the application of our methodology in static TSM and dynamic TSM, along with MCDM optimization formulations. In

optimization, we use a different approach for each case. For the static case, the optimization model is based on an assignment problem formulation. On the other hand, the optimization model is based on a perishable capacity management problem formulation for the dynamic case.

1.3. Research Objectives and Contributions

The main objective of research in this work is to identify and formalize criteria in an unbiased way for two-sided matching problems. We developed a framework to generate unbiased criteria while considering both sides' preferences. Solving a problem starts with formulating the problem properly. Our goal in this work is to properly formulate the problem parameters and constraints to ensure we find a good solution. This thesis addresses a critical gap in literature by proposing an unbiased methodology for two-sided matching problems through problem definition alone, ensuring an objective selection of criteria. Furthermore, it introduces an enhanced approach for deriving decision criteria, contributing to the field of operations research and advancing methodologies for multi-criteria optimization (MCO). Developing a systematic, unbiased criteria identification methodology is the first contribution of this thesis. Our method discovers unbiased and complete criteria for both sides while avoiding algorithmic favoritism or systemic bias.

While MCDM refers to the process of making decisions in scenarios where multiple conflicting criteria need to be considered, MCO focuses on finding the optimal solution to a problem that involves multiple conflicting criteria through mathematical models. It aims to optimize all criteria simultaneously, often under certain constraints. This thesis introduces an unbiased method to discover the parameters of such a mathematical model. Furthermore, this work not only addresses the critical need for unbiased criteria identification in two-sided matching markets but also introduces a novel approach to modelling MCDM problems in operations research.

The first step of matching is to have alternatives, and the second is to define some criteria to evaluate alternatives. Often, in two-sided matching markets, the agents are human. Furthermore, discovering human decision-making criteria is a complex task. Much research still aims to explain rational human behavior by the complex interplay between emotion, affect, and reason in the human brain. The more we know about the input interpretation of the human brain, the more we understand output generation. Therefore, we can better support decision-making by generating

desirable results with necessary and sufficient input. In two-sided matching literature, we often see stability, satisfaction, and fairness as evaluation criteria. However, methods to discover each criterion that affects the weight of the alternatives have not been studied yet. Because of these reasons, there is an increasing need for two-sided matching methodologies that lead to better outcomes. In this research, our objective is first to demonstrate that a set of criteria for any kind of matching problem can be extracted from natural language that describes the matching problem. Then we show applications of our methodology.

To demonstrate the applicability of our unbiased criteria identification methodology, the method is implemented in both a static and a dynamic TSM context. In the static case, the focus is on evaluating the method's ability to produce fair and effective matching outcomes using a fixed set of participants and preferences. An assignment problem-based optimization model is developed for the static case. Therefore, the formulation of static matching with unbiased criteria is the second contribution of this work. In the dynamic case, the method is adapted to accommodate changes in the matching environment over time, such as participant arrivals or shifting preferences. The optimization model is based on a perishable capacity management approach where the dynamic nature of the problem is handled by reserving reasonable capacity for last-minute changes. Through these objectives, the research seeks to contribute a flexible and equitable approach to unbiased criteria identification in TSM, applicable across diverse domains and matching scenarios. Demonstrating the method's applicability in dynamic matching context and formulating capacitated resource management using unbiased criteria is the third contribution of this thesis.

This work introduces a novel interdisciplinary field that bridges optimization theory and engineering design science, offering a new perspective on how matching problems should be formulated and solved. We treat TSM not merely as an algorithmic task but as a design problem, where the quality of the matching outcome is rooted in how well we understand and formalize what both sides truly value.

At the core of our approach is Natural Language Processing (NLP), used to extract decision-making criteria from unstructured descriptions of stakeholder needs. This enables the automated discovery of latent, human-centric criteria in a way that avoids expert bias and enhances transparency. Our method incorporates tools from Environment-Based Design (EBD),

environment-based Life Cycle Analysis (eLCA), and the Recursive Object Model (ROM) to rigorously model and refine the decision environment.

The originality of the research lies in:

- Integrating NLP with multi-criteria optimization (MCO) to discover criteria from natural language, addressing the long-standing problem of subjective and biased input in TSM systems.
- Formulating a generic, design-based problem definition methodology that reveals unbiased and complete criteria sets without relying on prior expert judgment or fixed questionnaires.
- Developing both static and dynamic matching optimization models that use the extracted criteria:
    - A static assignment model demonstrating how unbiased criteria enhance fairness and satisfaction in fixed markets.
    - A dynamic perishability-aware model that reserves capacity for late arrivals, simulating real-world scenarios with time-sensitive decisions.
- Pioneering the application of design science principles to matching markets, a novel contribution that treats decision-making as an iterative, stakeholder-informed process.
- Establishing mutual satisfaction as a new evaluative benchmark for match quality, extending beyond technical stability to include human-centered notions like alignment, contribution, and long-term engagement.

In essence, this research redefines how we formulate and solve two-sided matching problems by foregrounding the quality and objectivity of decision criteria. It lays the groundwork for more inclusive, adaptable, and efficient matching systems—ones that truly listen to both sides and are better equipped to support equitable outcomes.

1.4. Thesis Organization

This thesis is organized as follows: Chapter 2 critically reviews the literature and formulates the basis for proposing the research method. Chapter 3 presents the theoretical basis of the utilized tools along with the introduction of our method. Chapter 4 demonstrates the application of our method in two different varieties of two-sided matching problems where we show the practical

relevance and generalizability of our methodology. Chapter 5 discusses the theoretical and practical implications of this research where Chapter 6 outlines conclusion and future work.

2. Literature Review

2.1. Multi-Criteria Decision Making

Multi-criteria decision-making (MCDM) or multiple criteria decision analysis (MCDA) is a subfield of operations research that evaluates multiple conflicting criteria in decision making. MCDM can be divided into two as Multi-Objective Decision Making (MODM) and Multi-Attribute Decision Making (MADM) (Zimmermann, 2011). MODM studies decision problems with the continuous decision space, whereas MADM focuses on decision problems with the discrete decision space.

The decision-making problems based on searching for a match between two sets are called two-sided matching decision making (TSMDM) problems (Sönmez & Ünver, 2010). In general, TSMDM can be considered as a subset of multi-criteria decision-making problems (Korkmaz et al., 2008). Hence, the successful identification of criteria and their analysis is the foremost important aspect of TSMDM problems. Accordingly, this thesis introduces an unbiased criteria identification method to be utilized in TSMDM. Moreover, perishable capacity management problems such as task assignment on engineers, doctor-patient scheduling or crew/equipment assignment on infrastructure projects are analyzed in line with the TSMDM.

The two-sided matching decision-making problems are a sub-field of MADM. The similarity is that the decision is based on various criteria contributing to the objective in different ratios where the decision alternatives have been predetermined. According to the type of data they use, MADM methods can be classified as deterministic, stochastic, or fuzzy (Triantaphyllou et al., 1998). MADM is the field that is interested in making preference decisions such as selecting, classifying or sorting over the finite number of available alternatives, which are characterized by attributes (multiple, conflicting, weighted, and incommensurable) (Yoon & Hwang, 1995).

MADM methods can be classified as elementary methods, value-based methods, and outranking methods. Elementary choice methods include dominance relation, even-swap, elimination by aspects, maximax, and maximin methods. These often involve basic scoring and simple weighted sums. The most common example is the Weighted Sum Model (WSM) (Fishburn, 1967). Lexicographic and median ranking are elementary ranking methods, whereas conjunctive and

disjunctive are elementary classification methods. The second class, value-based methods, use a value function to aggregate preferences. Alternatives are scored and compared using utility or priority values. Some early examples of value-based methods are Analytic Hierarchy Process (AHP) (T. L. Saaty, 1980), Simple Additive Weighting (SAW) (Zionts & Wallenius, 1983), and Weighted Product (WP) (Bridgman, 1922). Some other value-based methods are Multi-Attribute Value Theory (MAVT) (Keeney & Raiffa, 1993), VIšekriterijumsko KOmpromisno Rangiranje (VIKOR) (Serbian for: Multi-Criteria Optimization and Compromise Solution) (Opricovic, 1998), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Hwang & Yoon, 1981). The third class, which is called outranking methods, compare alternatives pairwise to establish a preference relation instead of assigning a total score to each alternative. Outranking methods include the preference ranking organization method for enrichment evaluation (PROMETHEE) (Hwang & Yoon, 1981) and the elimination and choice translating reality (ELECTRE) (Roy, 1968). These are good methods for dealing with incomplete or inconsistent preferences.

The MCDM research can also be classified by methods developed for the following four decision-making steps: criteria selection, weighting, evaluation, and final aggregation methods. The criteria selection step is about defining the attributes or factors affecting the decision. It is important to make sure that the criteria are complete, independent, measurable and relevant. The most common approaches are literature review, i.e. relying on past data; expert judgment, i.e. relying on experts; and the Delphi method (OBrien, 1978), i.e. relying on surveys. None of these methods are prone to bias. The weighing step is about assigning weights to criteria. The weighing methods can be classified as subjective, objective and integrated. AHP is a subjective method, Entropy (Weaver, 1963) is an objective method, and combining AHP with Entropy is an integrated method. AHP is used both for weighing and evaluation, thanks to its pairwise comparison process. The evaluation step is where the alternatives are scored and ranked based on their performance. Common evaluation methods include scoring methods like AHP, outranking methods like ELECTRE, distance-based methods like TOPSIS and fuzzy methods like Fuzzy AHP. The last step is final aggregation methods. At this step, the scores and rankings are combined to come up with a final decision. Common approaches contain weighted sum like AHP, compensatory methods like SAW, non-compensatory methods like ELECTRE, and distance-based methods like TOPSIS. In our

work, we address the criteria selection step by developing an unbiased method to fill the gap in literature. Our methodology proposes a systematic, unbiased approach to selecting criteria.

2.2. Two-Sided Matching Problem

Two-sided matching is a fundamental concept in economics and computer science, as well as in market design. Two-sided matching, also known as two-sided market matching or bipartite matching, is a mathematical problem that involves matching elements from two distinct sets based on their preferences or characteristics. In other words, the decision-making problems looking for a match between two sets of entities are called two-sided matching problems. The two sides consist of two distinct groups of entities or agents looking for a match from the other set. For example, these sets are male and female marriage matching, jobs and candidates in the labour market matching, and schools and students in college admissions matching. The goal is to find a good match that satisfies the preferences and requirements of both sides at the same time. The objective is commonly to achieve stability or optimality in matches.

The two-sided matching problem is introduced by Gale and Shapley in a marriage matching problem for the first time (Gale & Shapley, 1962). In their novel work, researchers have proposed an algorithm with the objective of stability, widely known as the Gale-Shapley algorithm or the deferred acceptance (DA) algorithm, as a solution method to the two-sided matching problem. The researchers called their method the deferred acceptance algorithm, as shown in Table 1 (Gale & Shapley, 1962). This work established the concept of stability in two-sided matching markets. If a pair of agents prefers to be matched with each other instead of their assigned matches, the current match is an “unstable” match. Otherwise, the current match is a “stable” match. A blocking pair is a pair of entities that strictly prefer each other over their assigned matches. A matching is stable if and only if there is no blocking pair. In other words, a stable match exists if there are no pairs who prefer each other to their current assigned match. The researchers also provide proof that stable matching always exists.

Many researchers have mastered the deferred acceptance algorithm and used advanced versions in various fields. Numerous significant contributions have expanded, refined, and applied the concept

of two-sided matching. Two-sided matching problems are everywhere in our daily lives. In the next chapter, we list the most common two-sided matching problems.

Table 1: The Deferred Acceptance Algorithm (Gale-Shapley Version) Generalized

Step 0	Each agent in group 1 ranks each agent in group 2 Each agent in group 2 ranks each agent in group 1
Step 1	Each agent in group 1 proposes their top choice Each agent in group 2 rejects all but their top suitor
Step n+	Each agent in group 1 who was rejected on step n proposes to their next top choice Each agent in group 2 rejects all but their top suitor
Termination	When each agent in group 1 is engaged with an agent in group 2

2.3. Common Two-Sided Matching Problems

Two-sided matching problems have been studied widely. Alongside marriage matching, some common, widely studied two-sided matching problems include i. resident matching problem, ii. school matching problem, iii. kidney exchange matching problem, and iv. content delivery network matching problem. The literature on these problems is mentioned as follows.

i. Resident matching problem

The National Resident Matching Program (NRMP) is a centralized job matching clearinghouse in the USA. The hospitals are looking for new medical school graduates to employ them as residents. This problem has been modelled as a two-sided matching problem where residency candidates have a preference list of hospitals, and hospitals have a priority list of candidates. Roth has addressed this problem by generating an algorithm (Roth, 1984) based on DA algorithm after he

has realized there is already a similar method in place in these markets. Roth has developed their version of the deferred acceptance algorithm to address labour matching in medical labour clearinghouses (Roth, 2008a). This helped to reach the stability in the market while avoiding too early position offers. Later, they introduced a version of the deferred acceptance algorithm where additional constraints have been considered, such as allowing couples to match together (Roth & Peranson, 1999). To this day, the research in this field continues (Cheng et al., 2008).

ii. School matching problem

This two-sided matching problem is about matching candidate students and high schools. In school choice matching, the researchers make sure as many students as possible are assigned to their first choices, the deferred acceptance mechanism makes it safe for people to reveal actual preferences, and random lottery numbers are assigned at step zero for tie-breaking purposes (Abdulkadiroğlu & Sönmez, 2003, 2013). These algorithms are applied in school-choice system design in high schools of New York (Abdulkadiroğlu, Pathak, & Roth, 2005) and public schools in Boston (Abdulkadiroğlu, Pathak, Roth, et al., 2005).

iii. Kidney exchange matching problem

This two-sided matching problem was introduced by Rapaport in 1986 (Rapaport, 1986). Paired kidney exchange is a version of the two-sided matching problem where two donor-patient pairs are matched (Ross et al., 1997). Later, just like the other two-sided matching problems, the deferred-acceptance algorithm is also used to address the kidney paired donation problem (Roth et al., 2005). Nowadays, the practice is expanded to generate transplant chains rather than simple exchanges. The chains have more than two donor-patient pairs matched. To connect two separate chains, the ‘bridge donor’ concept has been adopted to ensure simultaneous or non-simultaneous chains, which allow some acceptable mismatches (Ashlagi et al., 2011).

iv. Content delivery network matching problem

In content delivery networks, a match has users and servers. A content delivery network, or content distribution network (CDN), is a geographically distributed network of proxy servers and data centers. Map units with unit demand for content are matched with clusters with the unit capacity to server content. The goal is to provide high availability and performance by distributing the

service spatially relative to end-users. Users provide their preferences based on packet loss and latency, whereas web servers have preferences based on costs of bandwidth and co-location (Maggs & Sitaraman, 2015). Every 10 seconds, billions of users are assigned to servers. Addressing this problem is essential, considering the daily number of internet operations worldwide.

Other than these four major problems, some other two-sided matching problems studied are money exchange markets such as the radio spectrum auctions (Cramton, 2013), bid auctions (Milgrom & Segal, 2013) and house allocation with existing tenants (Abdulkadiroğlu & Sönmez, 1999) in the past. Some other problems include project-resource matching (Kelso Jr & Crawford, 1982), successful dating applications (Bloch & Ryder, 1994), and dorm roommate matching (Arkin et al., 2009). Two-sided matching problems are everywhere in our daily lives.

Lately, some other two-sided matching problems that have not been addressed widely in literature have gained importance. These are v. job-candidate matching problems in the labour market, vi. engineer-task matching problem in project-based workplaces, vii. doctor-case matching problem in emergency rooms, and viii. resource-project matching in infrastructure management.

v. Job-candidate matching problem in the labour market

In the other labour market matching examples such as intern-position matching for medical labour, the matching process is often carried out by a centralized clearinghouse. This clearing house has a populated list of members and their preferences. In this specific market, each intern candidate has a similar profile, therefore can be seen as substitutes for each other. The use of centralized matching fits in such labour markets. Whereas, in other types of labour markets, each job seeker often, has a unique profile that creates imperfect substitutes. The centralized labour market matching has already been addressed widely as mentioned above in resident matching problem. But non-centralized labour matching markets have not been researched yet. Therefore, more research in this field needs to be carried out to optimize the matching in non-centralized labour matching markets. For non-centralized matching markets, we recently see more research done on the online labour markets such as matching for IT services (Zheng et al., 2016) and providing better recommendations (Kokkodis & Ipeirotis, 2023). This open field can greatly benefit from

our proposed unbiased criteria identification method and optimized dynamic matching based on the discovered unbiased criteria.

vi. Engineer-task matching problem in project-based workplaces

The proposed solution methods in engineering workforce management are not capable of capturing the dynamic nature of the engineering industry. Due to the increase in the usage of computerized systems in many aspects of human life, more service companies hire engineers to be part of their workforce. Service companies run projects for external clients. Employees in these companies are grouped into teams to be matched with projects. The number of engineers hired in project-based companies increases every year. Thus, the workforce planning of these engineers is a necessary but not yet profoundly studied field (Hargaden & Ryan, 2010). Our proposed unbiased criteria identification methodology can be applied in this field along with the optimized dynamic matching to ensure stability in the market is achieved at minimum cost.

vii. Doctor-case matching problem in emergency rooms

Engineering workforce management is not the only scheduling problem with a dynamic and stochastic nature. Another field with a similar challenge of task assignment is physician scheduling. In emergency rooms (ERs), a physician may be needed when a new patient with an urgent need for care arrives. This new task, or duty as it is called in healthcare literature, must be assigned to one of the physicians scheduled for the current shift in the emergency room. In such a case, rescheduling physicians' duties might be needed, and it must be done promptly.

Dantzig did the first work on staff scheduling using the simplex method, i.e. linear programming to schedule workers in toll booths (Dantzig, 1954). Vassilacopoulos used dynamic programming, stochastic models and simulation to allocate capacity to ER patients (Vassilacopoulos, 1985). Some researchers used computer simulation to improve patients' waiting time in ERs (Blake et al., 1996). Carter and Lapierre used mathematical programming to schedule physicians in ERs to reduce the time needed to develop better schedules (Carter & Lapierre, 2001). Mathematical programming models are also adopted to address physician scheduling problems in which the day-to-day duties of physicians and available time slots are matched (Gunawan & Lau, 2013). The nurse scheduling problem has been studied for longer than the ER scheduling problem in

healthcare management literature. Several mathematical models and heuristics can be adopted to solve the physician scheduling problem in ERs (Carter & Lapierre, 2001). Gross et al. proposed mixed-integer programming models that provide high-quality and timely decision updates of duty scheduling (Gross et al., 2018). However, such methods still have gaps in retaining stability as real-life cases are highly dynamic. The dynamic nature of duty scheduling problems could be addressed by developing new methods.

To be able to address all urgent demands, the workforce planning of physicians must be done carefully. Considering the physician workforce as the leading resource, we can take a physician's time as a perishable resource. If no patient is assigned to a physician, the resource of time is gone for all. If a physician is kept busy with a low-urgency case, there is the risk of not addressing a high-urgency case. Thus, the worth of a physician's time should be carefully measured before assigning any patients. So, duty scheduling could be based on the value of the physician's time. Knowing that the duration of several healthcare treatments, such as surgeries, is stochastic (Erhard et al., 2018), dynamic methods are needed to better address the problem of physician scheduling in ERs.

Considering each physician's individual preferences in emergency room scheduling has received positive feedback (Carter & Lapierre, 2001). The metaheuristic algorithm has considered the scheduling requirements of the hospital and each physician's days off requests and circadian rhythm. They were considering the needs of the agents in the decision-making process as the input makes a significant difference in the output of decision-making processes. Therefore, utilizing these design methods to capture human factors is worth working on to improve the solutions. Our submitted paper shows that an unbiased system to expose all criteria involved in the decision-making processes, including human criteria, can be designed for two-sided matching markets. Our proposed dynamic matching optimization with unbiased criteria can be applied to doctor-case matching.

viii. Resource-project matching in infrastructure management

Asset management or infrastructure resource management consists of the development, operation, and maintenance of assets. In the private and public sectors, asset management aims to minimize costs. There are many decisions in the asset management process, starting from asset development

up to retirement. After development, procurement, and operating decisions, we have maintenance, rehabilitation, and repair decisions. Thus, making cost-effective and cost-efficient decisions has excellent importance in asset management. The approach of taking an engineer's or physician's time as a perishable resource and appraising its worth can be taken for non-human resources. In asset management, some resources can be assigned to infrastructure projects. For example, an excavator is an asset of a municipality and can be assigned to one or more construction projects. If we can measure the value of an asset's available time, we can make asset assignment decisions based on it. If there is a high chance of the need for an asset later for a high-importance project, it could be a good decision not to assign the asset to a low-importance project at that time. As follows, there appears to be a need to determine the importance of projects. The evaluation criteria should be specified along with the evaluation method to decide the importance level of projects. Therefore, an unbiased criteria identification method is needed along with a two-sided matching method to ensure satisfaction of demand and efficient usage of assets. Utilized with our dynamic matching optimization method, this problem can be solved successfully.

2.4. Market Design

A market is a medium for the exchange of demand and supply, and the providers in markets are called agents. A market is called two-sided if there are two distinct sets of agents, where each agent is looking for a match from the other set. A match is an agreement on the exchange. The exchange can be of labour in labour markets, of residency for medical students, or of admissions in school choice programs. This is why two-sided matching problems are also called market design problems.

Many matching problems occur in markets or market-like settings, such as labour markets, school admissions, or online platforms. By addressing these problems effectively, two-sided matching algorithms contribute to market design, optimization, and the efficient functioning of these markets. This led to a new research field called market design (Roth & Wilson, 2019). It involves designing the rules, mechanisms, and institutions that govern how agents interact and allocate resources. The goal of market design is to overcome various market failures and achieve desirable outcomes such as efficiency, fairness, and competition. Studies reveal that revenue is influenced by fairness concerns (Gui et al., 2024) and competitive equilibrium (Sotomayor, 2019). Market

failures can arise due to factors like information asymmetry, externalities, monopoly power, transaction costs, and coordination problems.

Market design mainly focuses on the design of rules and regulations of markets. It also investigates how this design affects the functioning and outcomes of that market. Therefore, the market design tries to introduce the minimum number of necessary properties to ensure the market functions properly. A market can function properly if the following three criteria are ensured (Roth, 2008b). The first criterion is thickness. A market must have many agents that provide an opportunity for the most agents in the market to find stable matches. If the market is thin, finding a desirable match is much less likely (Roth, 2015). The second criterion is safety and confidentiality (Sönmez & Ünver, 2014). A market must create a safe and confidential medium for agents to reveal true preferences while the information moves around. Protection must be provided for private information. If the market is neither transparent nor confidential, true preferences may not be captured and as a result, stable matching conditions cannot be sustained. And the third criterion is overcoming congestion. A market cannot function if thickness creates congestion. Therefore, each market must develop efficient and effective ways to overcome congestion. Among these three criteria, this work contributes to the advancement of the research in the second criterion, the true preference extraction for agents in two-sided matching markets. Several studies overlook the changes in the subject's psychological perception resulting from the interrelation between external and internal comparisons (Pu & Yuan, 2023). Our goal is to fill this gap by revealing the true preferences of both sides of the market using a new engineering design methodology in this thesis.

2.5. Stability in Two-Sided Matching Markets

In two-sided matching markets, there are three typical objectives: stable matching, maximum cardinality matching, and maximum weight matching. Many researchers consider finding stable matching as the most important objective. Ensuring stability means the matched entities cannot do better with another match and therefore continue with their current match. Taking stability as a core component ensures the algorithms provide optimal solutions. Research shows that some real-life matching markets failed because of the lack of stability (Roth, 1984; Hatfield & Kominers, 2010; Roth, 2008b). Therefore, stability is the first objective to achieve.

Gale and Shapley show that stable matching always exists in the two-sided matching problem (Gale & Shapley, 1962). Roth and Vande Vate also prove that the set of stable matchings is always nonempty (Roth & Vande Vate, 1990). Various research has been conducted based on the goal of stability. For example, Roth has investigated if giving agents incentives would help them reveal true preferences honestly and contribute to the stability of matches (Roth, 1982). For various two-sided matching problems, the impact of incentives on agents' willingness to reveal their true preferences honestly is investigated. Research has shown that incentives can promote agents' honest revelation of true preferences (Roth, 1982; Abdulkadiroğlu et al., 2015; Echenique & Yenmez, 2015). So, another purpose is the agents' honest revelation of true preferences.

Two-sided matching algorithms aim to achieve efficient and stable allocations while maximizing overall satisfaction or utility. By pairing agents optimally, these problems can lead to better outcomes and enhance the overall efficiency of resource allocation or matching processes. On the other hand, matching problems often involve allocating scarce resources or opportunities. By considering the preferences of both sides and finding a mutually acceptable solution, two-sided matching algorithms can promote fairness and equity in the allocation of these resources (Budish & Cantillon, 2012; Hatfield & Kominers, 2010). Also, two-sided matching problems often involve many agents or entities. The size makes it impractical or time-consuming for each agent to search for suitable matches individually. Two-sided matching algorithms can reduce search costs by efficiently matching agents based on their preferences. This way, participants save time, effort, and resources (Hatfield & Milgrom, 2005). Last, but not least, it allows for considering the preferences, characteristics, or compatibility of the agents on both sides. By accounting for the preferences and characteristics of both parties, matching algorithms can lead to higher levels of satisfaction and compatibility among the matched agents (Budish & Cantillon, 2012). Better matches provide higher satisfaction and utility, therefore improving efficiency. Tackling two-sided matching problems are important because they help us optimize resource allocation, improve efficiency, maximize satisfaction, and promote fairness and equity. Overall, two-sided matching problems are significant in designing stable, efficient, and fair systems across various domains, benefiting both individuals and society (Roth & Peranson, 1999; Kominers et al., 2017).

2.6. Existing Criteria Identification and Evaluation Methods

The first step in two-sided matching algorithms is to identify and define the relevant criteria or objectives for the decision problem. These criteria should capture the different aspects or dimensions of the problem. The aspects can be quantitative such as cost, time, and efficiency or qualitative such as resource allocation and satisfaction. Criteria identification in two-sided matching refers to the process of identifying the relevant criteria which will be used to assess the preferences or characteristics of the agents on both sides. It involves determining the key attributes or qualities that are important for making mutually beneficial matches between the two sets of agents to ensure stability.

In TSMDM problems, matches are identified based on preferences and priorities, whereas preferences and priorities are determined based on criteria. Most of the two-sided matching literature focuses on finding preferences and priorities (Roth, 1984). At the same time, the identification of criteria is of great importance. Not only identification but also evaluation and ranking of criteria are among crucial inputs of the overall problem. In traditional methods, some of the fundamental challenges in identifying the complete set of criteria that leads to long-term optimal matching solutions are a poor match of the sample to the population, response bias, inflexibility, researcher bias, lack of randomness, and fixation (Drigas et al., 2004; Roth, 2012; Sönmez & Ünver, 2014; Ogle et al., 2015).

According to the review paper by Guindo et al., frequently utilized criteria identification and selection methods for the two-sided matching problem can be counted as i. surveys; ii. interviews; iii. focus groups; and iv. literature reviews (Guindo et al., 2012). The criteria can be identified using a combination of these methods as well. For example, Sonmez and Moorhouse have validated the decision-making criteria that have been identified from interviews and literature review using the survey method (Sonmez & Moorhouse, 2010). Traditional data collection methods, such as surveys, interviews (such as Brothers & Wetherholt, 2007), and focus groups, rely on a limited participant pool. Consequently, these methods unfortunately result in criteria that lack sufficient representation among diverse decision-makers (Duthie et al., 1999). The results are limited in terms of representing the population. This is a significant limitation of qualitative

research. To develop unbiased methods to discover an accurate and complete list of important criteria for decision-makers, further research should be conducted.

Along with the cost of preparing surveys and interviews, there are also concerns about the nature of the items on the survey and their suitability for research questions. Focus groups, which are more costly than surveys, make it difficult to get honest opinions and complete information from people who might not accurately represent the target group. Therefore, an unbiased method is critical to ensure optimal matches.

Weight identification and calculation methods are extended by various researchers such as multi-granularity linguistic term sets (Yue et al., 2015) and fuzzy axiomatic design (FAD) (X. Chen et al., 2016). Other researchers developed approaches called probabilistic linguistic term sets (PLTSs) (Zhang, Kou, et al., 2021) and hesitant fuzzy linguistic term sets (Zhang, Gao, et al., 2021). Other criteria ranking methods such as TOPSIS, MAVT, ELECTRE and PROMETHEE has already been mentioned in Chapter 2.1. Yet, the most popular criteria evaluation and ranking method is AHP according to a review article by Kabir et. al.. AHP counts for almost half of the total 330 articles covered between the years of 1980 and 2012 (Kabir et al., 2014).

AHP found applications in various application areas. AHP has been adopted to make decisions in different infrastructural areas. Herath has utilized AHP to rank different wetland management options (Herath, 2004). In contrast, other researchers have used AHP to make decisions regarding maintenance, repair and rehabilitation projects in highway infrastructure management (Šelih et al., 2008) or railway infrastructure management (Nyström & Söderholm, 2010). Several infrastructural areas need to be managed: water resources, water distribution networks, bridges, buildings, pavements, transportation infrastructure, and underground infrastructure. Management of every one of the infrastructural areas requires careful assessment to establish effective and efficient use of resources. MCDM methods are widely applied in the infrastructure management field. They are preferred because of their transparency in expressing and weighting decision criteria and their capability of stakeholder involvement (Kabir et al., 2014). Therefore, the development of MCDM methods capable of transparency in decision criteria and stakeholder involvement in the decision-making process is an essential open field for researchers.

2.7. Natural Language Processing

Natural Language Processing (NLP) is a field that focuses on enabling computers to understand, interpret, generate, and interact in human language. NLP is one of the most popular areas of artificial intelligence (AI), computer science, and linguistics. Some common NLP tasks include but are not limited to text classification, named entity recognition (NER), speech recognition, text summarization, chatbots, and voice assistants. NLP can be classified into various subfields. Tasks such as machine translation, content analysis, text categorization, semantic analysis, and NER falls under the subfield of language understanding (Samant et al., 2022). Speech and audio processing can be considered as another widely studies subfield (Khan et al., 2023). Tasks like text classification go under the subfield of text mining (Antons et al., 2020). Natural Language Generation, machine translation, and text summarization are listed under the subfield of language generation (Ji et al., 2023). Chatbots such as ChatGPT go under this category. We use ChatGPT output as an input in one step of our methodology. Therefore, we utilize large language models (LLMs) outputs as the source for extraction. Last but not the least, there is a subfield called information extraction. Our work falls into this subfield. Information extraction tasks can be listed as keyword extraction, relation extraction, information retrieval, and question answering (Singh, 2018). Our proposed methodology aims to pull criteria from problem descriptions therefore can be classified under the NLP subfield information extraction as ROM is a method to represent natural language (Zeng, 2008).

2.8. Research Gaps

When it comes to decision-making that involves people, the reality is much more complicated than a simple list of preferences. Human decisions are shaped by emotions, changing perceptions, personal contexts, and psychological states — yet most two-sided matching (TSM) models still reduce them to fixed, static preferences. Especially in fields like engineering workforce management, critical human factors like physical abilities, cognitive capacity, emotional resilience, stress, fatigue, and awareness are often overlooked. To truly understand and plan for human capacity, these dimensions need to be considered. However, today's decision-making models rarely reflect this complexity. Recognizing this gap, this thesis introduces an unbiased

criteria identification tool that brings human factors to the forefront. Built on Environment-Based Design (EBD), Recursive Object Model (ROM), and extended Life Cycle Assessment (eLCA) methodologies, the tool aims to create a fuller, more realistic picture of decision-making — one that sees people not just as data points, but as dynamic, evolving individuals. In doing so, it helps build matching systems that are more fair, accurate, and human-centered.

Mismatch in two-sided matching markets costs a significant number of resources to governments, companies, organizations, individuals, and societies every year (Hatfield & Kominers, 2010). These costs are not just financial; they also include lost opportunities, wasted potential, and inefficiencies across entire systems. Minimizing mismatching costs is possible by improving the way matches are decided. To improve the matching process, firstly, organizations must adopt global solutions to problems rather than individualistic where each position and each candidate are considered individually. Considering the global system of agents in the system is crucial in achieving a more efficient and stable matching outcome (Roth & Peranson, 1999). Another major challenge is transparency. Current market design literature emphasizes stability, safety, and thickness while lacking robust methods to reveal true agent preferences. To match people and opportunities well, decision-makers need a clear view of what each position requires and what each individual hope for. Unfortunately, in many cases, this information is incomplete, biased, or hidden, leading to matches that miss the mark (Sönmez & Ünver, 2014). There is a need for methodologies that can capture hidden, unconscious, or even evolving preferences in matching process without relying on self-reported interviews. In this thesis, we take on these challenges directly. We propose a method to reveal matching criteria in a way that is unbiased, fair, and transparent — a way that gives everyone a better shot at finding the right fit. By focusing on building a more complete, honest foundation for matching decisions, our goal is to help create systems that are not only more efficient, but also more human-centered, stable, and fair across a wide range of applications.

Existing TSM systems mainly rely on methods that often introduce bias, miss important factors, and are not systematic. These are mostly expert opinions, surveys and interviews. Therefore, there is a lack of an unbiased, systematic, data-driven approach for identifying decision criteria in TSM problems. None of these existing methods effectively discover full sets of criteria in a way that is adaptive, inclusive, and fair for both sides of a matching system. Current literature focusses more

on ranking rather than discovering complete and relevant criteria. We want to fill the gap of automatic criteria generation which is done directly from domain knowledge. In the current literature of optimization models, the criteria are assumed to be already correctly and completely identified, which is not the case most of the time. Very few studies tackle how criteria discovery affects optimization outcomes, stability and fairness along with the overall system efficiency.

In recent years, researchers have turned to artificial intelligence to improve how we model two-sided matching problems—like matching students to schools or workers to jobs—by capturing a wider range of factors that influence outcomes (Ravindranath et al., 2023). One example is (Zhang, Gao, et al., 2021), who developed a model that uses linguistic terms to express preferences and then evaluates them using a gain-loss function. While their work brings valuable nuance into the modeling process, it still depends on human-defined preferences, which introduces subjectivity. More broadly, machine learning has been widely used to tackle multi-criteria decision problems by analyzing past data to guide future choices (Liu & Vicente, 2024). Our approach takes a different path. Instead of relying on historical data or subjective inputs, we use a natural language-based method that focuses solely on the structure and content of the problem at hand. This allows us to identify decision criteria in a way that is both unbiased and grounded in the actual problem—not in assumptions or past outcomes. In doing so, we address a major gap in the current literature and offer a fresh way to approach two-sided matching problems, one that promotes fairness, transparency, and stronger decision-making across a range of applications.

Even though static matching has been widely studied, dynamic matching problems are not sufficiently addressed. There is no strong framework for dynamic, and perishable-resource based matching. This novel approach is applied to dynamic TSM for the first time in this thesis to fill a gap in literature. This method can catch the dynamism in new and unexplored application areas. This thesis aims to fill the gap in applying unbiased criteria identification and dynamic optimization in these emerging real-world matching problems.

3. Methodology

3.1. Unbiased Criteria Identification (UCI)

3.1.1. Theoretical Framework

3.1.1.1. Multi-Criteria Decision Making is a Design Problem

The development of an unbiased criteria discovery algorithm is a design problem because it fundamentally requires creating a systematic, context-sensitive, and human-centered method to address this challenge. Unlike traditional optimization problems, the formulation of what should be optimized is uncertain and context dependent. The process is open-ended, aiming to reflect real-world complexity while avoiding bias. Therefore, it is not a technical task to develop such an algorithm, but a design challenge. Therefore, we can use the environment-based design (EBD), which is a method for solving a design problem, to develop an unbiased algorithm to discover the criteria of a two-sided matching problem accurately and adaptively. EBD allows us to consider the full context in which decisions are made while ensuring that environmental constraints are captured systematically rather than arbitrarily. Additionally, we can use other design tools such as environment-based life cycle analysis (eLCA) and Recursive Object Model (ROM) because of the design nature of our problem. ROM allows us to extract functional requirements by deconstructing the problem into objects and relationships in a structured and hierarchical way. On the other hand, eLCA makes sure that the criteria reflect sustainability and adaptability by capturing long-term impact of decisions in the lifecycle of the product. Together, EBD, ROM, and eLCA allow designers to move from vague human needs to precise, optimized and unbiased fair matching. The motivation for using these design methodologies stems from the need to create a comprehensive, unbiased, and adaptable framework for two-sided matching problems.

3.1.1.2. Environment-Based Design (EBD)

The Environment-Based Design (EBD) theory (Zeng, 2011, 2015) is a design methodology that efficiently integrates human factors into design. The EBD approach focuses on the product environment in the first step. The methodology analyzes the product's life cycle in detail by considering conflict as the driving force behind the design. The approach defines three recursive stages of design as environment analysis, conflict identification, and solution generation. Keeping the recursive nature of design in mind, the EBD approach leads the designers to move between

those three design stages naturally by staying creative. We utilized this method as it is a comprehensive engineering design methodology with proven applications. The EBD approach has proven its effectiveness across diverse domains, showcasing successful applications in areas ranging from physical product design, exemplified by air turbines (Yang et al., 2022), to service design, as illustrated in market design (Xu et al., 2015). It has been also used to extend the application of AHP (D. Chen et al., 2016).

The EBD methodology defines design as a recursive process. The three stages of design are recursively repeated as long as needed. Let us start with the environment. Environment analysis hands over product-environment interactions, and the synthesis of these interactions lead the designer to the design solution. However, design activities do not end when we reach a design solution. Design solution evaluation hands over more information on product-environment interactions, and analysis of these interactions lead the designer to the environment. Now we are where we started. Therefore, before stopping the design activity and declaring the ultimate design solution, we must go over these stages a couple more times. Furthermore, design is an evolving process. The product requirements, knowledge collected on the desired product, and generated product solutions evolve until they are all true.

The EBD, introduced by Zeng in 2011 and further expanded in 2015, is a highly efficient design methodology that incorporates human factors into the design process by putting the environment in the base of design (Zeng, 2011, 2015). According to EBD, the product serves the environment as much as the environment serves the product. Therefore, exploring the product or service environment is the first design step. The conflicts identified in the environment are the primary source of the design. Therefore, discovering the elements in the product environment starts the design process. The EBD methodology views design as an ongoing recursive process, where the three stages of design are repeated as needed. It starts with environment analysis, leading to product-environment interactions and design solutions. The evaluation of the design solution then provides more information on product-environment interactions, completing the loop back to the environment analysis. This recursive approach is crucial because design is an evolving process, with product requirements, collected knowledge, and generated solutions constantly evolving until they align (Zeng, 2015). The recursive nature of design ensures flexibility, adaptability, and inclusive problem-solving.

We want unbiased criteria in two-sided matching to ensure fairness, transparency, and equality for both sides. This is important to avoid any favoritism or discrimination in the matching process. It helps create a system where both sides have a fair chance to be matched. The EBD approach puts a focus on the environment using the ROM tool, which provides a simple yet powerful graphical language for technical English discovered in a naturally unbiased way. For example, by employing ROM to create a collection of terms and concepts about job matching, the relationships between the concepts can be enumerated with input from common knowledge sources. This facilitates defining the necessary skills, knowledge, and experience requirements for employees and employers in an unbiased way.

To achieve unbiasedness, we utilize common widely accepted data resources such as dictionaries, published research, online search tools, and large language models (LLMs) such as ChatGPT (ChatGPT, 2025). These sources are commonly adopted and generally seen as neutral, making them a solid foundation for reducing bias. For example, ChatGPT defines unbiasedness as "the absence of prejudice, favoritism, or systematic distortion in judgment, measurement, or decision-making." Being unbiased implies fairness and neutrality, ensuring the outcomes are free from subjective judgment, external pressure, or pre-measurement. The goal is to make impartial, objective, and fair decisions that are free from bias or favoritism. In our algorithm, we use responses from these well-established sources as input to help ensure that the criteria we generate are as objective and balanced as possible.

To achieve unbiased criteria in a two-sided matching context or any decision-making process, several conditions need to be met. The criteria used for matching should be clear, objective, and easily understandable. Ambiguous or subjective criteria can introduce interpretation biases, leading to unfair matches. Criteria should be relevant to the goals and requirements of the candidates and the jobs. Irrelevant factors can lead to arbitrary decision-making and favoritism. The criteria should be consistently applied across all candidates and jobs. Inconsistencies in the application of criteria can lead to perceptions of unfairness. Both sides of the matching process should be subject to similar evaluation criteria because we want to ensure equivalence so that it helps to maintain balance and fairness between the two sides. Criteria should not discriminate against individuals based on characteristics such as gender, age, race, and religion. The matching process, including the criteria and their weights, should be transparent to all participants.

Transparency helps build trust and allows individuals to understand how decisions are made. Using the language extraction model called ROM and the recursive design method called EBD, our method enforces the identification of unbiased, clear, relevant, consistent, equivalent and transparent criteria. This eventually reinforces the inclusiveness and fairness in two-sided matching problems.

3.1.1.3. Environment-Based Life Cycle Analysis (eLCA)

The environment-based life cycle analysis (eLCA) is a valuable tool for locating the product environment. This analysis provides a detailed understanding of the product's environment and unbiased discovery of its components. Using the Recursive Object Model (ROM) tool enables the designer to discover all attributes of the product environment components (Zeng, 2008). According to the EBD approach, design is a recursive process. This approach defines three recursive stages of design as environment analysis, conflict identification, and solution generation. Keeping the recursive nature of design in mind, the EBD approach leads the designers to move between those three design stages naturally by staying creative. Discovering the product environment leads the designer to identify conflicts, and discovering conflicts leads to design solution generation. Going over these steps as many times as needed, the designer generates a unique unbiased solution for the design problem based on the product environment.

Life cycle analysis (LCA) refers to the process of gathering data and details about a product, process, or service throughout its entire life cycle. It involves capturing information about various stages. For example, lifecycle of a physical product can consist of extraction of raw materials, manufacturing, distribution, use, maintenance, disposal, and recycling. The Environment-based Life Cycle Analysis, aka eLCA, is a valuable tool for precisely locating the product environment and unbiasedly discovering its components (Yang et al., 2022).

The process of Environment-Based Life Cycle Analysis (eLCA) (Yang et al., 2022) can be summarized as follows. The analysis starts with a design problem. The first step is understanding the design problem via object analysis using the Recursive Object Model (ROM) method. The second step is collecting life cycle information via question-driven information collection. In the collection phase, the three sub steps followed are generating the right questions, answering questions and developing the proper knowledge regarding the design problem. The third step of

the analysis is to integrate the life cycle information into the current ROM and generating the merged ROM diagram. The fourth and last step of the analysis is modelling life cycle dependency via interaction analysis. This step reveals essential design requirements via the interaction dependency network. The eLCA for the labour market can be found in Table 2.

Table 2: Environment Life Cycle Analysis Chart for Labour Market Design

Physical Artifact Environment	**Natural Environment**
• Organizations and Companies	• Time
• Employee and Employer Unions	• Space
• Labour and Employment Infrastructure	• Natural laws
• Recruitment and Job Search Infrastructure	• Natural resources
• Social Laws, Rules and Norms; Social Security	• Direct Stakeholders: Recruiters, Candidates, Managers, Coworkers
• Occupational Safety Policies, Employees Insurance, Employers Liability Insurance	• Indirect Stakeholders: Customers, Suppliers, Business Partners, General Public
• Technical Laws and Regulations	• Experience, Mastered Knowledge, Mastered Skills
• Wages, Benefits, Working Conditions	• Education, Training, Qualifications
• Documents: CV, Resume, Portfolio, Cover Letter	• Goals, Tastes, and Motivation
• Websites, Job Boards, Data Sets, Software Tools and Apps	• Preferences, Interests and Emotions
Digital Artifact Environment	**Stakeholder Environment**

3.1.1.4. Recursive Object Model (ROM)

The three stages of design in the EBD approach are captured based on a tool titled the Recursive Object Model (ROM). Zeng has proposed a simple yet exclusive graphical language for technical English called ROM (Zeng, 2008). This mathematically proven method is sufficient and valuable to enumerate relationships between different ideas in engineering design. Therefore, ROM can be used to create the vocabulary of any topic. For example, generating the job vocabulary in a company helps companies denominate employees' skills, knowledge, and experience requirements. The ROM diagram assists designers in defining relationships between different characteristics of requirements. Coming up with the requirements helps the decision-making process to be inclusive.

ROM is a conceptual tool that generates a diagram representing various relationships between components of the product environment, guiding the design direction. ROM aids designers in uncovering all attributes of the product environment components while preserving the recursive nature of the design. ROM's inherent capability to extract knowledge from English statements and EBD's capability of incorporating environmental factors and conflict between influential factors are valuable assets for tackling complex design problems such as labour market design. In this research, we leverage ROM's knowledge extraction capability to analyze a set of questions and descriptive statements relevant to the two-sided matching problem. By doing so, we aim to identify conditions, requirements, and expectations for the matching problem, ensuring an unbiased and optimal matching process for all parties involved. Overall, the EBD methodology, guided by the ROM, presents a comprehensive and creative approach to design, allowing for iterative improvement and efficient integration of human factors into the decision-making process.

3.1.2. Step-by-Step Formulation of Unbiased Criteria Identification

In this thesis, we introduce the following unbiased criteria identification method for the two-sided matching problem based on EBD, eLCA and ROM. Our objective is first to demonstrate that a set of criteria for any kind of matching problem can be extracted from natural language that describes the matching problem using the ROM. We discover the product environment via eLCA and update ROM diagrams accordingly to lead us to comprehensive understanding of the desired product.

Next, we show that the identified criteria using the natural language processing method are superior to the criteria found by currently utilized criteria identification methodologies using examples.

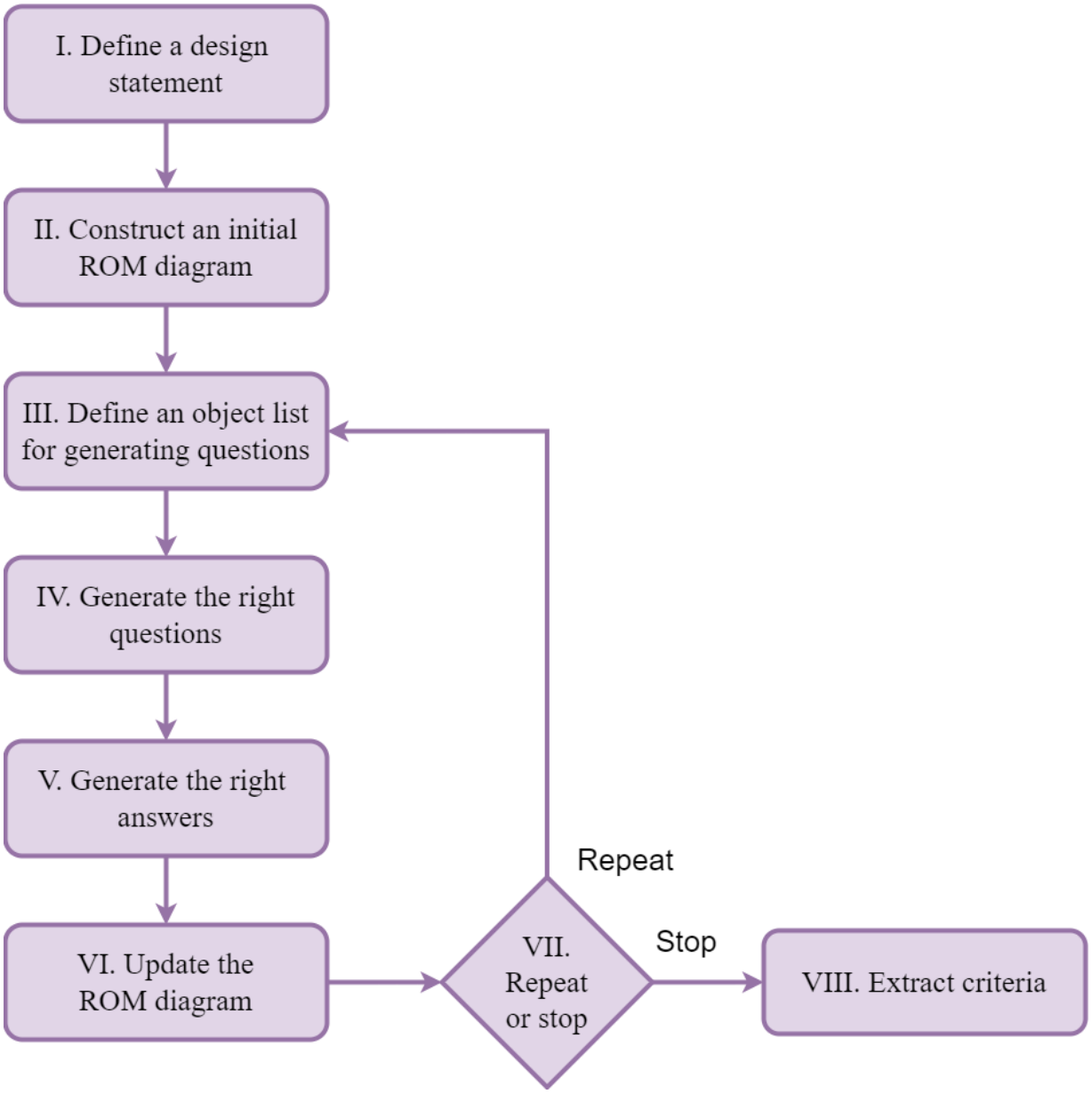


Figure 1: The unbiased criteria identification methodology flow chart

The proposed unbiased criteria identification methodology consists of eight steps as shown in Figure 1. The process starts with defining the design statement in Step I. In Step II, the design statement is transferred into the initial ROM diagram. The diagram is a way of deconstructing the statement to allow designers to further dive into each word individually. The word-by-word analysis provides us with a deeper understanding of the environment of the design which gives an unbiased discovery method. In Step III, we come up with a well-organized list of objects. This list gives us the order of questions to be asked. We generate questions and answers in Steps IV and V consecutively. We use EBD methodology to collect information about the questions before constructing answers. The product environment is discovered from all four angles to reveal the environment components of the central object of the design statement. The collected information about the environment is used in answering the questions in Step V. Then all answers become new objects in the ROM diagram in Step VI. After integrating all answers into the extended ROM diagram, the designer decides to repeat or stop. If there are more objects to be discovered in the environment, we repeat the steps by going back to Step III. This is the recursive part of the process. Until there is no more to discover, we continue going back and repeating steps III-VII. When we are satisfied with the environmental details and the amount of information collected, we stop and move to the last step. In the last step, we pull the information from the final ROM diagram. As follows please find the explanations and introductory samples of each step.

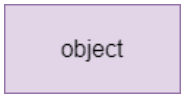
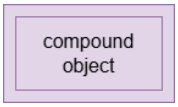
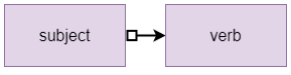
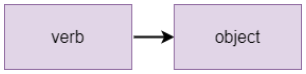
I.Define a design statement

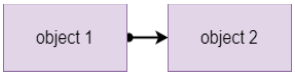
This step refers to the process of clearly identifying and articulating the specific issue that needs to be addressed in the design process. The item to be designed could be a product, process, or service. The statement should ideally follow the simplest sentence structure, which starts with a subject, follows by a verb and an object, if any. Any details specific to the design problem should briefly be mentioned in the design statement with no detail. The statement should be concise, focused, and clear. A well-crafted design statement sets the direction and acts as a reference point throughout the design process. The outcome of this step is a design statement. Let's give an example of school admission matching. Let's assume our purpose is designing an algorithm. The design statement can be written as "Designers design an algorithm for matching students with schools."

II.Construct an initial ROM diagram

This step refers to the process of initiating a ROM diagram that gives a visual tool that helps analyze the structure of a design system (Zeng, 2008). A ROM diagram depicts the relationships and interactions between words within a design system. A ROM diagram involves identifying the key objects within the system and representing them as nodes in a diagram. Each word in the design statement becomes one node. There are two types of objects: primitive and compound. If an object consists of more than one word and cannot be separated into words without losing its meaning, we keep it as a compound object. The relationships between these objects are illustrated using connecting lines and specific arrows. There are three main types of relationships between objects: a subject-verb relationship, a verb-object relationship, and a constraint relationship. Each type of relationship has its graphical representation adapted from Zeng (Zeng, 2008) as in Table 3.

Table 3: The types of objects and relationships in a ROM diagram

Type		**Graphical Representation**	**Definition**
Objects	Primitive objects		Everything in the universe is an object.
	Compound objects		An object that includes at least two other objects in it.
Relations	Predicate [$Subject$] - [$Verb$]		The [$Subject$] is the one performing the action or is described by the [$Verb$].
	Predicate [$Verb$] - [$Object$] or		The [$Verb$] is the action or state of being, and the [$Object$] is the recipient of that action, or the entity

	[$Preposition$] - [$Object$]		affected by it.
	Constraint [$Object$] - [$Object$]		It is a descriptive, limiting, or particularizing relation of one [$Object$] to another.

As an example, let's create a sample initial ROM diagram for the design statement from the previous step: "Designers design an algorithm for matching students with schools." We have a sentence with nine words, so our diagram has nine nodes. The first two words are a subject and a verb therefore they have the first type of relationship. The subject-verb relationships are represented by a connecting line starting as a square from the subject and ending as an arrow in the verb. The words "design" and "algorithm" have a verb-object type of relationship which is illustrated with a connecting line starting flat from the verb and ending as an arrow in the object. Along with verbs and objects, prepositions and objects have this kind of relationship too. The word "an" is an adjective and represents a constraint type of relationship with the word "algorithm." The constraint type of relationship is represented by a connecting line starting as a circle from the constraining word and ending as an arrow in the constrained word. Not only do adjective-object or object-object combinations carry the constraint type of relationship. Many prepositions also constrain verbs or objects in sentences as well. For example, the words "algorithm" and "for" have this kind of relationship as it is not any algorithm, it is an algorithm for something specific indicated in the design statement. So, the words "algorithm" and "for" have a constraint relationship with "for" being the constraining and "algorithm" being the constrained object. Whereas the words "for" and "matching" have a preposition-object type of relationship which is the second type mentioned above. To make things clear, we transfer the words on how they appear in the dictionary, without any suffixes, the plural marker or the gerund form. The word "matching" becomes "to match" and nouns are put in the singular form. We continue constructing the diagram following these rules and we obtain Figure 2.

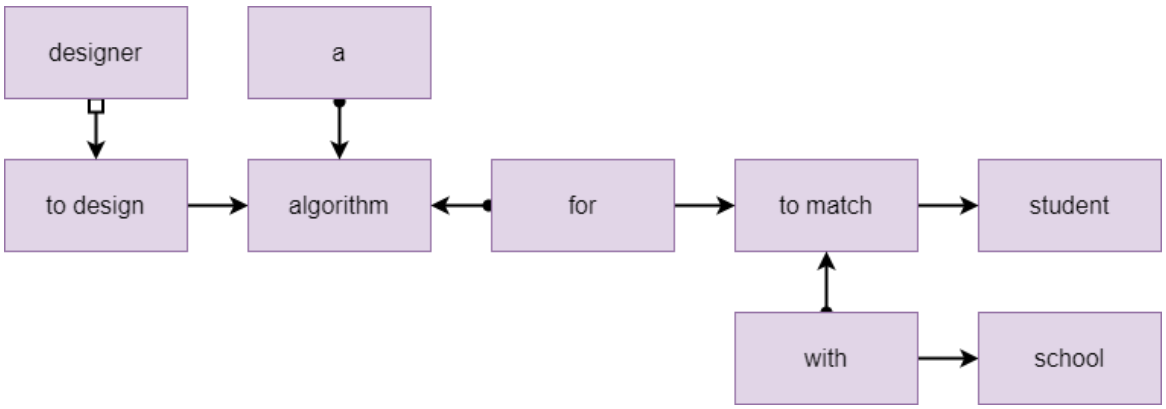


Figure 2: A sample initial ROM diagram

This is how the design statement is transferred into the initial ROM diagram. The diagram is a way of deconstructing the statement to allow us to further dive into each word individually. The word-by-word analysis provides us with a deeper understanding of the environment of the design. The outcome of this step is the initial ROM diagram.

III.Define an object list for generating questions

This step refers to the process of creating an ordered list of objects to be questioned, where objects are the words or phrases that construct the design statement. There are two rules in deciding the order of objects on the list adapted from Wang and Zeng (Wang & Zeng, 2009) as shown in Table 4. Following these two rules, we generate an object list which is the outcome of this step.

Table 4: Rules for the right order of objects for questioning

Rule 1	Among all the candidate objects, the object with the most undefined constraints and predicates should be considered for questioning first.
Rule 2	Before an object can be asked for a question, the objects constraining or predicating them should be asked.

Following our example from the previous steps, let's define the object list for questioning. All objects except the prepositions are candidate objects for the first member of our list. Following Rule 1, we observe the objects "algorithm" and "to match" are the ones with the greatest number of connections of any kind. Following Rule 2, the constraining or predicating objects should be asked first. The object "algorithm" is constrained by the object "to match" so let's start with "to match" first. Before questioning the object "to match", we need to ask for the object "student". We can ignore prepositions so the second object to be questioned is "school". So, the first three members of our list are "student", "school" and "to match". Now we need to discover the other constraining or predicating objects of the object "algorithm". There is "to design" but it is predicated by "designer" so "designer" is asked before others. That makes the next in our list "designer", "to design", and "algorithm". The outcome of this step would be the list of objects for questioning as follows: student, school, to match, designer, to design, and algorithm.

IV.Generate the right questions

This step refers to the process of generating questions for each object in the object list to be able to extend the ROM diagram. To be able to enhance information about the product environment, every part of the design statement will be asked questions. We follow the question-asking template provided by Zeng (Zeng, 2015). The template specifies how the questions should be asked for a noun or verb object with or without constraints as shown in Table 5. The outcome of this step is an ordered list of questions.

Table 5: Guideline for generating the right questions

	Condition	**Questions Guideline**
$[Noun]$	Without any constraint	What/Who is $[Noun]$?
$[Noun]$	With a constraint	What is $[Adjective]$?

	of [$Adjective$]	What is [$Adjective$] [$Noun$]?
[$Verb$]	With or without a [$Subject$] and/or an [$Object$]	What do you mean by [$Subject$] [$Verb$] [$Object$]? Why does [$Subject$] [$Verb$] [$Object$]? When does [$Subject$] [$Verb$] [$Object$]? Where does [$Subject$] [$Verb$] [$Object$]? How does [$Subject$] [$Verb$] [$Object$]?

Following our example from the previous step, we know that the first object to be questioned is the "student". The template states that for a noun object without any constraint, the question to be asked is "What/Who is a student?" This will be the first question to be answered in Step V.

V.Generate the right answers

This step refers to the process of answering the generated questions in Step IV. To find universally accepted definitions, explanations, and information, open-source resources such as dictionaries, large language models (LLMs) such as ChatGPT (*ChatGPT*, 2025) and other widely accepted online resources are utilized. Having the assumption that these common accessible data resources are unbiased, we rely on the widely accepted definitions of terms. Unbiased information collection ensures unbiased solution generation. We adopted the question-answering guideline provided by Zeng (Zeng, 2021) as shown in Table 6 and Table 7.

Table 6: Guideline for generating the right answers based on questions

Question	**Answers Guideline**
What/Who is [$Noun$]? What is [$Adjective$]? What is [$Adjective$] [$Noun$]?	If [$Noun$] is the product to be designed or the environment component of a product, then should add: 1. The purpose of [$Noun$]. 2. The life cycle of the [$Noun$]. 3. The categorization of environment components for each event

	in the life cycle following the dimensions of the eLCA environment structure.
What/Who is $[Noun]$? What is $[Adjective]$? What is $[Adjective]$ $[Noun]$?	If $[Noun]$ is an attribute of a product environment component, then define its relationship with the product or product environments.
Why does $[Subject^1]$ $[Verb^1]$ $[Object^1]$?	To $[Verb^2]$ $[Object^2]$, $[Subject^1]$ $[Verb^1]$ $[Object^1]$.
When does $[Subject^1]$ $[Verb^1]$ $[Object^1]$?	In/On a time, $[Subject^1]$ $[Verb^1]$ $[Object^1]$. When/During $[Subject^2]$ $[Verb^2]$ $[Object^2]$, $[Subject^1]$ $[Verb^1]$ $[Object^1]$.
Where does $[Subject^1]$ $[Verb^1]$ $[Object^1]$?	In/Along a place, $[Subject^1]$ $[Verb^1]$ $[Object^1]$. $[Subject^2]$ $[Verb^2]$ $[Object^2]$, where $[Subject^1]$ $[Verb^1]$ $[Object^1]$.
What do you mean by $[Subject]$ $[Verb]$ $[Object]$? How does $[Subject]$ $[Verb]$ $[Object]$?	If $[Subject]$ or $[Object]$ is not the product, the answer should include the life cycle of $[Verb]$. Else, skip the question.

Table 7: The guideline for generating answers based on object type

Object Type	**Guideline**
An attribute of a product environment component	The answer should define $[Object]$ according to the life cycle of the product and its relationship with the product or product environment.

The product to be designed	The answer should define [$Object$] according to the life cycle of the product. Add the purpose of [$Object$]. Add the lifecycle of [$Object$]. Add the categorization of environment components for each event in the life cycle, following the four dimensions of environment structure.
Others	For [$Subject$] [$Verb$] [$Object$], the answer should define the components and attributes of [$Subject$] in the context of [$Verb$] [$Object$].

To ensure the collection of the right answers, we conduct an environment analysis based on the EBD methodology whenever needed. EBD classifies environment components into four: human, natural, physical artifact, and digital artifact as shown in Table 2. The purpose of environment analysis is to gain a comprehensive understanding of the external factors and influences that impact the product in its life cycle. Exploring through the details of human, natural, physical artifact and digital artifact environments, we discover all the information we need in the design process. Human environment includes all human-related factors where natural environment has all nature-related data. Physical artifact are the physical-world related factors and digital artifact are intangible data.

As a second tool, we use eLCA in this step to reveal the life cycle components of the product to be designed. The outcome of this step is answers encapsulating information about all aspects of the product.

Following our example from the previous steps, the first question we ask is What/Who is a "student?" We answer this using the question-answering guideline. If we need further information collection, we conduct environment analysis and lifecycle assessment. The guideline states that the question "What/Who is [$Noun$]?" should be answered as follows: If [$Noun$] is the product to be designed or the environment component of a product, then add the purpose of [$Noun$], the life cycle of the [$Noun$], and the categorization of environment components for each event in the life cycle. [$Noun$] is "student", and it is not the product to be designed. It is an environment component of the product "algorithm". So, we should find the purpose of "student", the lifecycle of "student"

and the categorization of environment components for each event in the life cycle. To find this information, we use EBD and eLCA. The outcome of this step is information on the product itself, the product life cycle, and the product environment.

Carrying out an environment analysis on the object "student" will look as follows. EBD divides the environment into four. The first aspect is the physical environment. There are schools, classrooms, dorms etc. in the physical environment of a "student." The second aspect, the human environment, consists of teachers, families, parents, managers, classmates, roommates etc. The third one, the digital artifact environment, includes a student ID number, student records, admissions, grades, diplomas etc. Finally, the fourth aspect is the natural environment. But it does not include any specific natural conditions or climate etc. This information unbiasedly discovered about the keyword "student" will be included in the answers generated to the questions. As a second tool, we use eLCA. This helps us discover the life cycle of an object. For a "student", the lifecycle includes admission, enrollment, orientation, course registration, academic progression, attendance, examinations, extracurricular activities, higher education preparation, graduation, networking, and continuous learning. Next, we can discover the categorization of environment components for each event in the life cycle. For example, for the admission event, the physical artifact environment includes the school building, the human environment includes an admissions officer, the digital artifact environment includes an application, and the natural environment is negligible. Moving further with this analysis for every step in the life cycle, we collect information. We put this information to use when we are generating answers to questions generated in the previous step. The answer to our sample question can be constructed as in Table 8.

Table 8: The components of the answer to the sample question

The definition	The term student typically refers to an individual who is engaged in learning, particularly someone who is enrolled in an educational institution such as a school, college, or university. The term can be applied to people of various ages and levels of education, from primary school students to university students pursuing advanced degrees.

The purpose	Students actively participate in the process of acquiring knowledge, skills, and understanding within a structured educational environment.
The lifecycle	Admission, enrollment, orientation, course registration, academic progression, attendance, examinations, extracurricular activities, higher education preparation, graduation, networking, and continuous learning.

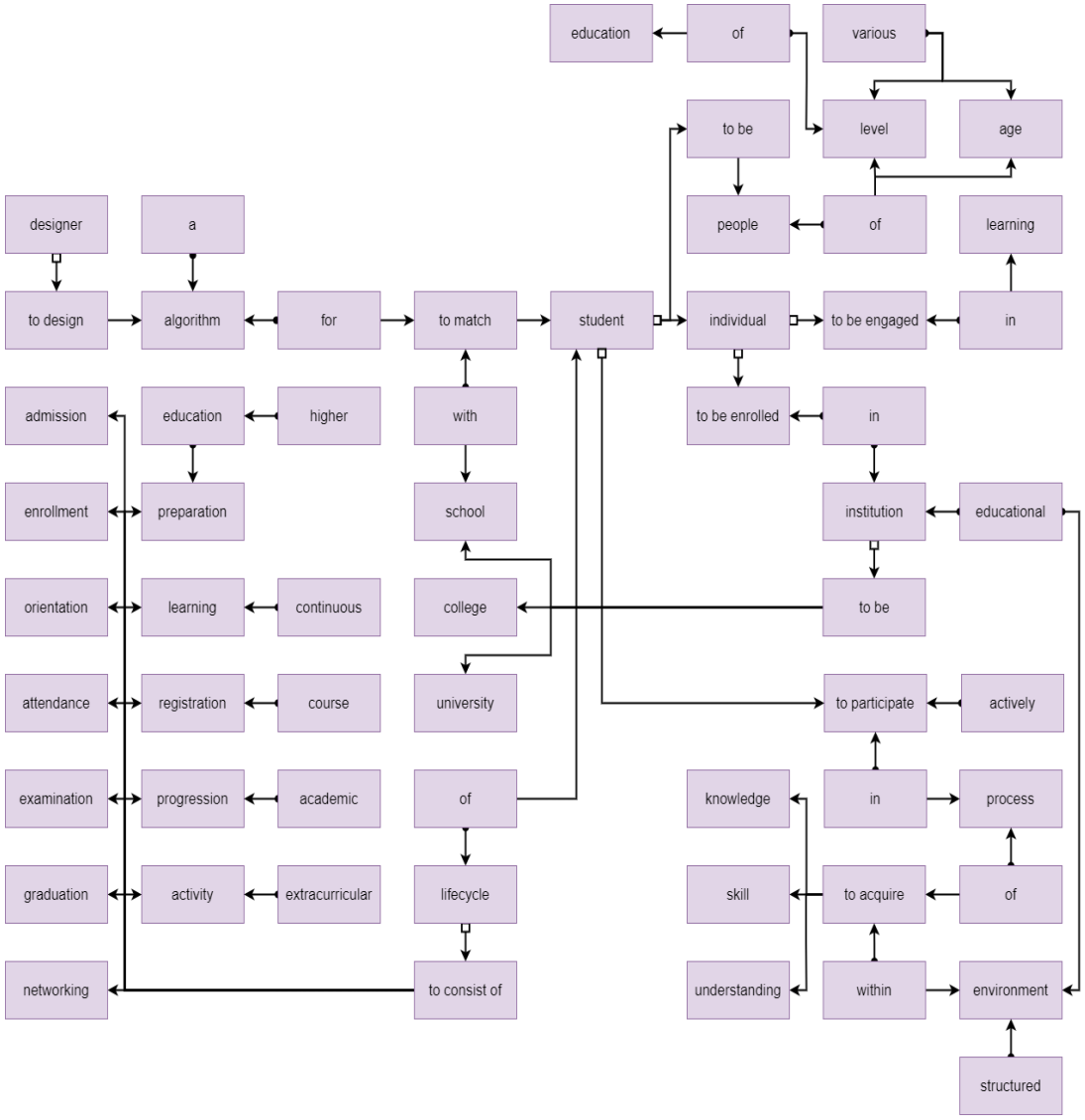


Figure 3: A sample extended ROM diagram

VI.Update the ROM diagram

This step refers to branching out the current ROM diagram with new objects following the guidelines in Table 3. If some objects have already been added to the diagram as nodes or blocks, only add new lines or arrows indicating the relationship type between the objects. One object can be added as only one node or block. This way, the final ROM diagram as shown in Figure 3 reveals all relationships related to each object. The outcome of this step is the extended ROM diagram which uncloaks relationships between questioned objects.

VII.Repeat or stop

At this step, we decide whether to stop or not. Design is a recursive process. Therefore, starting from the current ROM diagram, we continue generating and answering questions until we analyze the environment in enough depth. After every repetition, the extended ROM diagram will be extended to show the key components of the environment. If you decide to continue, return to Step III and repeat the steps. These steps can be repeated recursively as many times as needed. Once possible questions are exhausted, stop and proceed to the next step. The outcome of this step is the final ROM diagram.

VIII.Extract criteria

As the final step, we extract criteria from the final ROM diagram. This extended diagram illustrates the interconnections between the product environment components. The discovered relationships enable us to identify critical criteria that directly impact on the product in its lifecycle. Considering the product environment in detail, we compile an exhaustive list of criteria that significantly influence the design problem. The outcome of this step is unbiasedly extracted criteria. The criteria can be grouped to better be listed as shown in Table 9.

Table 9: The criteria identified

Criteria for individuals	**Criteria for organizations**

Values, goals, motivation, preferences, interests	Values, vision, mission, business goals, business plan, job family, industry, line of service, seniority level
Personality, emotions	Desired characteristics
Experience	Desired experience

3.2. Mathematical Model for Optimal Two-Sided Matching

3.2.1. Static Two-Sided Matching Problem: Assignment Approach

Two-sided matching problems can be classified into two as static and dynamic based on the availability of the entities. Static TSM is when all agents from both sides are available and known at the same time. In this case the matching is done once and there are no changes afterwards. If the system has agents from any side arriving or leaving over time, then the problem is called dynamic TSM and the system must update matches at multiple intervals. In this chapter we talk about static TSM.

To solve two-sided matching problems, mathematical optimization techniques can be adopted. Mathematical optimization is the process of selecting the best element from a set of available alternatives following specific criteria. It involves maximization or minimization of an objective function subject to a set of constraints. Many subtypes of optimization problems can be listed as follows, but are not limited to linear optimization, nonlinear optimization, integer programming, stochastic optimization. Common techniques to solve include, but are not limited to simplex method, LaGrange multipliers, gradients descent, genetic algorithms, dynamic programming, heuristics.

The static two-sided matching problems can be formulated as an integer programming problem. Let’s take the job candidate matching on focus. There are two bipartite sets: one of available jobs and one of available candidates. Each candidate has a preference list over the jobs. And each job has a preferred list of candidates. Typically, we want to maximize the total satisfaction of

matchings. We can model this as an integer program using a binary decision variable representing the matchings. There will be constraints such as each candidate can be matched with a maximum of one job, and vice versa. The preference lists will be fed into the objective function to achieve the maximum satisfaction. The unbiased criteria are fed into the model as parameters. Therefore, we can use the generated unbiased criteria in an optimization model and obtain optimized matchings solely based on our own criteria.

Our unbiased criteria identification method helps create fair and meaningful lists of what matters to each side in a two-sided matching situation—like matching students to schools or candidates to jobs. These criteria can then be used in optimization models to make better matching decisions. Typically, two-sided matching problems are represented using graph theory, where two groups of people or organizations are shown as separate sets of points connected by possible matches. Each person or group has their own preferences, which are usually shown as ranked lists or scores. What our method does is help build those preference lists in a more objective and consistent way, which makes the whole matching process more reliable and fairer.

The main goal of these mathematical models is to find the best match possible—one that meets specific goals, like being stable (where no one would rather switch partners) or optimal (where satisfaction is maximized). Real-world situations also come with limitations: for example, one person can only be matched with one partner, or there may be rules about who is compatible with whom. Our method plays an important role in defining these rules by helping identify key factors, like what compatibility means in each case.

The proposed unbiased criteria identification methodology extracts a list of criteria for both sides of the two-sided matching problem. This data can be transferred to the input data of the optimization model of a two-sided matching problem. The two-sided matching problem can be modelled using various mathematical frameworks, with the most common approach being using graph theory and optimization techniques. In the two-sided matching problem, there are two sets of agents or entities looking to be matched with counterparts from the other set. This can be represented as a bipartite graph, where one set of nodes represents the agents on one side (e.g., job seekers, students, or individuals seeking partners), and the other set represents the agents on the other side (e.g., employers, schools, or potential partners). Each agent in the model has preferences

over the agents on the other side of the market. These preferences can be represented using preference lists or utility functions. Preference lists rank the agents on the opposite side based on the preferences of each agent, while utility functions assign numerical values to potential matches based on their desirability. Our unbiased criteria identification methodology results can be used to generate the preference lists as the preferences are based on their decision-making criteria and our methodology generates all criteria impartially, improving accuracy, reliability, and utility in addressing real-world matching problems.

The goal of the mathematical model is to find a match that satisfies certain desirable properties, such as stability or optimality. The objective function maximizes the number of stable pairs or minimizes the number of unstable pairs. Various constraints need to be incorporated into the model to ensure feasibility and consideration of real-world factors. These constraints can be about capacity, compatibility or stability. The capacity constraints ensure that each agent can be matched with at most one agent from the other side. The compatibility constraints ensure that matched pairs meet certain compatibility criteria. And finally, the stability constraints ensure that no unmatched pair prefers each other to their current matches. Our proposed methodology can be used to find the parameters that build in the constraints of the mathematical model. For example, all compatibility criteria in compatibility constraints can be discovered through our methodology. This comprehensive incorporation of constraints enhances the model's ability to accurately capture the essential dynamics of the two-sided matching problem. This, in turn, enhances the model's effectiveness in practical applications, such as optimizing matching outcomes, improving resource allocation, and fostering stable and satisfactory matches between agents from both sides.

Another commonly used mathematical framework by which the two-sided matching problem can be modelled is the Analytic Hierarchy Process (AHP), developed by Saaty (R. W. Saaty, 1987). This model helps decision-makers arrive at the most logical choice. Using AHP, decision-makers first find the available options and their goals in making decisions. These options and goals are then transferred to an analytic hierarchy, revealing the importance of various factors in the decision-making process. The output of AHP is a priority vector, which lists the order of choice for the options of decision-makers. This priority list serves as an input for the job matching problem's mathematical model which optimally finds a stable matching for a list of jobs and candidates (Korkmaz et al., 2008). Once all the pieces are in place—preference lists, goals, and

constraints—optimization algorithms like the Gale-Shapley Deferred Acceptance method or linear programming can be used to find the best matches. We can also test how sensitive the results are to change and check how well the model reflects reality by comparing it to real-world data.

Suppose we have a list of jobs in front of a candidate. Each job is an 'alternative' for the candidate. The candidate has various criteria such as the ones found using our unbiased criteria extraction algorithm to evaluate each job. Each criterion is an 'objective' for the candidate. First, we measure the importance of each objective to the candidate, compared to the importance of the other objectives. This relative importance is called the 'weight' of the objective. Then we measure how well each of the alternatives serves each of the objectives as a numerical value. This value is called the 'score' of the alternative on that objective. Taking the sum of the product of the scores on an objective and the weight of that objective, we calculate the total score of an alternative. Repeating the same process for each alternative gives us the total score of each alternative. In the last step, we order the alternatives with decreasing total scores. This gives us the 'priority list' of candidates. Repeating the above-mentioned AHP steps for each candidate, we obtain a priority list for each candidate. Repeating the process for each job, where alternatives are candidates, we obtain a priority list for each job.

We can formulate the AHP problem in mathematical modelling as follows. Suppose we have o objectives and p alternatives. In the first step, AHP generates a weight w_i for the i^{th} objective. In the second step, AHP obtains a score s_{ik} for the k^{th} alternative on the i^{th} objective. The total score of the k^{th} alternative is then calculated by the following formula: $\sum_{i=1}^{o} w_i \, s_{ik}$. Once the total scores for all alternatives have been computed, we create a priority list by arranging them in descending order. The priority lists of jobs and candidates are input parameters to the job-matching mathematical model. Therefore, our unbiased criteria extraction algorithm serves as a parameter detection method in mathematical modelling.

Once the mathematical model is formulated with the graph structure, preferences representation, objective function, and constraints, optimization techniques can be applied to find an optimal or near-optimal matching solution. The most common method for finding stable matching is the Gale-Shapley algorithm which is also known as the Deferred Acceptance algorithm. Linear programming can be used for optimization-based matching algorithms. For finding maximum

cardinality or maximum weight matching, combinatorial algorithms can be utilized. In our case, we introduce a linear optimization model to address the static two-sided matching problems.

3.2.2. Optimized Static Two-Sided Matching

Now, let us introduce a mathematical model that can successfully match a set of agents or entities seeking to be matched with counterparts from the other set. To illustrate the model more clearly, we will consider a problem where a set of candidates are seeking to be matched with a set of jobs. Let S represent the set of candidates and J represent the set of jobs. There are m candidates and n jobs in total. The number of criteria is o. The decision variables are binary x_{ij} where the value is 1 if candidate i is matched with job j and 0 otherwise. In this context, candidates have qualifications C^Q and expectations C^E related to the job, while each job has specific requirements C^R for candidates. The total set of criteria associated with system C is composed of these three subsets: $C = \{C^Q, C^E, C^R\}$. As in any multi-criteria optimization problem, each criterion has a different level of importance to the stakeholders (candidates and employers). Therefore, the weight of importance for each criterion is determined as follows:

w_{ci}^S: $Importance\ of\ criterion\ c\ for\ the\ candidate\ i$

w_{cj}^J: $Importance\ of\ criterion\ c\ for\ the\ job\ j$

For each criterion, there is an associated compliance score for both jobs and candidates. In the case of AHP, candidates are evaluated pairwise for each criterion, resulting in a compliance score for each candidate. The following two parameters are used to quantify the compliance of candidates and jobs for a given criterion:

π_{cij}^S: $Compliance\ score\ of\ job\ j\ for\ criterion\ c\ according\ to\ candidate\ i$

π_{cij}^J: $Compliance\ score\ of\ candidate\ i\ for\ criterion\ c\ according\ to\ job\ j$

Finally, x_{ij} is the decision variable where:

$$x_{ij} = \begin{cases} 1, if\ candidate\ i\ is\ paired\ with\ job\ j \\ 0, otherwise \end{cases}$$

Various objective functions can be considered:

a. Maximizing individual satisfaction: Best matching for a given candidate and a job that does not consider the stability or the well-being of the entire market.
b. Obtaining the most stable matching: In this case, the objective is to construct such matching that rather than focusing on individual matchings, the entire two-sided matching problem will be served at the highest level; however, individuals may have less satisfaction. For instance, an individual who may have better compensation at a certain job may be matched with another position due to his/her qualifications and other candidates' qualifications.

The objective function formulated below in Eq. (1) maximizes the total benefit to the entire job market (maximizes the overall satisfaction of both candidates and jobs). Accordingly, the following mathematical model can be formulated with an objective to determine optimal matching where constraints Eq. (2) and Eq. (3) ensure that each candidate is matched with at most one job and each job is filled by at most one candidate, consecutively.

$$\max z = \sum_{i\in S}\sum_{j\in J} x_{ij}\left(\sum_{c\in C} w_{ci}^{S}\pi_{cij}^{S} + w_{cj}^{J}\pi_{cij}^{J}\right) \quad (1)$$

subject to

$$\sum_{j\in J} x_{ij} \leq 1, \ \forall i \in S \quad (2)$$

$$\sum_{i\in S} x_{ij} \leq 1, \forall j \in J \quad (3)$$

$$x_{ij} \in \{0,1\}, \ \forall i \in S, \ \forall j \in J \quad (4)$$

For the proposed mathematical model to achieve its objectives, the following conditions must be satisfied:

1. Stable Market: The model must generate a set of matchings such that no alternative solution improves outcomes for all agents in the market.

2. Optimality: The primal and dual formulations of the model must achieve the same optimal solution with integer values.

Lemma 1. Proof that the Mathematical Model Defined by Eq. (1–3) Produces a Stable Matching:

Vande Vate (Vande Vate, 1989) demonstrated that the stable marriage problem can be formulated as a linear programming (LP) problem. Our mathematical model is a generalized version of Vande Vate's formulation. Their proof establishes that the extreme points of the LP solution space correspond to integer solutions, thus bridging stable matchings and LP formulations. This makes LP a robust tool for solving stable matching problems.

Moreover, Vande Vate proved that the results of the deferred acceptance algorithm align with the outcomes of the LP formulation. The stability and integer property of the extreme points are foundational to any LP-based stable matching framework, including ours.

By leveraging Vande Vate's theorem, we ensure that our LP-based model produces stable, integer-valued solutions. Fractional solutions are inherently invalid in two-sided matching problems, underscoring the importance of integer extreme points for stability.

Lemma 2. Proof that the Primal and Dual Models Yield the Same Optimal Integer Solutions

Roth, Rothblum, and Vande Vate, in *Stable Matchings, Optimal Assignments, and Linear Programming*, explored the duality properties of the LP formulation for stable matchings (Roth et al., 1993). They rigorously demonstrated that the stability constraints inherent in the assignment problem guarantee that optimal solutions to the dual problem are also optimal for the primal.

Their work further validated that the extreme points of the LP formulation correspond to integer solutions, ensuring these solutions represent stable matchings in the problem's context. The duality theorem and complementary slackness, as established in their research, are pivotal to the correctness of our model. These theorems confirm that the stability constraints in our formulation preserve alignment between the primal and dual solutions.

Our linear programming formulation adopts the same LP constraints as those presented in Vande Vate (Vande Vate, 1989) and Roth, Rothblum, and Vande Vate (Roth et al., 1993). Consequently,

all proofs developed in these works regarding stability and optimality constraints using the duality theorem and complementary slackness theorem applying to our model. However, our contribution lies in extending the objective function to optimize the collective well-being of the market. This modification remains consistent with the foundational framework, as the stability and feasibility constraints derived from the theorems continue to hold. By building based on these established theorems, we avoid the need to reprove fundamental properties like stability and optimality. Instead, our work focuses on applying these principles to broader objectives, bridging the gap between classical stability-focused models and contemporary needs for market-wide optimization. This ensures that our methodology is both theoretically sound and practically implementable.

3.2.3. Dynamic Two-Sided Matching Problem: Perishable Capacity Approach

Perishable capacity management is a field that specializes in managing the use of time-sensitive resources. The value of perishable resources diminishes if not utilized within a specific time frame. This concept is applied in sales of airline tickets, hotel rooms, car rentals, production slots and some retail products. These commodities expire if not used or sold at the right time. The available resources cannot be stored, renewed or saved for later use or sale. Therefore, these resources are time sensitive. Businesses use dynamic pricing strategies benefiting from the time sensitivity of the resources. For example, a flight might be the last one of the days for a specific destination. There could be only one last seat left. If the customer wants to go on this date, they may be willing to pay extra on a last-minute ticket. As the time for the flight approaches, the tickets gain value. But right after the flight time, it will be worth zero. Therefore, businesses have the challenge of balancing the capacity and demand to ensure they maximize revenue by using pricing strategies. The goal is to sell all available capacity before the deadline while maximizing the price. The field of yield management arises at this point. Yield management specializes in adjusting prices in real-time to manage demand and capacity effectively. The industries like airlines, hospitality, tourism, events, and manufacturing commonly use yield management principles.

One of the most studied problems in revenue management is the airline seat inventory control problem. The airline inventory control problem addresses the allocation of seats on a flight into

different fare classes to maximize airline revenues. The effective control is concerned with the number of seats available to lower-fare passengers and the number of seats to keep available for higher fare passengers who could demand the seats later than those who want to travel for lower prices. As soon as the flight takes off, the tickets for the seats do not have any more monetary value. Therefore, the seats in a flight are a perishable resource, and the airline inventory control problem is a subfield of the perishable capacity management field. By nature, the airline inventory control problem strongly resembles the problems we want to work on. Focusing on the perishability of the resource on hand, blending matching theory and revenue management principles can be a powerful approach which has never been addressed in two-sided matching literature. The concepts of perishable inventory control and capacity reservation provides a framework for some two-sided matching problems. Agents have time-sensitive value as their availability or utility will expire or diminish. In other words, matching capacity is finite and perishable. Therefore, reserving capacity for high-value or late-arriving agents can increase overall system utility — just as airlines hold back tickets for premium-paying customers. This approach has many benefits such as getting higher total match utility by avoiding early assignments, providing better matches through deferral, and capturing realistic decision tension. The challenges of this approach are computational complexity and the need for good forecasts.

Highly qualified personnel capacity management and infrastructure resource management problems are based on a limited number of perishable assets. Therefore, perishable capacity management methods developed to address the airline inventory control problem can be utilized to provide effective and efficient solutions to these kinds of two-sided matching problems. In this chapter, we discuss the similarities and differences of these problems to provide us with a ground for applying solutions methods from this field in problems of other fields.

The airline inventory management problem has been addressed by many researchers utilizing several methods, including optimization, forecasting, and decision-making algorithms. This problem has been covered in yield management research that focuses on maximizing the revenue from perishable resources. The perishable resource can be airline seats, hotel room reservations, or car rentals. Considering the marginal revenue of a seat before deciding to sell it is a significant contribution as this approach can capture the dynamic nature of the problem. In the same way, the time of a physician in an emergency room, the utilization time of an asset in an infrastructural

project, and the time of an engineer in a service company can be optimized by being considered a perishable resource. The decision-making method easily adapts to the dynamic nature of these problems. The workforce management of engineers is a problem with such a dynamic nature. The number of tasks and available employees to be matched changes dynamically. Similarly, the potential demand and the available seats change dynamically in the airline inventory management. At any time, a new task may become prioritized, or an engineer may go unavailable or vice versa. To make sure each task is addressed based on its priority; the decision-making method should capture the dynamic nature of the problem. Just as a seat is as valued as the chances of prospective customers, an engineer's time is as valuable as the chances of a possible future task. As another example, just as there are no shows in airlines, there are cancellations of tasks in engineering projects. These similarities in the two problems give us a basis to develop a similar marginal profit approach or perishable asset-based approach to address the engineering workforce management problem.

The common practice of airline companies is pricing tickets for identical seats of a flight at different prices. The difference in such tickets is in the fare classes. By creating different fare classes and placing booking limits on each fare class, airline companies generate incremental revenue with no increase in operating costs. Coming up with the best booking limits is part of the airline seat inventory control problem. Most researchers develop protection levels for each fare class to calculate booking limits. The booking limit of a fare class is equal to the capacity of the flight, minus the sum of protection levels of all higher fare classes. Thus, calculating protection levels helps to calculate booking limits easily. To address this part, several researchers proposed many different approaches and methods. The rest of this section is dedicated to focusing on those approaches.

The first solution approach for seat inventory control was proposed by Littlewood (Littlewood, 1972). The method known as Littlewood's Rule finds the protection level for the high fare class in a flight with two fare classes to maximize the revenue. The protection level is the number of seats to save for higher fare classes and make unavailable for sale to the lower fare classes. Without the protection of seats, seats could be sold to low fare classes, and the marginal seat revenue would be lost. This model incorporates the probabilistic nature of the problem but is not realistic as there are more than two fare classes in most of the airlines.

The most popular airline seat inventory control method was introduced by Belobaba (Belobaba, 1989). The Expected Marginal Seat Revenue (EMSR) model has been widely adopted ever since (See Equation 1 in Appendix G). The proposed heuristic is a probabilistic decision model to address the airline seat inventory control problem. The main goal is to calculate the protection levels, defined as the number of seats protected from the low fare class and made available exclusively to the high fare class. By using protection levels, the possible high-fared class demand is aimed to be addressed at any time (See Equation 2 in Appendix G). Lee and Hersh have extended Belobaba's EMSR heuristics into the Expected Marginal Seat Value (EMSV) heuristics (Lee & Hersh, 1993), which can work with multiple seat bookings (See Equation 3 in Appendix G). In this model, group bookings in the same fare class are allowed, which is more related to the real-life case of airline bookings.

Determining protection levels and booking limits is a class-based control method in airline seat inventory management. Another type of control method is revenue-based control, where researchers calculate bid prices. A bid price is the minimum acceptable fare for the next seat in inventory. So, one can accept the request for ticket sales if the requested price is higher than the bid price of the seat. Brumelle and McGill have extended Belobaba's EMSR in a method by proposing an approach to optimally solve the airline seat inventory problem with discrete and continuous demand (Brumelle & McGill, 1993). They provide optimal protection levels for multiple nested fare classes scenarios. This research has provided a precise method to follow the performance of past decisions without going in too deep to model demand distributions or forecasts by using optimality conditions.

There are also some heuristic approaches for airline seat inventory management in literature. Ryzin and McGill have introduced a simple adaptive approach with nested fare classes to solve the airline seat inventory management problem (Van Ryzin & McGill, 2000). The method does not require forecasting as traditional simulation methods or optimization. The adaptive algorithm still makes sure of optimality. Even though the algorithm does not always provide better performance than previously introduced simulation for optimization approaches, it is promising for some specified cases and open to being developed furthermore in future research. The contribution of Belobaba's work is to provide protection levels and booking limits for fare classes according to expected demand and the remaining number of seats. Using seat protection limits for the high fare class is

a strategy that ensures the availability of seats to the high fare class whenever there is a chance of demand for a high fare ticket. This approach makes sure of the maximization of revenue. Our contribution to the literature is applying the same perishable asset management approach to two-sided matching problems by taking advantage of the similarities between these problems.

Airline revenue management methods are developed based on the perishability of the resource. Perishability indicates the loss of value over time. Considering the value of seats crushes down to zero as soon as the flight takes off, the goal is to maximize the seat revenue until then. In the moment seats go on sale, tickets start being purchased. The more tickets purchased, the fewer seats available for potential buyers. Therefore, the scarcity of seats allows dynamic pricing where the price varies over time. The first half of the seats sold are of less value than the rest of the seats. As the flight tickets will not be available after flight time, the value of the left seat increases. Just like the rest of the seats gain value over time, the remaining capacity of an engineer is more valued than the already allocated capacity. Any unutilized capacity of engineers is called capacity perished. Any unscheduled capacity is perishable.

In project-based workplaces, the number of current projects and tasks is rapidly changing. Meanwhile, the availability of multi-skilled engineers is changing with the completion of projects or tasks. The heuristics developed to address the airline inventory control problem can catch the dynamism of the airline industry. Keeping this in mind, adopting those heuristics to find better solution methods for workforce management in engineering is a promising opportunity. Moreover, perishable asset revenue management methods are also helpful in managing resources in companies with high-priority customers. As the engineer's work hours are not fully scheduled until the last minute, this gives us the agility to supply last-minute demand from a high-priority customer. Being able to respond to customers in such a quick manner might be not only beneficial financially for the companies and organizations but also beneficial in terms of building trust and gaining referrals. Therefore, for the dynamic two-sided matching problems we use a perishable-capacity management-based optimization approach to find stable and optimal matching.

3.2.4. Optimized Dynamic Two-Sided Matching

In this chapter, we adapt the perishable capacity management methodology to solve the dynamic two-sided matching problem. Our approach develops a dynamic two-sided matching model with reservation logic, being inspired by the EMSV heuristic which has been developed and widely used for airline seat revenue management problems.

Let's consider engineer-task matching problem as the two-sided matching problem on focus. Engineers and tasks arrive over time therefore we do not have complete information at the time of decision making, we expect more engineers and tasks to arrive in future time. This gives the problem its dynamism. Both engineers and tasks have perishability, meaning after certain time they may expire or lose value. We want to reserve some engineers for higher-value or late-arriving tasks instead of assigning them immediately. Some engineers have unique skills that may be worth reserving for future tasks. The model chooses whether to match an engineer now or hold them for a better task later.

Let the planning period be divided into T discrete time steps as in $T = 1, 2, \dots t$. Let S represent the set of engineers and J represent the set of tasks. At each time t, S_t represents engineers available at time t and J_t represents tasks available at time t. The binary decision variable x_{ijt} represents the assigned tasks. The second binary decision variable r_{it}^S represents reserved engineer time where the third binary decision variable r_{jt}^J represents reserved task time.

$$x_{ijt} = \begin{cases} 1, if\ engineer\ i\ is\ matched\ with\ task\ j\ at\ time\ t \\ 0, otherwise \end{cases}$$

$$r_{it}^S = \begin{cases} 1, if\ engineer\ i\ is\ reserved\ at\ time\ t \\ 0, otherwise \end{cases}$$

$$r_{jt}^J = \begin{cases} 1, if\ task\ j\ is\ reserved\ at\ time\ t \\ 0, otherwise \end{cases}$$

Similar to the static model context, engineers have qualifications C^Q and expectations C^E related to the task, while each task has specific requirements C^R for engineers. The total set of criteria

associated with system C is composed of these three subsets: $C = \{C^Q, C^E, C^R\}$. The weight of importance for each criterion is determined as follows for the dynamic model:

w_{ci}^S: $Importance\ of\ criterion\ c\ for\ the\ engineer\ i$

w_{cj}^J: $Importance\ of\ criterion\ c\ for\ the\ task\ j$

For each criterion, there is an associated compliance score for both tasks and engineers in the dynamic model as indicated below and can be found by AHP:

π_{cij}^S: $Compliance\ score\ of\ task\ j\ for\ criterion\ c\ according\ to\ engineer\ i$

π_{cij}^J: $Compliance\ score\ of\ engineer\ i\ for\ criterion\ c\ according\ to\ task\ j$

The deterministic mathematical model provided will make sure that an engineer's capacity is reserved if the expected future match value is higher than the max utility gained in assigning the engineer now. The model makes sure a task is reserved for the future only if the expected future match value if higher than the value earned by assigning it now. The objective function formulated below in Eq. (5) maximizes the overall satisfaction of both engineers and tasks. Accordingly, the following mathematical model can be formulated where constraint Eq. (6) ensures that each engineer is either matched with a job j at time t or engineer's capacity is reserved for a future possible task. Constraint Eq. (7) ensures that each task is either matched with an engineer or is reserved for the future. In the overall time horizon, one engineer can be assigned only once as ensured by Eq. (8) and one task can be assigned only once as ensured by Eq. (9).

$$\max z = \sum_{t\in T}\sum_{i\in S_t}\sum_{j\in J_t} x_{ijt}\left(\sum_{c\in C} w_{ci}^S \pi_{cij}^S + w_{cj}^J \pi_{cij}^J\right) + \sum_{t\in T}\sum_{i\in S_t} r_{it}^S\, p_{it}^S + \sum_{t\in T}\sum_{j\in J_t} r_{jt}^J\, p_{jt}^J \quad (5)$$

subject to

$$\sum_{j\in J_t} x_{ijt} + r_{it}^S \le 1,\ \forall i \in S_t, \forall t \quad (6)$$

$$\sum_{i\in S_t} x_{ijt} + r_{jt}^J \le 1,\ \forall j \in J_t, \forall t \quad (7)$$

$$\sum_{t=1}^{T} \sum_{i \in S_t} x_{ijt} \leq 1, \ \forall j \quad (8)$$

$$\sum_{t=1}^{T} \sum_{j \in J_t} x_{ijt} \leq 1, \ \forall i \quad (9)$$

$$\sum_{i \in S_t} r_{it}^{S} \ \leq \ R_t^{S}, \ \forall t \quad (10)$$

$$\sum_{j \in J_t} r_{jt}^{J} \ \leq \ R_t^{J}, \ \forall t \quad (11)$$

$$x_{ijt} \in \{0, 1\}, \forall i, j, t \quad (12)$$

$$r_{it}^{S} \ \in \{0, 1\}, \forall i, t \quad (13)$$

$$r_{jt}^{J} \in \{0, 1\}, \forall j, t \quad (14)$$

In the objective function (5), there are two additional parts that account for expected future reward for reserving the capacity to future tasks. These values are estimated based on historical matching and preference forecasting. This structure encourages the model to reserve an agent only when the expected reward for waiting outweighs the best available match now. While calculating the value of these coefficients, we must be mindful of the scale of the coefficients. We must ensure that p_{it}^{S} and p_{jt}^{J} are compatible in magnitude to the match utility scores $\sum_{c \in C} w_{ci}^{S} \pi_{cij}^{S} + w_{cj}^{J} \pi_{cij}^{J}$ to ensure no overweight reservation or not making it negligible. Also, one must observe that these values are expectations of future outcomes, therefore making our model a deterministic reformulation of a stochastic problem. A full stochastic formulation would require enumerating all possible future matching scenarios and scenario trees or distributions over future values, agent sets, etc., which is computationally intractable for real-sized problems. So, we use a deterministic approximation that incorporates the expected values instead of modeling the full probability distribution or decision tree. This is a pragmatic and widely used approach (also called sample average approximation or certainty-equivalent approximation in operations research).

p_{it}^{S}: $Expected\ future\ reward\ for\ reserving\ engineer\ i\ at\ time\ t$

p_{jt}^{J}: $Expected\ future\ reward\ for\ reserving\ task\ j\ at\ time\ t$

Constraints Eq. (10) and Eq. (11) ensure that the limits of the reserved time are not exceeded. These constraints encourage the model to assign a minimum number of tasks and engineers in each time period by utilizing the following reserved capacity parameters. This prevents the system from undermatching tasks, ensuring that matching is used strategically. This constraint supports strategic capacity management by preventing over-reservation and encouraging timely engagement of available talent.

$$R_t^S: Maximium\ number\ of\ engineers\ that\ can\ be\ reserved\ at\ time\ t$$

$$R_t^J: Maximium\ number\ of\ tasks\ that\ can\ be\ reserved\ at\ time\ t$$

Additionally, a perishability constraint can be added to ensure any capacity or task known to perish at a specific time is reflected in the model. In this constraint, we have a new parameter τ which represents a time-based availability limit, also called a perishability threshold. It defines the latest time at which an engineer or a task can still be considered for matching or reserving.

$$\tau_i: Expiration\ time\ for\ engineer\ i$$

$$\tau_j: Expiration\ time\ for\ task\ j$$

The perishability constraint can be added as follows for specific time periods to ensure engineers and tasks can only be matched or reserved only before the expiry:

$$x_{ijt} = 0, \quad r_{it}^S = 0\ if\ t > \tau_i\ , \quad r_{jt}^J = 0\ if\ t > \tau_j$$

The perishability constraint helps us reflect the real-world temporal constraints within dynamic two-sided matching problems. The added parameter defines the last period in which a task remains available for matching, after which it is considered expired and can no longer be matched or reserved. This is useful in environments where high-priority or time-sensitive tasks arrive at the last-minute and mut be matched quickly to avoid being forfeited. By assigning different expiry dates to tasks based on urgency or maybe service-level agreements, the model prevents allocation of expired entities.

4. The Unbiased Criteria Identification Method Applied

In this chapter, the proposed methodology is applied in two case studies: a static two-sided matching problem and a dynamic two-sided matching problem.

4.1. Case 1: Application in a Static Case

4.1.1. Two-sided Matching in the Labour Market

Job-candidate matching is an example of the two-sided matching problem. Candidates have preferences over the jobs based on some criteria, and employers have preferences over the candidates based on some other criteria. Having two sets in need of a match, the primary objective is finding a stable match, i.e. the match that will last long. Mercer Turnover Survey reveals that the average turnover rate is 21% for Canadian companies and 22% for US companies for total separations in 2019 (US Mercer Turnover Survey, 2025). Considering over 10% is alarming, companies and organizations are constantly looking to improve their recruitment, acquisition and retention strategies. After all, job mismatch is costly to individuals, firms and society as it negatively impacts income, productivity, innovation and growth (Brunello & Wruuck, 2021). Therefore, addressing the job-candidate two-sided matching problem is a crucial and hot topic for many stakeholders. One of our objectives in our research is minimizing the mismatch costs.

Another objective of unbiased criteria in labor market matching is fairness. In the context of labour market matching, unbiased criteria would mean that the selection process does not unfairly benefit either the jobs or the candidates. Fairness ensures trust in the organization. Efficient matching in labour markets boosts productivity of the current workforce, leads to increased job satisfaction, and reduces unemployment. Employees with a well-suited position are more engaged, motivated and also committed to their work. This improves productivity and lowers turnover rates in the long run. Employee turnover rate is a crucial metric for companies and organizations. Expressed as a percentage, this metric measures the rate at which employees leave an organization. It is used as an indicator of workforce stability and retention. An organization with a significant number of employees leaving has a high turnover rate. These organizations have increased recruitment costs, reduced productivity and potential disruption to operations.

When we look at the turnover rate in Canada, organizations reported that 17% of their separations were from employees within their first six months of employment, and 26% were from employees within their first year (Canada Mercer Turnover Survey, 2025). In the US, the average amount of money spent making a hire is estimated to be $4,425, whereas the average for executive positions adds up to 15K (US Mercer Turnover Survey, 2025). Considering the number of hires per year can climb up to more than a hundred, recruitment costs quickly make up 15% of all human resources budget (Talent Acquisition Benchmarking Report, 2017). Therefore, good management of recruitment activities and decreasing employee turnover rates are essential for each company or organization to minimize recruitment expenses.

Recruitment activities take place in the labour market. Any medium designed to exchange goods, services, and money is called a market. In the same way, the labour market or the job market is defined as a place of exchange for employment and labour. A labour market is where recruiters meet job seekers to fill open positions. The nature of the labour market is dynamic. Therefore, new job seekers or new job openings show up in the system at any time. On the other hand, both parts of the labour market want stability. A candidate would like to find a position with job safety, whereas a recruiter would like to find the best candidate for the job opening. The need to design a labour market to achieve effectiveness and efficiency rises at this point. The labour market mechanism is efficient if it can find stable matchings of job seekers and job openings. It is also effective if stable matchings in this dynamic environment are found with minimum cost and time.

Labour market design focuses on defining requirements and expectations of labour and jobs and how the design affects the functioning and outcomes of the market. Keeping this in mind, let us model the labour market as a two-sided matching market once more as follows. There are two distinct sets of job seekers and job positions. Each job seeker has a list of preferences for job positions. Moreover, there is a preference list of job seekers for each job position. To create the preference lists, we can use pre-defined requirements for each job position and pre-defined expectations for each job applicant. Therefore, pre-defining or discovering the requirements and expectations is vital in generating good results. Considering that the decision-makers on both sides of the job market are human, making good decisions based on human factors becomes a challenge. Thus, capturing the human decision-making process is significant to ensure the efficiency and effectiveness of markets.

The mechanisms lying within should be designed carefully to obtain a labour market with effectiveness and efficiency. The markets can be classified based on the coordination type in the market: free, open, or controlled. Each type of market differs in regulations and restrictions. Thus, designing the market is closely associated with designing the regulations and restrictions that affect market mechanisms.

Aiming for productivity, organizations are often concerned with having a suited workforce. Simultaneously, employees have increasing concerns about their well-being and job satisfaction. On one side, companies try to avoid vacancies, and on the other, candidates try to avoid unemployment. These unsatisfactory scenarios are caused by mismatches, which cost organizations a lot every year. We aim to minimize all kinds of costs associated with the mismatch in two-sided matching markets by improving the quality of matches, starting from the first step of the matching process.

Considering the labour market as the exchange of labour, it can be modelled as a two-sided matching problem. On one side, job positions are introduced into the market by recruiters. On the other hand, labour is introduced by job seekers. Each job position is available until a job seeker is matched with it, and each job seeker is in the market until a job is matched with them. Consider two distinct sets: job seekers and job positions. Each job seeker has a list of preferences for job positions. Furthermore, there is a preference list of job seekers for each job position. To create the preference lists, we can use pre-defined requirements for each job position and pre-defined expectations for each job taker.

In the labour market design, the purpose is to find stable matches. Then, algorithms such as the deferred-acceptance algorithm can find stable matches in the labour market. Each job seeker is matched with the best available job position. If no job seeker prefers to be matched to another job position other than their current match, the match is stable. Moreover, the stability of matches ensures stability in the market. This part of the thesis proposal contributes to the literature on the two-sided matching problem by introducing an unbiased method to capture the evaluation criteria.

The preferences of both sides of the market must be discovered truthfully and explicitly to provide stable matches. This work uses two tools called Environment-Based Life Cycle Analysis (eLCA) and Recursive Object Model (ROM), and a methodology called Environment-Based Design

(EBD) to design an inclusive, holistic and unbiased system to discover true preferences of both sides in two-sided matching markets. The preferences of job candidates and job recruiters are revealed in three steps: modelling the design problem, collecting life cycle information, and modelling life cycle dependency.

We use the EBD methodology to reveal the agents' preferences in the labour market. We utilize the eLCA method to discover the product environment, the ROM method to collect product requirements and the EBD methodology to generate solutions where the product is the requirements and expectations of the two sides. Once we reveal the requirements and expectations, we can create the preference lists, which are the inputs of the matching algorithms.

Modelling linguistic information provides better integration of intuition into mathematical models. As intuition is the most challenging part to model in human processes and is often overlooked, using ROM to create the components of the decision-making approach will address future client projects more efficiently and effectively. Furthermore, the EBD approach has been previously successfully applied in market design (Xu et al., 2015). We show that the methodology provides us with unbiased identification of decision-making criteria, and this method is our main contribution to literature.

Another potential contribution is that EBD can define parameters in multi-objective optimization problems. Multi-objective optimization is a subfield of MCDM concerned with mathematical optimization problems with more than one conflicting objective to be optimized simultaneously. Optimization methods also address the TSMDM problems. For example, Li et al. have developed a multi-objective two-sided matching optimization model for task-matching problems (Li et al., 2019). Optimizers primarily focus on defining decision variables, objective functions and constraints in mathematical optimization models. In parallel, we need to analyze the parameters of the problems explicitly to ensure the mathematical model represents the real-life scenario in the best way possible. Therefore, the unbiased criteria identification methodology developed can also be adapted to generate the input of mathematical optimization problems. Discovering a comprehensive list of parameters of optimization problems is a beneficial contribution to literature.

4.1.2. Job-Candidate Matching Problem

If the workforce has the right knowledge, skills, and experience, they can perform their jobs more efficiently. This fit contributes to the organization's overall success significantly. Aligning candidates' expectations with position requirements results in long-term employee retention. This reduces turnover and hiring costs. Therefore, good decision-making in recruitment has great importance in enhancing productivity and job satisfaction while decreasing recruitment costs. The problem in focus is job market two-sided matching. This involved pairing potential workers with potential employers in an optimal way that satisfies worker preferences and job requirements. Each side has specific criteria over the others. The criteria of candidates can be salary, location, and job title while the criteria of employers can be experience, specific skills, and specific education.

The identification of criteria is of great importance as it is the foundation of achieving successful and efficient matches between the two parties involved. Clear criteria identification helps minimize friction and inefficiencies in the matching process, ensuring fairness and equity. When both sides have a clear understanding of their preferences and requirements, the matching algorithm can produce outcomes that lead to more optimal and fulfilling matches. The challenge lies in finding a mechanism that efficiently and unbiasedly discovers all decision-making criteria of both sides, leading to matches of job seekers with suitable job opportunities. Researchers and practitioners continue to explore innovative approaches to optimize this process, ultimately contributing to a more effective and prosperous job market for all stakeholders involved.

In this section, we present our unbiased criteria identification methodology for the job-candidate matching problem. Our objective is to discover the evaluation criteria through an unbiased method. With two sets needing a match, our primary goal is to find a stable match that endures over time. The criteria discovered through our methodology will then be used as input in the matching algorithms to generate a stable matching as the output. We use the unbiased criteria generated in an assignment optimization model to obtain stable and optimal matches in static matching.

4.1.3. Unbiased Criteria Identification in Job-Candidate Matching

In this section, we show how our unbiased criteria identification methodology applies to the job-matching problem. We follow the eight-step method proposed in Chapter 3. Additional tables can be found in the Appendix. The methodology is taken from the published work of Tozlu et al., 2025.

I. Define a design statement

The design statement is chosen as: "Obtain stable matching in the labour market". There are no other specific constraints to be mentioned at this step.

II.Construct an initial ROM diagram

The initial ROM diagram has a 'constraint' type of relationship between the objects 'labour' and 'market'; 'stable' and 'matching'; 'in' and 'matching'. There is a 'predicate verb-object' type of relationship between the objects 'obtain' and 'matching'. There is a 'predicate preposition-object' type of relationship between the objects 'in' and 'market' as in Figure 4.

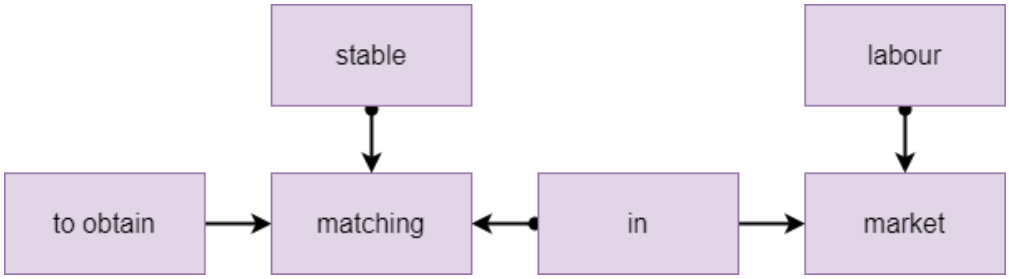


Figure 4: The initial ROM diagram

III.Define an object list for generating questions

We examine the initial ROM diagram to reveal the number of relationships each object has. As shown in Figure 4, the object with the greatest number of connections is 'matching' therefore this object is the central object. According to the two rules of defining an object list as in Table 3, we

must ask questions about the environment components first before asking questions about the central object. Before questioning 'matching', the constraining and predicating objects should be questioned. Therefore, we should ask questions to 'obtain', 'stable' and 'market' first. To question 'market', 'labour' should be questioned first. As 'stable' is an adjective, it will be used in the questions of the noun constrained by it. Thus, we obtain the following list: labour, market, obtain, and matching. This list will be used to generate the right questions in the next step.

IV.Generate the right questions

Following the guideline for generating the right questions, the following questions are generated for the design statement of 'Obtain a stable matching in the labour market.' These are the first set of questions asked to investigate the product environment. Following the guideline for generating the right questions given in Table 5, we obtained Table 10. In Table 10, the first column shows the objects, the second column shows what the guideline gives us, and the third column shows the generated questions. The outcome of this step is the generated questions.

Table 10: The right questions generated

Object	**Guideline**	**Question Generated**
labour	What is [$Noun$]?	What is labour?
market	What is [$Noun$]? What is [$Adjective$] [$Noun$]?	What is a market? What is a labour market?

obtain	Who $[Verb]$ $[Object]$? Why $[Verb]$ $[Object]$? How $[Verb]$ $[Object]$? What do you mean by $[Subject]$ $[Verb]$ $[Object]$?	Who obtains a stable matching in a labour market? Why obtain a stable matching in a labour market? How to obtain a stable matching in a labour market? What do you mean by obtaining a stable matching in a labour market?
matching	What is $[Adjective]$ $[Noun]$?	What is stable matching? What is a stable matching in a labour market? What is the purpose of a stable matching in a labour market? What is the lifecycle of a stable matching in a labour market?

V.Generate the right answers

Following the question-answering guidelines provided in Table 6 and Table 7, we enlist the amount of information that should be included in the answers to the right questions generated in Step IV. The right answers to these right questions should include the information in Table 11.

Table 11: The answers-generating guideline following our design problem

Object	**Guideline**

labour	The answer should define ‘labour’ according to the life cycle of the product and its relationship with the product or product environment.
market	The answer should define ‘market’ according to the life cycle of the product and its relationship with the product or product environment.
obtain	For ‘designers obtain stable matching’, the answer should define the components and attributes of ‘designers’ in the context of ‘obtaining stable matching’.
matching	The answer should define ‘stable matching’ according to the life cycle of the product. Add the purpose of ‘stable matching’. Add the lifecycle of ‘stable matching’. Add the categorization of environment components for each event in the life cycle, following the four dimensions of environment structure.

After observing what types of information should be collected about each object, we find definitions using common information resources such as dictionaries, published resources, and online search tools. To collect product environment information, we conduct environment analysis with EBD to discover the design environment in depth. To collect life cycle information, we conduct eLCA. Only after using these two tools, do we have enough information to generate the right answers to the questions generated according to EBD.

The EBD methodology explores the environment of the designed product by categorizing it into four categories: human or stakeholder, natural, physical artifact, and digital artifact. In Table 12, we provide the components classified in these four categories for matches in the labour market.

Table 12: The EBD analysis results for job matching problem

Physical Artifact Environment	**Natural Environment**	**Digital Artifact Environment**	**Stakeholder Environment**

Companies and organizations	Type: full-time / part-time / contract	Wage, commission, benefits, working conditions, social security	Direct stakeholders: recruiters, candidates, workers, employers, managers
Workplace conditions and workspace	Dates, Location, Weather	Technical / security / health laws and regulations, occupational safety and insurance policies, social laws, rules and norms	Indirect stakeholders: coworkers, customers, suppliers, business partners, general public
Recruitment and job search infrastructure	Space: indoors / outdoors, safety measures	Career websites, job boards; job positions, responsibilities, functions, requirements	Experience, mastered knowledge, mastered skills, education, training, qualifications
Labour and Employment Infrastructure	Travel requirements, accessibility	CV, resume, portfolio, cover letter, contracts, confidentiality agreements	Characteristics, goals, tastes, motivation
		Organization's culture, values, vision, mission; business goals, plan, size, industry	Preferences, interests, emotions

According to Table 11, the life cycle of the product, the 'stable matching', should be discovered before generating the right answers. We utilize the eLCA tool to obtain life cycle information on the product to be designed and we provide the results in Table 13.

Table 13: The eLCA results for the product being designed

Object	**Life Cycle Components For Organizations**	**Life Cycle Components For Candidates/Workers**
matching	• vacancy & job posting • interview & selection • offer & hiring • recruitment & onboarding • performance management • separation	• availability & job search • job application & interview • offer & employment • performance management • separation & retirement

Following the guideline results for generating the right answers in Table 11, the EBD analysis results summarized in Table 12, and the eLCA results shown in Table 13, we can generate the right answers. In Table 14, we show the answers to the first question as a sample. Answers generated for all questions can be found in Appendix A. These are the answers to lead us to reveal the dynamics of the product environment.

Table 14: The right answers generated to the first question

	Question	**Answer**
Q1	What is labour?	Labour is the physical, mental, and social effort exerted by individuals in the process of producing goods and services. Labour is considered one of the factors of production, alongside land and capital. Labour refers to human input or work that contributes to the production of goods and services. In exchange for their labour, individuals typically receive compensation, which can come in various forms such as wages, salaries, bonuses, or other benefits.

VI.Update the ROM diagram

At this step, we extended the initial ROM diagram that was built in Step II based on the answers obtained in Step V. One thing that can be done is to simplify the right answers generated. This operation gives us the opportunity to transfer the information into the simple $[Subject]$ $[Verb]$ $[Object]$ $[Constraint]$ [format to easily construct our ROM diagram. We provide the ROM diagram extended with the answer to the first question in Figure 5. We continue building up our ROM diagram with the answers provided in Appendix A and simplified in Appendix B. The partial ROM diagrams generated from the answers are provided in Appendix C.

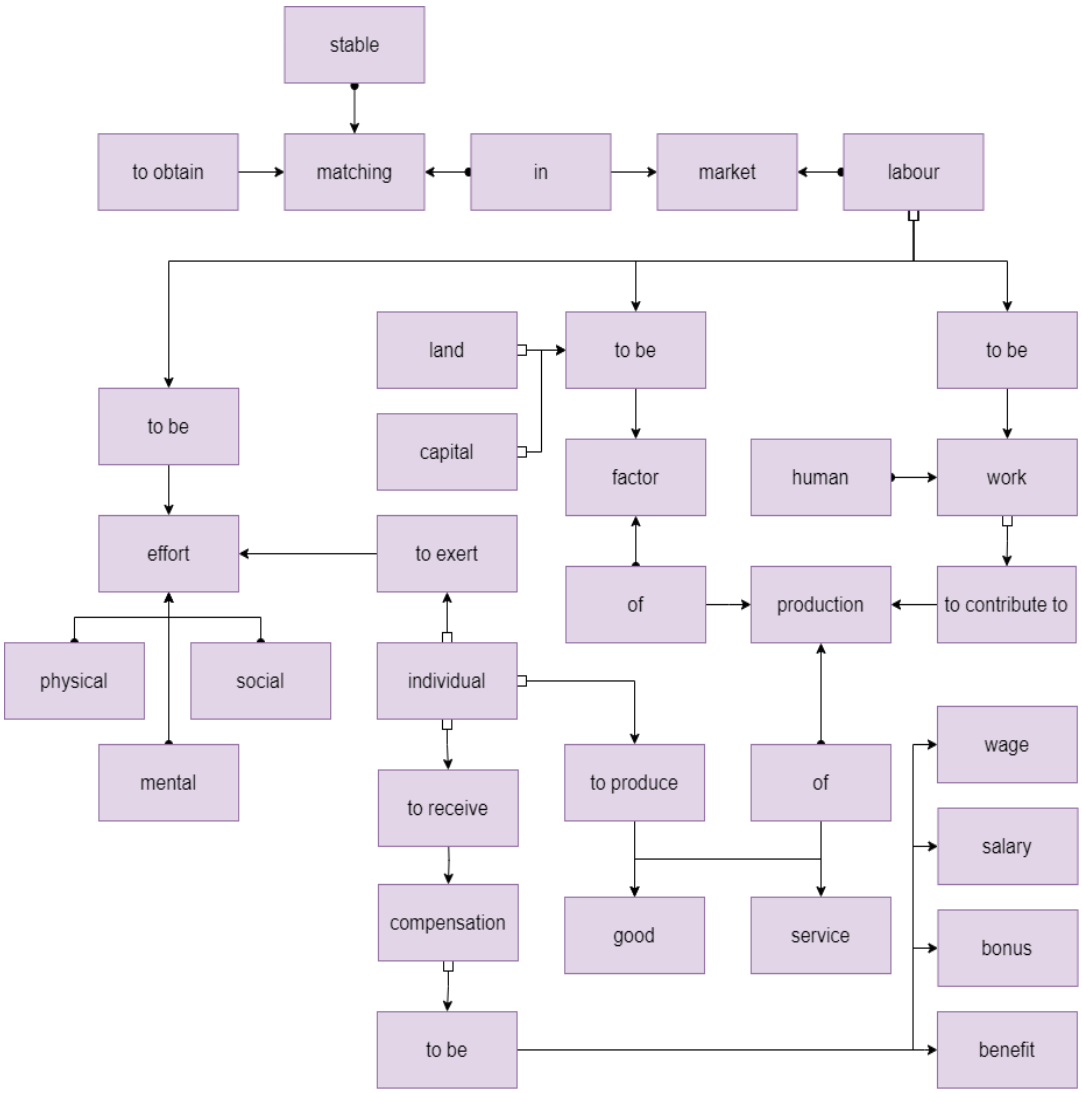


Figure 5: Partial ROM diagram extended by the answer to Question 1

VII.Repeat or stop

At this step, we decide whether to stop or not. Considering the recursive nature of design, new answers may bring new questions. An extended ROM diagram may have some unquestioned objects to reveal more about the product environment. Observing our final ROM diagram which consists of Figure A1, Figure A2, Figure A3, Figure A4, and Figure A5; we decide to stop.

VIII.Extract criteria

In the last step, we extract criteria after analysis of design variables and state variables. We define the design variables first, and then the state variables. We focus on the objective of our design problem using the final ROM diagram as the input. As discovered among the answers to the questions, the purpose of stable matching is to find mutually satisfactory pairs. Our design variables are candidates and organizations. One member from each one of these two distinct sets matches and meets under the concept of a job. The variables that define our design variables are state variables. We can extract a set of state variables from the final ROM diagram as shown in Table 15. Then we look for relationships between variables. Defining the relationships between the design and state variables, and state and state variables brings us the criteria of a matching.

Table 15: The state variables divided by design variables

	Design Variable: Individual	**Design Variable: Organization**
Input of individual	goals, tastes, motivation, preferences, interests, emotions, experience, mastered knowledge, mastered skills, education, training, qualifications, work history, availability	special qualifications, desired characteristics, requisite experience, degrees required, desired education, desired certifications, desired training, desired languages, desired experience
Input of	wages, salaries, bonuses,	job title, position, role, description, summary,

organization	benefits, paid time-off, start date, severance pay, schedule flexibility, remote-work policy, equipment, software, credentials, conditions, working conditions, weather, work location, travel requirements, accessibility, workplace, workspace	functions, employment type, wage, benefits, work location, main responsibilities, job requirements, travel requirements, accessibility, organization name, size, sector, business goals, business plan, trade union, job family, industry, line of service, seniority level, culture, values, vision, mission, business goals, business plan, organization's working culture, organization's values, necessary credentials, social laws, rules, norms, social security, occupational safety policies, worker insurance, technical laws and regulations, worker unions

When we explore the relationships between the state variables revealed in Table 15, we find the following mapping in Table 16. This mapping shows which criteria are related to which feature. For example, an individual has personality and emotions which are associated with desired characteristics on the organization's side. The education of an individual corresponds to the desired education of an organization. In other words, this analysis shows us how the demand of one side of matching fits the supply of the other side. For example, the individual supplies experience, which satisfies the demand of the organization. The match of these state variables gives us the pairs in our matching. The better fit of these state variables gives us stable matching.

Table 16: The criteria generated for the design variables

Criteria for Individuals	**Criteria for Organizations**
values, goals, tastes, motivation,	values, vision, mission, business goals, business plan,

preferences, interests	job family, industry, line of service, seniority level
personality, emotions	desired characteristics
experience	desired experience
mastered knowledge, mastered skills	degrees/field of study required, desired certifications, desired languages
education	desired education
training	desired training
qualifications	special qualifications
work history	requisite experience
wages, salaries, bonuses, benefits	wage, benefits
conditions, remote-work policy, paid time-off, start date, schedule flexibility, severance pay, availability	job title, job position, job role, job description, job summary, job functions, employment type, main responsibilities, job requirements, organization name, size, sector, social security, occupational safety, worker insurance, employers' liability insurance, technical laws, regulations, worker unions, employer unions
equipment, software, credentials, workspace	necessary credentials
work location, travel requirements, weather	work location, travel requirements
accessibility	accessibility
working conditions, workplace	working culture, social laws, rules, norms

4.2. Case 2: Application in a Dynamic Case

4.2.1. Two-sided Matching in Task Allocation

Task allocation is not just about filling empty slots—it is about creating meaningful matches between people and the work they do. In many real-world situations, both sides of the equation matter: tasks come with specific demands and requirements, where individuals bring their own skills, preferences, and limitations. Two-sided matching takes this mutual perspective into account. Instead of assigning work based solely on what the task needs or what the worker prefers, it looks for the best possible pairing by considering both. This kind of matching is especially valuable in complex environments, like project teams, technical workplaces, or flexible workforces, where a thoughtful match can lead to better performance, greater satisfaction, and fewer mismatches down the line.

4.2.2. Engineer-Task Matching Problem

Workforce planning is the recursive process businesses and organizations take to satisfy their needs while ensuring the organizational goals. In service companies, the central resource is the human workforce. Thus, it is in every service company's best interest to find ways to manage their workforce better. To ensure minimal operating costs, effective and efficient use of human resources is a significant issue to be addressed. Workforce planning has three stages depending on the duration of the decision items: the development of policies in the long term, staff planning in the mid-term, and staff scheduling in the short term. There are several decisions closely related to humans in each decision stage. The challenge is finding the best match between the demand for work and the supply of the human workforce. The problem complexity rises rapidly considering the hundreds of tasks and employees in the organization. Due to the complexity, it may not be possible to develop an optimal solution for many of these decisions. Thus, to ensure minimal cost and maximal resource management efficiency, decision-making methods for workforce planning are in high demand in today's fast-changing service industry companies. In this section, we show the application of our unbiased criteria identification methodology in engineer-task matching problem.

Considering the limited engineer workforce of a company, the challenge is to find idle engineers to match new project tasks. In current practice, current tasks in the schedule of engineers are shifted

with the arrival of a new project. However, this causes some projects to be delayed until they are forgotten. In more urgent cases, the engineers are asked to do overtime. However, this increases the workforce cost of the company. To overcome this challenge without any projects being overlooked or any added overtime cost, a new approach to engineer workforce planning where the time of the engineer is taken as a perishable resource can be taken. This approach requires an assessment of the worth of an engineer's time in a similar approach to measuring the worth of a seat in airline revenue management (RM). By defining all criteria affecting the worth of an engineer's time, a real-life decision-making process could be easily modelled while taking the dynamic and probabilistic nature of the workforce management problem into account.

4.2.3. Unbiased Criteria Identification in Engineer-Task Matching

In this section, our unbiased criteria identification methodology is applied to the engineer-task matching problem. We follow the eight-step method proposed in Chapter 3. Additional tables can be found in the Appendix.

I. Define a design statement

The design statement is written as: 'Find an optimal engineer-task matching.' No other specific constraints will be mentioned at this step.

II.Construct an initial ROM diagram

The initial ROM diagram has a 'constraint' type of relationship between the objects 'optimal' and 'matching'; 'engineer' and 'matching'; 'task' and 'matching'. There is a 'predicate verb-object' type of relationship between the objects 'find' and 'matching' as in Figure 6.

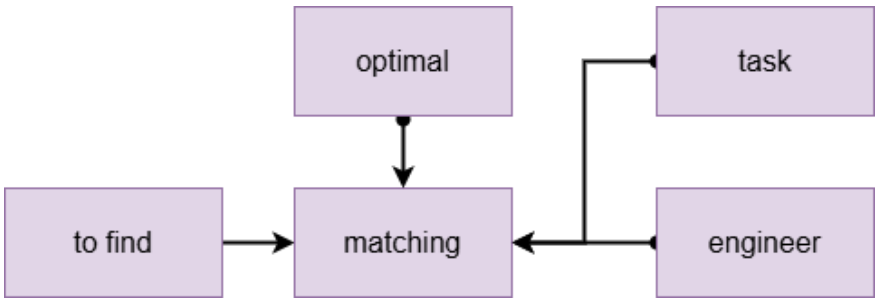


Figure 6: The initial ROM diagram

III.Define an object list for generating questions

We examine the initial ROM diagram to reveal the number of relationships each object has. As shown in Figure 6, the object with the greatest number of connections is 'matching' therefore this object is the central object. According to the two rules of defining an object list as in Table 3, we must ask questions about the environment components first before asking questions about the central object. Before questioning 'matching', the constraining and predicating objects should be questioned. Therefore, we should ask questions on the words 'obtain', 'optimal', 'engineer' and 'task' first. As 'optimal' is an adjective, it will be used in the questions of the noun constrained by it. Thus, we obtain the following list: engineer, task, find, and matching. This list will be used to generate the right questions in the next step.

IV.Generate the right questions

Following the guideline for generating the right questions, the following questions are generated for the design statement of 'Find an optimal engineer-task matching.' These are the first set of questions asked to investigate the product environment. Following the guideline for generating the right questions given in Table 5, we obtained Table 17. In Table 17, the first column shows the objects, the second column shows what the guideline gives us, and the third column shows the generated questions. The outcome of this step is the generated questions listed on Table 17.

Table 17: The right questions generated

Object	**Guideline**	**Question Generated**
engineer	What is [$Noun$]?	What is an engineer?
task	What is [$Noun$]?	What is a task?
find	Who [$Verb$] [$Object$]? Why [$Verb$] [$Object$]? How [$Verb$] [$Object$]? What do you mean by	Who finds an optimal engineer-task matching? Why find an optimal engineer-task matching? How to find an optimal engineer-task matching? When to find an optimal engineer-task matching?

	$[Subject]$ $[Verb]$ $[Object]$?	Where to find an optimal engineer-task matching? What do you mean by finding an optimal engineer-task matching?
matching	What is $[Adjective]$ $[Noun]$?	What is optimal? What is an optimal matching? What is an optimal engineer-task matching? What is the purpose of an optimal engineer-task matching? What is the lifecycle of an optimal engineer-task matching?

V.Generate the right answers

Following the question-answering guidelines provided in Table 6 and Table 7, we enlist the amount of information that should be included in the answers to the right questions generated in Step IV. The right answers to these right questions should include the information in Table 18.

Table 18: The answers-generating guideline following our design problem

Object	**Guideline**
engineer	The answer should define 'engineer' according to the life cycle of the product and its relationship with the product 'optimal engineer-task matching' or product environment.
task	The answer should define 'task' according to the life cycle of the product and its relationship with the product 'optimal engineer-task matching' or product environment.
find	For 'designers find optimal engineer-task matching', the answer should define the components and attributes of 'designers' in the context of 'finding optimal

	engineer-task matching'.
matching	The answer should define 'optimal engineer-task matching' according to the life cycle of the product. Add the purpose of 'optimal engineer-task matching'. Add the lifecycle of 'optimal engineer-task matching'. Add the categorization of environment components for each event in the life cycle following the dimensions of the eLCA environment structure.

After observing what types of information should be collected about each object, we find definitions using common information resources such as dictionaries, published resources, and online search tools. To collect product environment information, we conduct environment analysis with EBD to discover the design environment in depth. To collect life cycle information, we conduct eLCA. Only after using these two tools, do we have enough information to generate the right answers to the questions generated according to EBD.

The EBD methodology explores the environment of the designed product by categorizing it into four categories: human or stakeholder, natural, physical artifact, and digital artifact. In Table 19, we provide the components classified in these four categories for matches in task allocation.

Table 19: The EBD analysis results for engineer-task matching problem

Physical Artifact Environment	**Natural Environment**	**Digital Artifact Environment**	**Stakeholder Environment**
Companies and organizations	Indoors or outdoors spaces, lighting, sound proofing, heating,	Knowledge databases, documentation, note-taking apps, task allocation dashboard, digital whiteboards, collaboration software, task	Product owners, project managers, clients, tech leads, architects, business analysts, quality assurance teams, QA testers, HR managers, HR teams,

	cooling, ergonomics, safety measures.	tracking tools, cloud-based development environments, version control systems, real-time monitoring dashboards, employee databases, skill tracking systems, HR software, performance review tools, learning management systems, certification records.	DevOps teams, process improvement teams, engineering managers.
Workplace conditions. Engineer workspaces: offices, remote setups, development labs, dedicated quiet zones, workstations, meeting rooms, team collaboration areas.	Travel requirements, accessibility requirements.	Data dashboards, dynamic task boards, matching tools, matching software, decision making algorithms, decision support dashboards, performance dashboards, performance review tools, survey platforms, peer review systems, retrospective meeting tools, analytics dashboards, HR systems, task allocation dashboards, workload balancing tools, collaboration software, internal recommendation engines.	Engineers with experience level, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, preferred technologies, preferred work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.
		Technical / security / health laws and regulations, occupational safety and insurance policies, social laws, rules and norms, approval loops,	

		feedback loops, mentorship, training, deadlines, availability, current workload, parallel work, dependencies, customer impact, stakeholder impact, urgency, availability, project management tools, test tracking software, version control systems, monitoring dashboards, digital work tools, email tools, calendar tools, stakeholder communication channels, HR systems, learning platforms, code review tools, bug tracking tools, integrated messaging, video conferencing.	

According to Table 18, the life cycle of the product, “optimal matching”, should be discovered before generating the right answers. We utilize the eLCA tool to obtain life cycle information on the product to be designed and we provide the results in Table 20.

Table 20: The eLCA results for the product being designed

Object	**Life Cycle Components**
matching	● Task identification ● Engineer profiling ● Matching process & assignment ● Execution & monitoring ● Feedback & evaluation

	● Iteration & improvement

Following the guideline results for generating the right answers in Table 18, the EBD analysis results summarized in Table 19, and the eLCA results shown in Table 20, we can generate the right answers. Answers generated for all questions can be found in Appendix D. These are the answers to lead us to reveal the dynamics of the product environment. The answers are simplified as shown in Appendix E.

VI.Update the ROM diagram

At this step, we extended the initial ROM diagram that was built in Step II based on the answers obtained in Step V. One thing that can be done is to simplify the right answers generated. This operation gives us the opportunity to transfer the information into the simple [Subject] [Verb] [Object] [Constraint] format to easily construct our ROM diagram. We put our first answers in Appendix D. We continue building up our ROM diagram with the simplified answers provided in Appendix E. The partial ROM diagrams generated from the answers are provided in Appendix F.

VII.Repeat or stop

At this step, we decide whether to stop or not. Considering the recursive nature of design, new answers may bring new questions. An extended ROM diagram may have some unquestioned objects to reveal more about the product environment. Observing our final ROM diagram which consists of Figures in Appendix F, we decide to stop.

VIII.Extract criteria

In the last step, we extract criteria after analysis of design variables and state variables. We define the design variables first, and then the state variables. We focus on the objective of our design problem using the final ROM diagram as the input. As discovered among the answers to the questions, the purpose of stable matching is to find mutually satisfactory pairs. Our design variables are candidates and organizations. One member from each one of these two distinct sets matches and meets under the concept of a job. The variables that define our design variables are

state variables. We can extract a set of state variables from the final ROM diagram as shown in Table 21. Then we look for relationships between variables. Defining the relationships between the design and state variables, and state and state variables brings us the criteria of a matching.

Table 21: The state variables divided by design variables

	Design Variable: Engineer	**Design Variable: Task**
Input of engineer	Experience, knowledge, technical skills, education, training, qualifications, specialization, codebase familiarity, certifications, skill development, soft skills, characteristics, goals, tastes, motivation, preferences, interests, emotions, innovation, creativity, reliability, communication, cross-team collaboration	Requirements, team dynamics, product owners, project managers, clients, tech leads, architects, business analysts, quality assurance teams, QA testers, HR managers, HR teams, DevOps teams, process improvement teams, engineering managers
Input of task	Preferred technologies, preferred work style, preferred work conditions	Knowledge databases, documentation, note-taking apps, task allocation dashboard, digital whiteboards, collaboration software, task tracking tools, cloud-based development environments, version control systems, real-time monitoring dashboards, employee databases, skill tracking systems, HR software, performance review tools, learning management systems, data dashboards, dynamic task boards, decision making algorithms,

		decision support dashboards, performance dashboards, performance review tools, survey platforms, peer review systems, retrospective meeting tools, analytics dashboards, HR systems, task allocation dashboards, workload balancing tools, collaboration software, internal recommendation engines. Indoors or outdoors spaces, lighting, sound proofing, heating, cooling, ergonomics, safety measures, workplace conditions, engineer workspaces: offices, remote setups, development labs, dedicated quiet zones, workstations, meeting rooms, team collaboration areas, travel requirements, accessibility requirements

When we explore the relationships between the state variables revealed in Table 21, we find the following mapping in Table 22. This mapping shows which criteria are related to which feature. In other words, this analysis shows us how the demand of one side of matching fits the supply of the other side. For example, the individual supplies experience, which satisfies the demand of the organization. The match of these state variables gives us the pairs in our matching. The better fit of these state variables gives us stable matching.

Table 22: The criteria generated for the design variables

Criteria for Engineers	**Criteria for Tasks**

Experience, knowledge, technical skills, education, training, qualifications, specialization, codebase familiarity, certifications, skill development	Required technical skills
Soft skills, characteristics, goals, tastes, motivation, preferences, interests, emotions, innovation, creativity, reliability	Required soft skills
Communication, cross-team collaboration	Team dynamics, product owners, project managers, clients, tech leads, architects, business analysts, quality assurance teams, QA testers, HR managers, HR teams, DevOps teams, process improvement teams, engineering managers
Preferred technologies	Knowledge databases, documentation, note-taking apps, task allocation dashboard, digital whiteboards, collaboration software, task tracking tools, cloud-based development environments, version control systems, real-time monitoring dashboards, employee databases, skill tracking systems, HR software, performance review tools, learning management systems, data dashboards, dynamic task boards, decision making algorithms, decision support dashboards, performance dashboards, performance review tools, survey platforms, peer review systems, retrospective meeting tools, analytics dashboards, HR systems, task allocation dashboards, workload balancing tools, collaboration software, internal recommendation

	engines
Preferred work style, preferred work conditions	Indoors or outdoors spaces, lighting, sound proofing, heating, cooling, ergonomics, safety measures, workplace conditions, engineer workspaces: offices, remote setups, development labs, dedicated quiet zones, workstations, meeting rooms, team collaboration areas, travel requirements, accessibility requirements

5. Discussion

Criteria identification is a pivotal aspect of decision-making, involving the definition of specific factors to assess choices. It ensures objectivity and clarity in the decision-making process by establishing key attributes for evaluation. This framework aids in comparing and analyzing different options, facilitating informed decisions. In the context of the matching process, criteria identification is crucial for understanding agents' preferences and requirements, enabling fair evaluation and comparison of potential matches. The concept of unbiased criteria identification is paramount to eliminate intentional or systematic bias, promoting fairness and equal treatment for all agents involved. In the realm of Multi-Criteria Decision Making (MCDM) research, our work focuses on criteria selection, addressing this step through the development of an unbiased method.

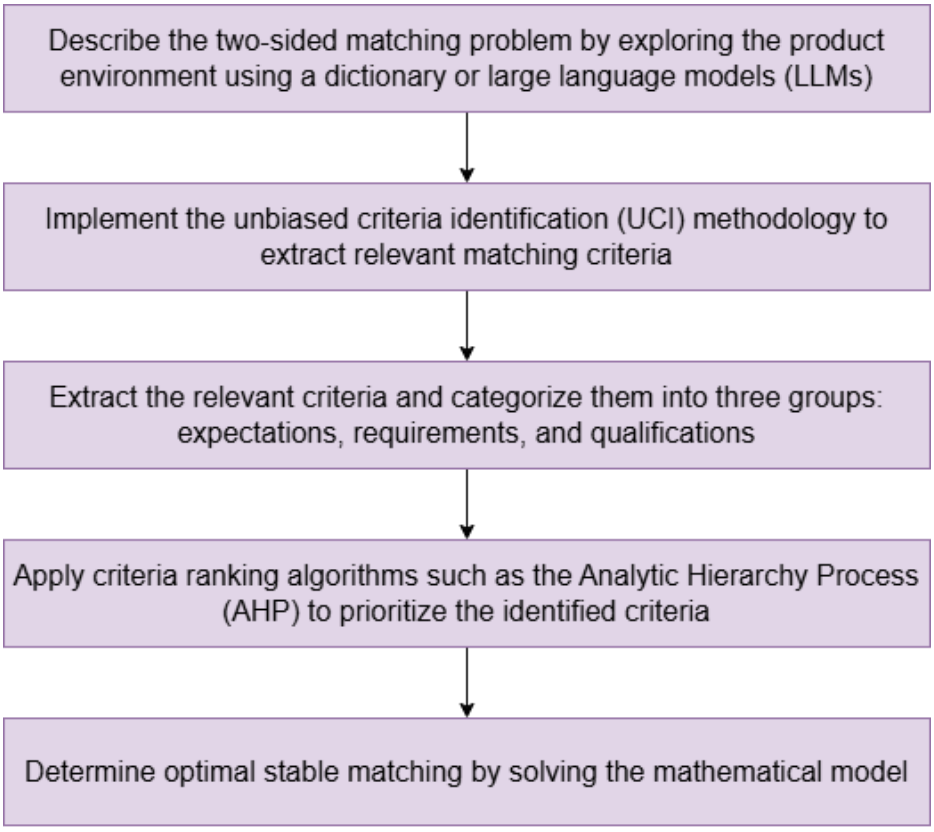


Figure 7: The method flow chart

The proposed method can be summarized as shown in Figure 7. First, we need to define our problem along with discovering the product environment. This allows us to discover all variables that affect and are affected by our product. Then we can apply our published proposed unbiased criteria identification methodology to generate all criteria. Now that we extracted all criteria, we can rank them before using them in the optimization model. For criteria ranking methods such as AHP can be utilized. Using the criteria and the ranks as an input to the model, we formulate the mathematical model. The optimization model provides us with optimal matching and unbiased criteria ensures the matching is also stable. This method can be used in any two-sided matching problem to generate optimal and stable matching. We showed its applications in both static and dynamic two-sided matching.

Unbiased criteria identification makes two-sided matching systems like pairing people with jobs more fair, thoughtful, and effective. Instead of relying on gut feelings, outdated habits, or hidden biases, it uses clear and objective factors to guide decisions. This helps ensure that both sides feel respected and genuinely satisfied with the match. When people are chosen based on what truly matters, their skills, goals, and needs, the result is often more stable and rewarding for everyone involved. It also gives the matching process a solid foundation, making it easier to apply in different areas and improve over time. In short, using unbiased criteria helps create smarter, more human-centered matches that actually work in the real world.

While unbiased criteria identification brings many benefits, it also comes with some challenges and limitations. One major drawback is the difficulty of fully capturing the complexity of human preferences and relationships through objective criteria alone. Real-world decisions often involve emotions, personal values, or subtle context that are hard to quantify or standardize. For example, some people end up rejecting job offers based on their children's school location. This kind of confidential information about people's personal lives, unfortunately, cannot be discovered by an algorithm. Gathering full and truly unbiased data can become time-consuming, pressuring, or impossible at times. Also, one should be careful in designing data collection to avoid unintentionally introducing new forms of bias. Implementing a new matching system might face resistance from stakeholders who are used to traditional methods. Some might feel that algorithmic decision-making lacks transparency or empathy. These little points can be counted as some drawbacks an unbiased criteria identification methodology might bring up.

Considering the static two-sided matching optimization model, one of the biggest advantages of it is its simplicity and clarity. Because everything is known in advance, who the candidates are, what tasks are available, and how everyone ranks the different criteria, it is possible to run the model once and get a complete, optimal solution. This assignment problem-based model is simple, easy to explain, and efficient to solve. It is useful where all information is available to be collected at the same time. Another strength of the model is weighing multiple and complete criteria. By weighing all criteria, the model combines them in a balanced and fair way. This way, the model is adaptable to a variety of real-world scenarios from assigning schools and students to engineers and tasks. The linear optimization model can be solved by solvers like CPLEX. This way even larger problems can be solved easily. Finally, by using unbiased criteria in ranking the alternatives, we ensure getting stable matching. And by optimizing with complete information, we ensure getting optimal matching. Therefore, our unbiased criteria-based static two-sided matching optimization model provides optimal and stable matching.

The static model does have some limitations, especially when you try to apply it in more dynamic, real-time environments. The biggest drawback is that it does not allow for change. Once the optimization is run, the matches are locked in. But in reality, things rarely stay fixed. New candidates may show up, priorities may shift, or urgent tasks may arise after the model has already been solved. Since the static model doesn't update or adapt to these changes, it can miss better matching opportunities that only become visible later. This is why we also tackled a dynamic two-sided matching problem in the second case study.

One of the biggest strengths of dynamic matching models is their ability to respond to change as it happens. Unlike static models, which make all decisions at once based on a fixed snapshot, dynamic models update as new candidates, tasks, or constraints enter the system. This makes them ideal for environments that are constantly evolving, like freelance platforms, emergency response, or agile development, where timing and flexibility really matter. The model can wait for better matches, respond to last-minute arrivals, and avoid premature assignments.

Another key advantage is that dynamic models give you room to think ahead. For example, you might choose to hold back a highly skilled engineer because you know that a more complex task is likely to come up in the next step. This kind of foresight mirrors real-life decision-making in

industries like airlines or logistics, where planners do not just fill every seat, but they think strategically about who to assign, when, and why. By modeling perishability and time-dependent value, dynamic matching can help avoid wasted opportunities. Rather than assigning a candidate to the first available task, the model can wait for a better fit. This helps organizations use their talent and time more effectively and ensures that urgent or high-impact tasks aren't left unassigned just because the timing was off. What makes dynamic models really appealing is how well they reflect the real world. Life is messy: people show up late, projects change, and priorities shift. Dynamic models are built to handle that kind of complexity. They're better equipped to deal with changing preferences, delays, and unpredictable schedules, making them a closer match to how decisions actually get made in practice.

The biggest downside is that dynamic models are a lot more complicated. They track everything over time, who's available when, what's coming next, what's already been done. That means more variables, more constraints, and longer solving times. Especially when you're working with lots of engineers or tasks across multiple time periods, the model can become too large to solve efficiently without simplifications or heuristics. The original problem is inherently stochastic, as future agent arrivals and matching values are uncertain. A full stochastic programming formulation would be computationally intractable due to the combinatorial explosion of possible future scenarios. Instead, we adopt a deterministic approximation that incorporates expected future rewards as static parameters in the objective function. This allows the model to consider the value of future opportunities without explicitly modeling uncertainty.

To make good choices about who to reserve or what to delay, the model often needs some idea of what's coming in the future. If those predictions are wrong, for example if a task doesn't arrive as expected, the model might hold someone back for nothing. That kind of misstep can reduce the overall match quality and create gaps in coverage. Because the logic of a dynamic model unfolds over time and may involve "what-if" thinking or forecast-based reasoning, it can be harder to explain to stakeholders. Why was the task delayed? Why was the candidate not matched right away? These decisions might make perfect sense within the model but could be less obvious to someone outside it, especially in high-stakes or regulated environments where transparency matters.

Finally, dynamic models often involve a lot of moving parts: reserved time limits, expiration windows, estimated future values, all of which need to be tuned carefully. Making sure everything reflects reality takes time, testing, and sometimes trial and error. Compared to a static model, which can be set up and solved relatively quickly, a dynamic approach requires more setup and more effort to maintain.

6. Conclusion and Future Work

At the heart of this thesis is a simple but powerful idea: better matches start with asking better questions. Two-sided matching problems, such as pairing people with jobs, are everywhere in our daily lives. Whether it is a employee finding the right role, a student being accepted into the right school, or an engineer getting assigned the right task, the success of these systems depends on how well we understand what both sides really need and value.

But here comes the challenge: the criteria used to make these decisions are often biased, incomplete, or based on historical assumptions. Many systems still rely on expert opinion, historical data, or standard surveys, which don't always reflect the full picture. This is where our work comes in. We set out to build a fairer, more transparent way to identify what truly matters to the people and institutions involved.

Our approach treats two-sided matching as a design problem. Using tools like Environment-Based Design (EBD), environment-based Life Cycle Analysis (eLCA), and the Recursive Object Model (ROM), we built a method to uncover criteria directly from how people describe their needs. And we also put our theory into two case studies. In this thesis, we applied the method to job-candidate matching and engineer-task matching.

A phrase that merges for matching with human agents is "mutually satisfactory". That phrase captures something deeper than just "good enough." It means both sides are genuinely happy with the match. The individual finds a role that aligns with their skills, goals, and values. The employer finds someone who contributes meaningfully to the team and shares the organization's vision. When that happens, something powerful follows: job satisfaction increases, turnover drops, productivity goes up, and recruitment costs go down. In short, everyone wins.

We tested our method in both static and dynamic settings. In the static case, we used a classic assignment model. In the dynamic case, where tasks and people do not all show up at once, we used a perishability-aware approach, reserving capacity for last-minute matches. This made the method more flexible, realistic, and ready for the unpredictability of the real world.

Our work fits into a growing field called market design, which focuses on creating better rules for how people and systems interact. One of its core goals is to help people share their true preferences safely and clearly. By focusing on unbiased criteria identification, we hope to contribute to that mission, making matching systems not only more efficient but also more human.

Our unbiased criteria identification methodology gathers information from widely accepted resources and extract decision making criteria from these human-centered descriptions. In the future, Retrieval-Augmented Generation (RAG), an NLP methodology can be adopted to make our methodology more structured and automated. RAG uses only pre-approved, unbiased data resources by nature. This ensures the content comes from neutral and accepted resources, therefore serves the unbiasedness goal. Also, it helps the output to come out more structured. This addition could help reduce hallucinations and repeatability in the results.

In the end, this research is about making decision-making more thoughtful. It is about designing systems that listen better, adapt more fairly, and treat people not as data points, but as individuals with goals, needs, and potential. And while there is still much work to do, we believe this is a meaningful step toward more stable, equitable, and mutually satisfying matches, in the workplace and beyond.

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8. Appendix

Appendix A. The right answers generated to the right questions for the static case

	Answers Generated
Q1	Labour is the physical, mental, and social effort exerted by individuals in the process of producing goods and services. Labour is considered one of the factors of production, alongside land and capital. Labour refers to human input or work that contributes to the production of goods and services. In exchange for their labour, individuals typically receive compensation, which can come in various forms such as wages, salaries, bonuses, or other benefits.
Q2	A market refers to the arrangement or system by which buyers and sellers come together to exchange goods, services, or assets. A market is a mechanism for the exchange of goods and services. Buyers seek products or services they need or desire, while sellers offer those goods or services for sale. Participants in a market can be classified into two main groups—buyers (consumers) and sellers (producers or service providers). A labour market refers to the marketplace where potential employees or workers supply their labour, and employers (organizations or businesses) demand labour. It is the economic structure through which the supply and demand for labour interact, leading to the determination of wages, employment levels, and other labour-related outcomes. The labour market is where employers and employees come together to establish employment relationships. Individuals seeking employment participate in the labour market. These individuals bring their knowledge, skills, and experience in exchange for compensation. Employers are organizations, businesses, or entities looking to hire individuals to perform tasks, contribute skills and fulfill specific roles within the organization. The labour market involves the existence of job openings and positions that need to be filled by qualified individuals. The labour market involves the matching of the

	knowledge, skills, and experience of job seekers with the requirements of available job positions.
Q3	Matching refers to the pairing of individuals or entities in a way that satisfies certain criteria or preferences. The goal of a matching process is to create mutually satisfactory pairs based on the preferences of the participants. Stable matching refers to a pairing of individuals or entities in a way that there are no pairs of participants who would prefer to be with each other rather than their current partners. In other words, a matching is considered stable when there are no blocking pairs – pairs of participants who, if not currently matched together, would both have an incentive to deviate from their current matches. In the context of a labour market, stable matching refers to a configuration where employers and employees are paired in a way that avoids situations where both parties would prefer to be matched with each other instead of their current counterparts. In other words, stability in a labour market matching means that there are no pairs of employers and employees who, if not matched together, would both have an incentive to break their current matches and form a new pairing. The purpose of achieving a stable matching in a labour market is to establish a system where both employers and employees are satisfied with their matches, fostering increased efficiency, job satisfaction, and overall stability in employment relationships. This stability contributes to the efficient allocation of resources, ensuring that job positions are filled by individuals with the necessary skills, qualifications, and preferences, thereby maximizing productivity and economic output. Higher levels of job satisfaction for both parties are associated with stable matching, creating a harmonious and stable working environment by eliminating incentives to seek alternative arrangements. Stable matching also plays a crucial role in reducing turnover and job churn. Satisfaction with current matches and the absence of blocking pairs diminish the likelihood of individuals seeking new employment opportunities or employers looking to replace their workforce. The

satisfaction of both employers and employees with their matches generally leads to increased productivity, as engaged and committed employees contribute to a stable and motivated workforce.

The lifecycle of a stable matching in a labour market includes

1) For organizations: vacancy and job posting; interview and selection; offer and hiring; recruitment and onboarding; performance management; separation.
2) For candidates or workers; availability and job search; job application and interview; offer and employment; performance management; separation and retirement.

Here are the environment components for each lifecycle event:

a) For the event of vacancy and job posting,
    i) the natural environment includes posting date, unposting date.
    ii) the physical artifact environment can be ignored.
    iii) the digital artifact environment includes organization websites, organization social media platforms, job posting sites, job fairs, industry publications, industry events, local newspaper advertisements, word-of-mouth recruitment, career websites, job boards, internal job posting, external job posting, job advertisement, organization name, size, sector, business goals, business plan, trade union, job family, industry, line of service, seniority level, organization's culture, organization's values, vision, mission, business goals, business plan, job title / position / role, job description and summary, job functions, employment type (full time, part time or contract), main responsibilities, job requirements, special qualifications, desired characteristics, requisite experience, degrees required, desired education, certifications, trainings, languages, experience, travel requirements, accessibility.
    iv) the stakeholder environment includes employers, workers, recruiters, human resources representatives, hiring team, hiring manager.

b) For the event of availability and job search,

i) the natural environment can be ignored.
ii) the physical artifact environment can be ignored.
iii) the digital artifact environment includes CV, resume, portfolio, cover letter, reference list.
iv) the stakeholder environment includes candidates, experience, mastered knowledge, mastered skills, education, training, qualifications, work history, availability, goals, tastes, motivation, preferences, interests, emotions.

c) For the event of job application, interview and selection,
i) the natural environment includes application date, interview date, interview time, interview place.
ii) the physical artifact environment includes companies, organizations, interview format.
iii) the digital artifact environment includes application tracking system, background check, phone interview, video interview, tests (measuring personality traits, problem-solving ability, reasoning, reading comprehension, emotional intelligence, and more), reference check (previous employment-job performance, experience, responsibilities, workplace conduct), additional interviews.
iv) the stakeholder environment includes candidates, employers, workers, recruiters, human resources representatives, hiring team, hiring manager.

d) For the event of offer, recruitment, and hiring,
i) the natural environment can be ignored,
ii) the physical artifact environment can be ignored,
iii) the digital artifact environment includes offer letter, disclosure agreement, negotiations, wage, benefits, paid time-off, start date, severance pay, schedule flexibility, remote-work policy, equipment, software, credentials, and conditions.

	iv) the stakeholder environment can be ignored. e) For the event of onboarding, employment, and performance management, i) the natural environment includes probation period, working conditions, weather, work location, travel requirements, and accessibility. ii) the physical artifact environment includes workplace, workspace. iii) the digital artifact environment includes training, orientation, worker handbook, occupational safety, worker insurance, employers' liability insurance, worker unions, employer unions, forms, paperwork, working culture, values, social laws, rules, norms, social security, technical laws, regulations. iv) the stakeholder environment includes employers, workers, coworkers, managers, mentors, customers, suppliers, business partners, general public. f) For the event of separation and retirement, i) the natural environment can be ignored, ii) the physical artifact environment includes unemployment benefits, retirement pension. iii) the digital artifact environment includes returning job market, leaving job market. iv) the stakeholder environment includes unemployed people, new candidates, retired people.
Q4	Obtaining a stable matching in the labour market involves implementing a mechanism or algorithm that considers the preferences of both employers and employees, ensuring that resulting matches are stable with no pairs of participants preferring each other over their current matches. The Gale-Shapley algorithm, a well-known method for the stable matching problem in the labour market, is designed to be fair to both parties and converges to stable matching.

Appendix B. Simplified answers for the static case

	Simplified Answers
Q1	Labour is physical, mental, and social effort. Individuals exert this effort. Individuals produce goods and services. Labour, land, and capital are factors of production. Labour is the human work that contributes to the production of goods and services. Individuals receive compensation. Compensation is wages, salaries, bonuses, or benefits.
Q2	A market is a system. Buyers and sellers come together by this system. Buyers and sellers exchange goods and services. Buyers seek, need and desire goods and services. Sellers offer goods and services. A labour market is a marketplace. Potential employees and workers supply labour in this marketplace. Organizations and businesses demand labour in this marketplace. The labour market is an economic structure. Supply and demand for labour interact through this economic structure. It leads to the determination of wages, employment levels, and other labour-related outcomes. Employers and employees come together in the labour market. Employers and employees establish employment relationships in the labour market. Individuals participate in the labour market. Individuals seek employment in the labour market. These individuals bring their knowledge, skills, and experience. They exchange their knowledge, skills, and experience with compensation. Employers are organizations and businesses. Organizations and businesses look and hire individuals. Individuals perform tasks, contribute skills, and fulfill specific roles within the organization. Job openings and positions exist in the labour market. Job openings and positions need and are filled by qualified individuals.
Q3	A matching refers to the pairing of individuals or entities. The pairing satisfies certain criteria or preferences. The goal of a matching is mutual satisfaction. Matching is based on the preferences. Absence of blocking pairs are in a stable matching. A stable matching fosters increased efficiency, job satisfaction, and overall stability in employment relationships. This stable matching contributes to the efficient allocation of resources. Individuals with the necessary skills, qualifications, and preferences fill job positions. The stable matching maximizes productivity and economic output. Higher levels of job satisfaction are associated

with stable matching. Job satisfaction creates a harmonious and stable working environment. Job satisfaction eliminates incentives to seek alternative arrangements. Stable matching reduces turnover and job churn. Current match satisfaction and the absence of blocking pairs diminish the likelihood of replacement. Individuals seek new employment opportunities for replacement. Employers seek a new workforce for replacement. Match satisfaction leads to increased productivity. Engagement and commitment of employees contribute to stability and motivation of the workforce.

The lifecycle of a stable matching in a labour market includes

3) For organizations: vacancy and job posting; interview and selection; offer and hiring; recruitment and onboarding; performance management; separation.
4) For candidates or workers; availability and job search; job application and interview; offer and employment; performance management; separation and retirement.

Here are the environment components for each lifecycle event:

g) For the event of vacancy and job posting,
    i) the natural environment includes posting date, unposting date.
    ii) the physical artifact environment can be ignored.
    iii) the digital artifact environment includes organization websites, organization social media platforms, job posting sites, job fairs, industry publications, industry events, local newspaper advertisements, word-of-mouth recruitment, career websites, job boards, internal job posting, external job posting, job advertisement, organization name, size, sector, business goals, business plan, trade union, job family, industry, line of service, seniority level, organization's culture, organization's values, vision, mission, business goals, business plan, job title / position / role, job description and summary, job functions, employment type (full time, part time or contract), main responsibilities, job requirements, special qualifications, desired characteristics, requisite experience, degrees required, desired education, certifications, trainings, languages, experience, travel requirements, accessibility.

iv) the stakeholder environment includes employers, workers, recruiters, human resources representatives, hiring team, hiring manager.

h) For the event of availability and job search,
   i) the natural environment can be ignored.
   ii) the physical artifact environment can be ignored.
   iii) the digital artifact environment includes CV, resume, portfolio, cover letter, reference list.
   iv) the stakeholder environment includes candidates, experience, mastered knowledge, mastered skills, education, training, qualifications, work history, availability, goals, tastes, motivation, preferences, interests, emotions.

i) For the event of job application, interview and selection,
   i) the natural environment includes application date, interview date, interview time, interview place.
   ii) the physical artifact environment includes companies, organizations, interview format.
   iii) the digital artifact environment includes application tracking system, background check, phone interview, video interview, tests (measuring personality traits, problem-solving ability, reasoning, reading comprehension, emotional intelligence, and more), reference check (previous employment-job performance, experience, responsibilities, workplace conduct), additional interviews.
   iv) the stakeholder environment includes candidates, employers, workers, recruiters, human resources representatives, hiring team, hiring manager.

j) For the event of offer, recruitment, and hiring,
   i) the natural environment can be ignored,
   ii) the physical artifact environment can be ignored,

	iii) the digital artifact environment includes offer letter, disclosure agreement, negotiations, wage, benefits, paid time-off, start date, severance pay, schedule flexibility, remote-work policy, equipment, software, credentials, and conditions. iv) the stakeholder environment can be ignored. k) For the event of onboarding, employment, and performance management, i) the natural environment includes probation period, working conditions, weather, work location, travel requirements, and accessibility. ii) the physical artifact environment includes workplace, workspace. iii) the digital artifact environment includes training, orientation, worker handbook, occupational safety, worker insurance, employers' liability insurance, worker unions, employer unions, forms, paperwork, working culture, values, social laws, rules, norms, social security, technical laws, regulations. iv) the stakeholder environment includes employers, workers, coworkers, managers, mentors, customers, suppliers, business partners, general public. l) For the event of separation and retirement, i) the natural environment can be ignored, ii) the physical artifact environment includes unemployment benefits, retirement pension. iii) the digital artifact environment includes returning job market, leaving job market. iv) the stakeholder environment includes unemployed people, new candidates, retired people.
Q4	Obtaining stable matching in the labour market involves implementing a mechanism. The mechanism considers the preferences of both employers and employees. The mechanism ensures stability. The Gale-Shapley algorithm is a well-known mechanism. It converges to stable matching.

Appendix C. The extended ROM diagrams per question for the static case

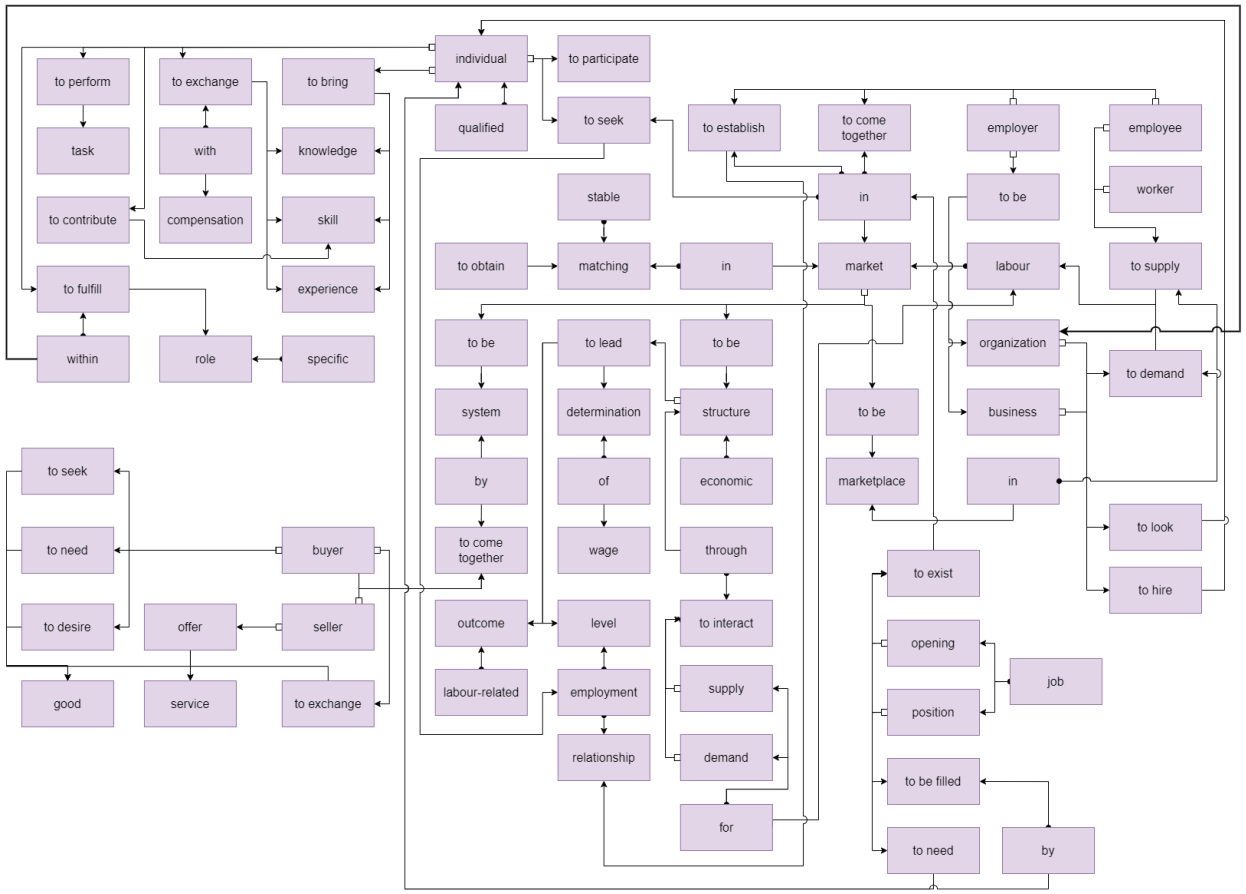

Figure 8: The partial ROM diagram extended by the answer to Question 2

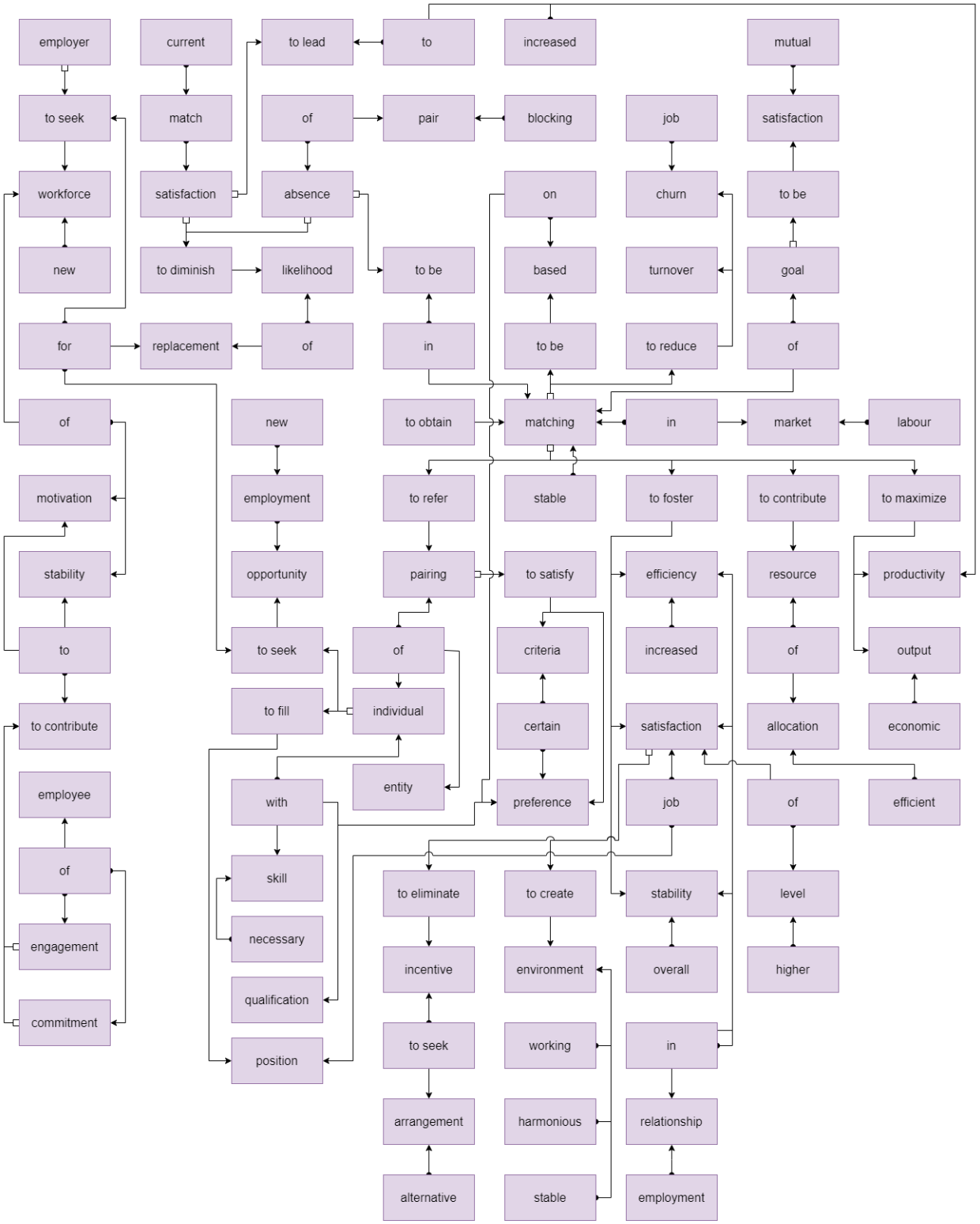

Figure 9: The partial ROM diagram extended by the answer to Question 3 - Part 1 of 3

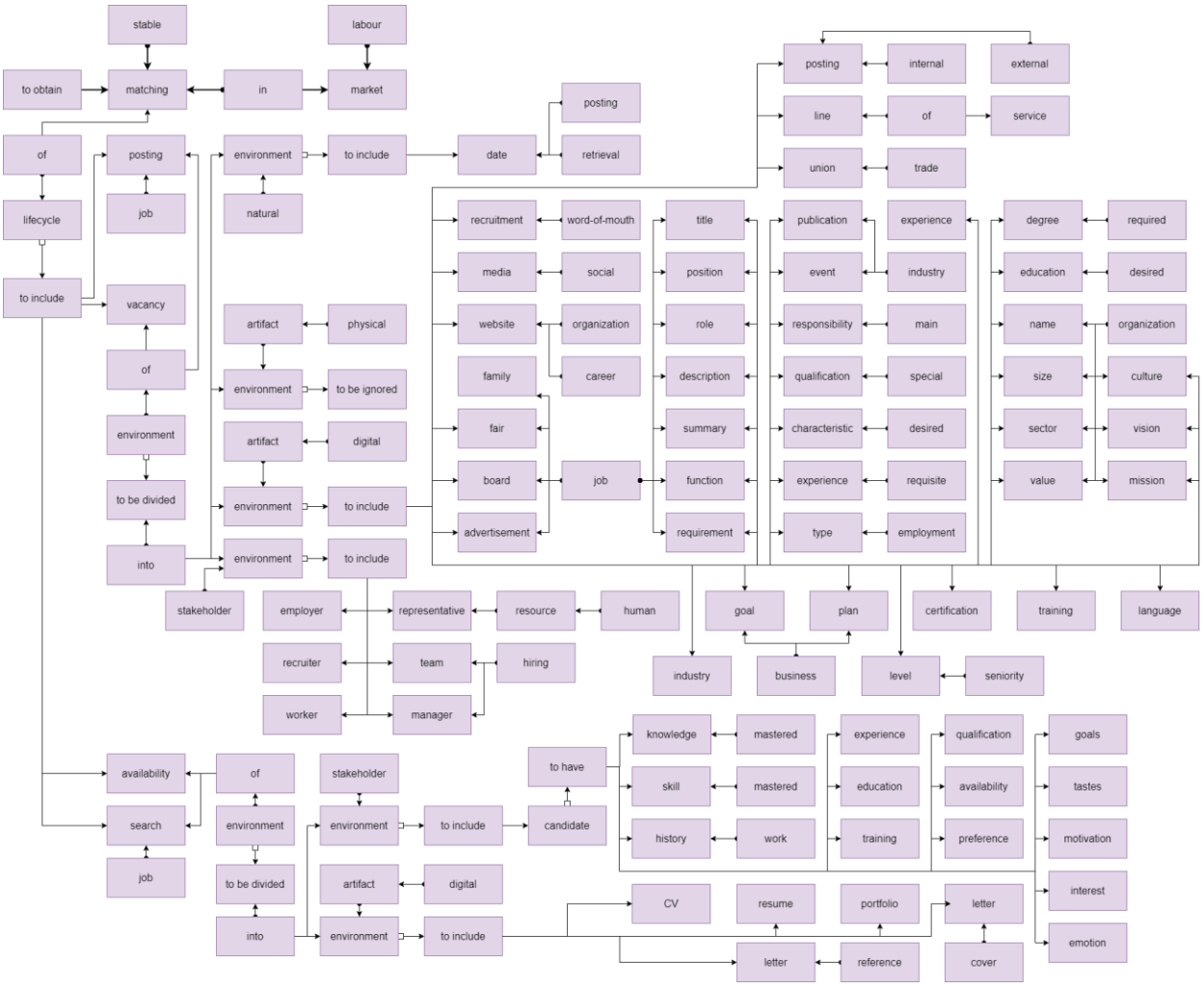

Figure 10: The partial ROM diagram extended by the answer to Question 3 - Part 2 of 3

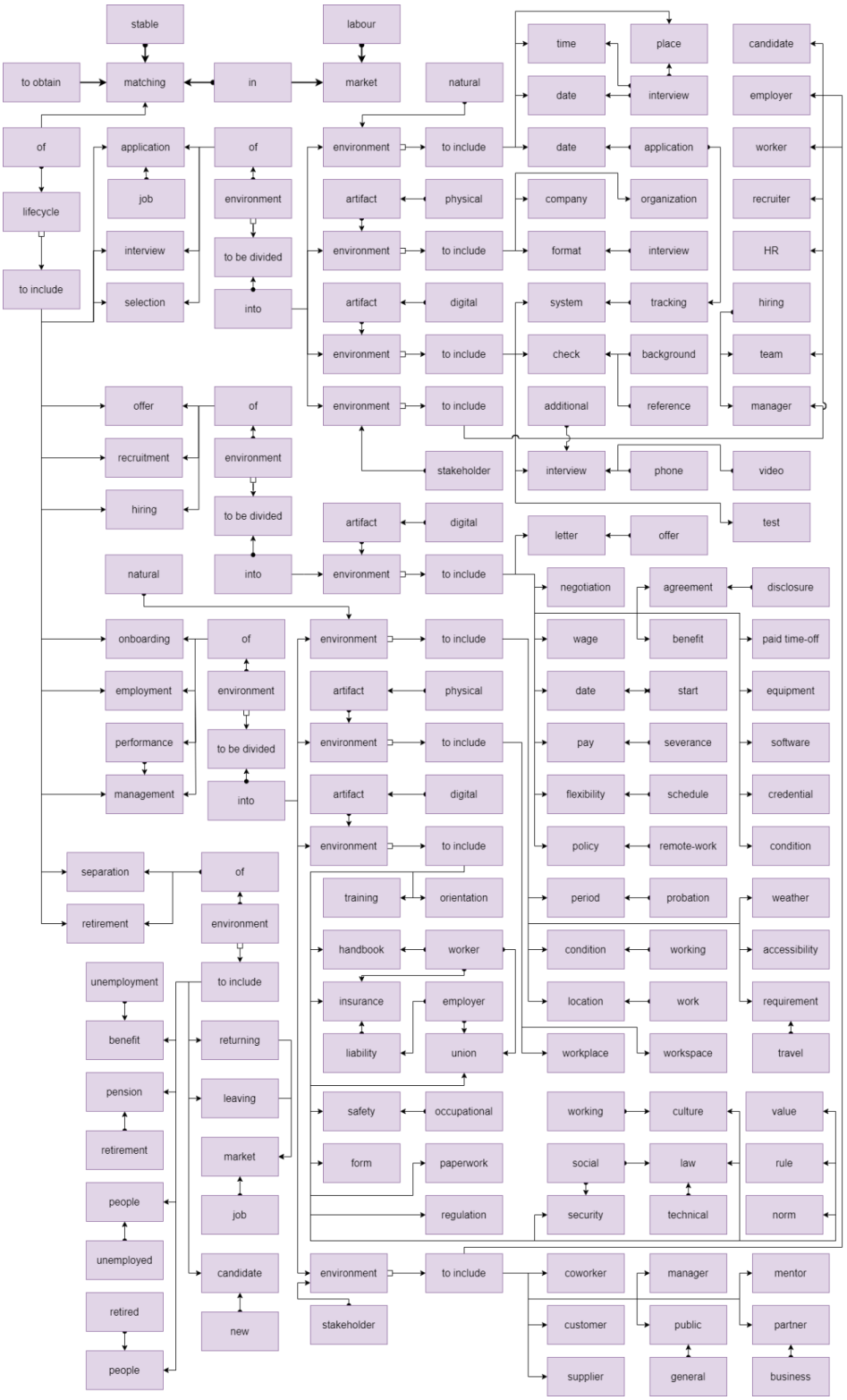

Figure 11: The partial ROM diagram extended by the answer to Question 3 - Part 3 of 3

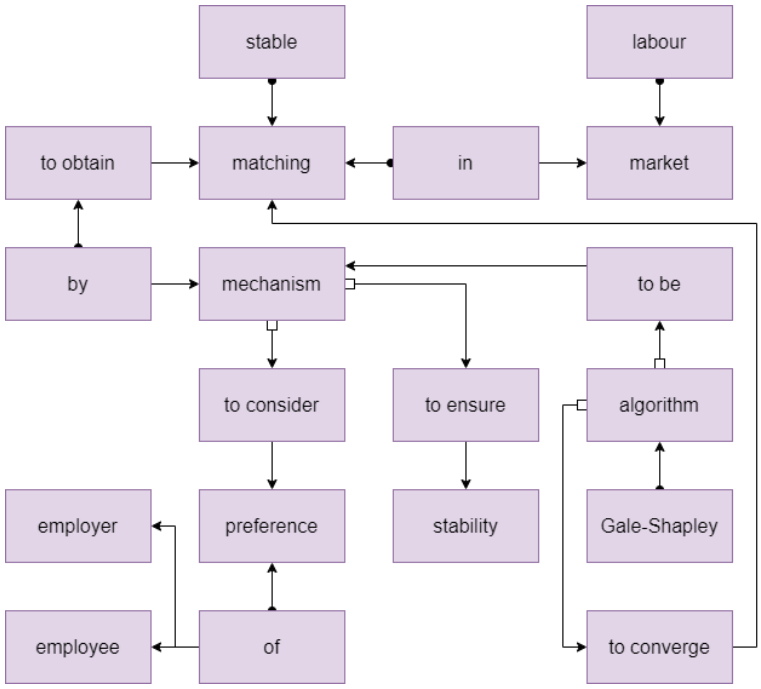

Figure 12: The partial ROM diagram extended by the answer to Question 4

Appendix D. The right answers generated to the right questions for the dynamic case

Table 23: Answers for the dynamic case

	Answers Generated
Q1	An engineer is a person trained and skilled in the design, construction, and use of engines or machines, or in any of the various branches of engineering. An engineer is a person who designs, builds, or maintains structures, machines, or systems using scientific and mathematical principles. In the context of 'Optimal Engineer-Task Matching', an engineer is not just a worker but a dynamic participant whose skills, workload, and experience directly influence task allocation. An engineer is both a data source and a beneficiary, improving efficiency, productivity, and engagement within a structured digital and physical product environment.
Q2	A task is a specific unit of work or activity that is assigned, planned, or undertaken to achieve a particular goal. Tasks can vary in complexity, duration, and purpose and are often part of a larger project, process, or workflow. In the 'Optimal Engineer-Task Matching' product, a task is not just a piece of work but a dynamic, structured entity that undergoes real-time analysis and intelligent allocation. The task is a core element of the system, interacting with engineers, digital tools, and business stakeholders to optimize workflow efficiency and project outcomes.
Q3	The answers to the questions who, when and where are not very specific therefore these questions could be ignored. Why: Finding the optimal engineer-task matching is essential for maximizing efficiency, productivity, and job satisfaction while ensuring high-quality project outcomes. By aligning

	tasks with engineers' skills, experience, and workload, companies can reduce errors, speed up task completion, and enhance overall performance. Proper task matching prevents burnout, increases engagement, and supports career growth, leading to higher retention and motivation. It also ensures that critical tasks are handled by the most qualified engineers, improving project quality and reducing rework. Ultimately, optimized task allocation leads to faster project delivery, better resource utilization, and stronger business success. How: To find optimal engineer-task matching, tasks should first be analyzed based on required skills, complexity, and urgency, while engineers are evaluated by skills, experience, workload, and availability. AI-driven or rule-based matching systems can then assign tasks efficiently, ensuring balanced workloads and minimal inefficiencies. Continuous monitoring and feedback allow for real-time adjustments, improving both task allocation accuracy and engineer satisfaction. Additionally, assigning tasks that support career growth helps engineers develop new skills while maintaining business priorities. This dynamic approach ensures higher productivity, better project outcomes, and a more engaged workforce.
Q4	Optimal means the best or most efficient possible outcome under given conditions. It refers to a solution, decision, or state that maximizes benefits while minimizing costs, effort, or drawbacks. Optimal matching refers to the best possible pairing of two or more elements based on specific criteria to maximize efficiency, performance, or satisfaction. In engineer-task matching, optimal means assigning the right engineer to the right task to achieve the highest efficiency, quality, and satisfaction. The lifecycle of a stable matching in engineer-task matching includes task identification, engineer profiling, matching process & assignment, execution & monitoring, feedback & evaluation, iteration & improvement. Here are the environment components for each lifecycle event: 1) For the event of task identification, a) the natural environment can be ignored. b) the physical artifact environment includes companies and organizations.

c) the digital artifact environment includes knowledge base, documentation, collaboration software, task allocation dashboard, digital whiteboards, note-taking apps, cloud-based development environments.
d) the stakeholder environment includes product owners, project managers, clients, tech leads, architects, business analysts.

2) For the event of engineer profiling,
   a) the natural environment can be ignored.
   b) the physical artifact environment includes companies and organizations.
   c) the digital artifact environment includes knowledge database, skill tracking systems, HR software, performance review tools, learning management systems, certification records, documentation, digital whiteboards, note-taking apps, cloud-based development environments.
   d) the stakeholder environment includes coworkers, product owners, project managers, HR managers, tech leads, engineers with experience level, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, preferred technologies, preferred work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

3) For the event of matching process and assignment,
   a) the natural environment can be ignored.
   b) the physical artifact environment includes companies and organizations.
   c) the digital artifact environment includes data dashboards, dynamic task board, task allocation dashboards, workload balancing tools, collaboration software, internal recommendation engines, matching tools, matching software, decision making algorithms, decision support dashboards, performance dashboards.
   d) the stakeholder environment includes product owners, project managers, tech leads, engineering managers, HR teams, engineers with experience level,

mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, preferred technologies, preferred work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

4) For the event of execution & monitoring,
    a) the natural environment includes indoors or outdoors spaces, lighting, sound proofing, heating, cooling, ergonomics, safety measures, travel requirements, accessibility requirements.
    b) the physical artifact environment includes companies and organizations, workplace conditions, workspaces, workstations, offices, remote setups, development labs, dedicated quiet zones, team collaboration areas, meeting rooms.
    c) the digital artifact environment includes technical / security / health laws and regulations, occupational safety and insurance policies, social laws, rules and norms, approval loops, feedback loops, mentorship, training, deadlines, availability, current workload, parallel work, dependencies, customer impact, stakeholder impact, urgency, availability, project management tools, test tracking software, version control systems, monitoring dashboards, knowledge base, documentation, digital work tools, collaboration software, task allocation dashboard, digital whiteboards, note-taking apps, cloud-based development environments, email tools, calendar tools, stakeholder communication channels, HR systems, learning platforms, code review tools, bug tracking tools, integrated messaging, video conferencing.
    d) the stakeholder environment includes quality assurance testers, tech leads, DevOps teams, product owners, project managers, engineers with experience level, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions,

preferred technologies, preferred work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

5) For the event of feedback & evaluation,
    a) the natural environment can be ignored.
    b) the physical artifact environment includes companies and organizations.
    c) the digital artifact environment includes performance review tools, survey platforms, peer review systems, retrospective meeting tools, analytics dashboards, HR systems.
    d) the stakeholder environment includes product owners, managers, QA teams, clients, coworkers, HR, engineers with experience level, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, preferred technologies, preferred work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

6) For the event of iteration & improvement,
    a) the natural environment can be ignored.
    b) the physical artifact environment includes companies and organizations.
    c) the digital artifact environment includes data dashboards, dynamic task board, matching tools, matching software, decision making algorithms, decision support dashboards, performance dashboards.
    d) the stakeholder environment includes product owners, engineering managers, process improvement teams, HR teams, engineers with experience level, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, preferred

	technologies, preferred work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

Appendix E. Simplified answers for the dynamic case

Table 24: Simplified answers for the dynamic case

	Answers Generated
Q1	An engineer is a person. An engineer is trained and skilled. Engineers design, build, use, or maintain structures, engines, machines, or systems. An engineer uses scientific and mathematical principles. Engineer's skills, workload, and experience influence task allocation. An engineer is both a data source and a beneficiary. An engineer improves efficiency, productivity, and engagement within a structured digital and physical product environment.
Q2	A task is a specific unit of work or activity. A task is assigned, planned, or undertaken to achieve a particular goal. Tasks vary in complexity, duration, and purpose. Tasks are part of a larger project, process, or workflow. A task is a dynamic, structured entity. A task undergoes real-time analysis and intelligent allocation. A task is a core element of the system. A task interacts with engineers, digital tools, and business stakeholders to optimize workflow efficiency and project outcomes.
Q3	Optimal engineer-task matching maximizes efficiency, productivity, and job satisfaction by aligning tasks with skills, experience, workload, and availability of engineers. It ensures high-quality project outcomes, reduces errors, speeds up task completion, and enhances overall performance. Proper task matching prevents burnout, increases engagement, supports career growth, leads to higher retention and motivation, and ensures the most qualified engineers handle critical tasks. It also improves project quality and reduces rework. Optimized task allocation enables faster project delivery, better resource utilization, and stronger business success. Companies analyze tasks based on requirements, complexity, and urgency, and evaluate engineers.
Q4	Optimal means the best or most efficient possible outcome under given conditions. Optimal refers to a solution, decision, or state that maximizes benefits while minimizing costs, effort, or drawbacks. Optimal matching refers to the best possible pairing of two elements based on

specific criteria to maximize efficiency, performance, or satisfaction. Optimal means assigning the right engineer to the right task to achieve the highest efficiency, quality, and satisfaction in engineer-task matching. The lifecycle of stable matching includes task identification, engineer profiling, matching process & assignment, execution & monitoring, feedback & evaluation, and iteration & improvement.

Here are the environment components for each lifecycle event:

1) For the event of task identification,
    a) the natural environment can be ignored.
    b) the physical artifact environment includes companies and organizations.
    c) the digital artifact environment includes knowledge base, documentation, collaboration software, task allocation dashboard, digital whiteboards, note-taking apps, cloud-based development environments.
    d) the stakeholder environment includes product owners, project managers, clients, tech leads, architects, business analysts.

2) For the event of engineer profiling,
    a) the natural environment can be ignored.
    b) the physical artifact environment includes companies and organizations.
    c) the digital artifact environment includes knowledge database, skill tracking systems, HR software, performance review tools, learning management systems, certification records, documentation, digital whiteboards, note-taking apps, cloud-based development environments.
    d) the stakeholder environment includes coworkers, product owners, project managers, HR managers, tech leads, engineers, experience, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, technology, work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

3) For the event of matching process and assignment,
    a) the natural environment can be ignored.
    b) the physical artifact environment includes companies and organizations.
    c) the digital artifact environment includes data dashboards, dynamic task board, task allocation dashboards, workload balancing tools, collaboration software, internal recommendation engines, matching tools, matching software, decision-making algorithms, decision support dashboards, performance dashboards.
    d) the stakeholder environment includes product owners, project managers, tech leads, engineering managers, HR teams, engineers, experience, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, technology, work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

4) For the event of execution & monitoring,
    a) the natural environment includes indoors or outdoors spaces, lighting, sound proofing, heating, cooling, ergonomics, safety measures, travel requirements, accessibility requirements.
    b) the physical artifact environment includes companies and organizations, workplace conditions, workspaces, workstations, offices, remote setups, development labs, quiet zones, team collaboration areas, meeting rooms.
    c) the digital artifact environment includes technical / security / health laws and regulations, occupational safety and insurance policies, social laws, rules and norms, approval loops, feedback loops, mentorship, training, deadlines, availability, current workload, parallel work, dependencies, customer impact, stakeholder impact, urgency, availability, project management tools, test tracking software, version control systems, monitoring dashboards,

knowledge base, documentation, digital work tools, collaboration software, task allocation dashboard, digital whiteboards, note-taking apps, cloud-based development environments, email tools, calendar tools, stakeholder communication channels, HR systems, learning platforms, code review tools, bug tracking tools, integrated messaging, video conferencing.

d) the stakeholder environment includes quality assurance testers, tech leads, DevOps teams, product owners, project managers, engineers, experience, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, technology, work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

5) For the event of feedback & evaluation,
    a) the natural environment can be ignored.
    b) the physical artifact environment includes companies and organizations.
    c) the digital artifact environment includes performance review tools, survey platforms, peer review systems, retrospective meeting tools, analytics dashboards, HR systems.
    d) the stakeholder environment includes product owners, managers, QA teams, clients, coworkers, HR, engineers, experience, mastered knowledge, mastered technical skills, mastered soft skills, education, training, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, technology, work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

6) For the event of iteration & improvement,
    a) the natural environment can be ignored.

	b) the physical artifact environment includes companies and organizations. c) the digital artifact environment includes data dashboards, dynamic task board, matching tools, matching software, decision making algorithms, decision support dashboards, performance dashboards. d) the stakeholder environment includes product owners, engineering managers, process improvement teams, HR teams, engineers, experience, mastered knowledge, mastered technical skills, mastered soft skills, education, qualifications, specialization, certifications, trainings, characteristics, goals, tastes, motivation, preferences, interests, emotions, technology, work style, project interest, project engagement, project criticality, cross-team collaboration, codebase familiarity, innovation, creativity, skill development, reliability, team dynamics, communication.

Appendix F. The extended ROM diagrams per question for the dynamic case

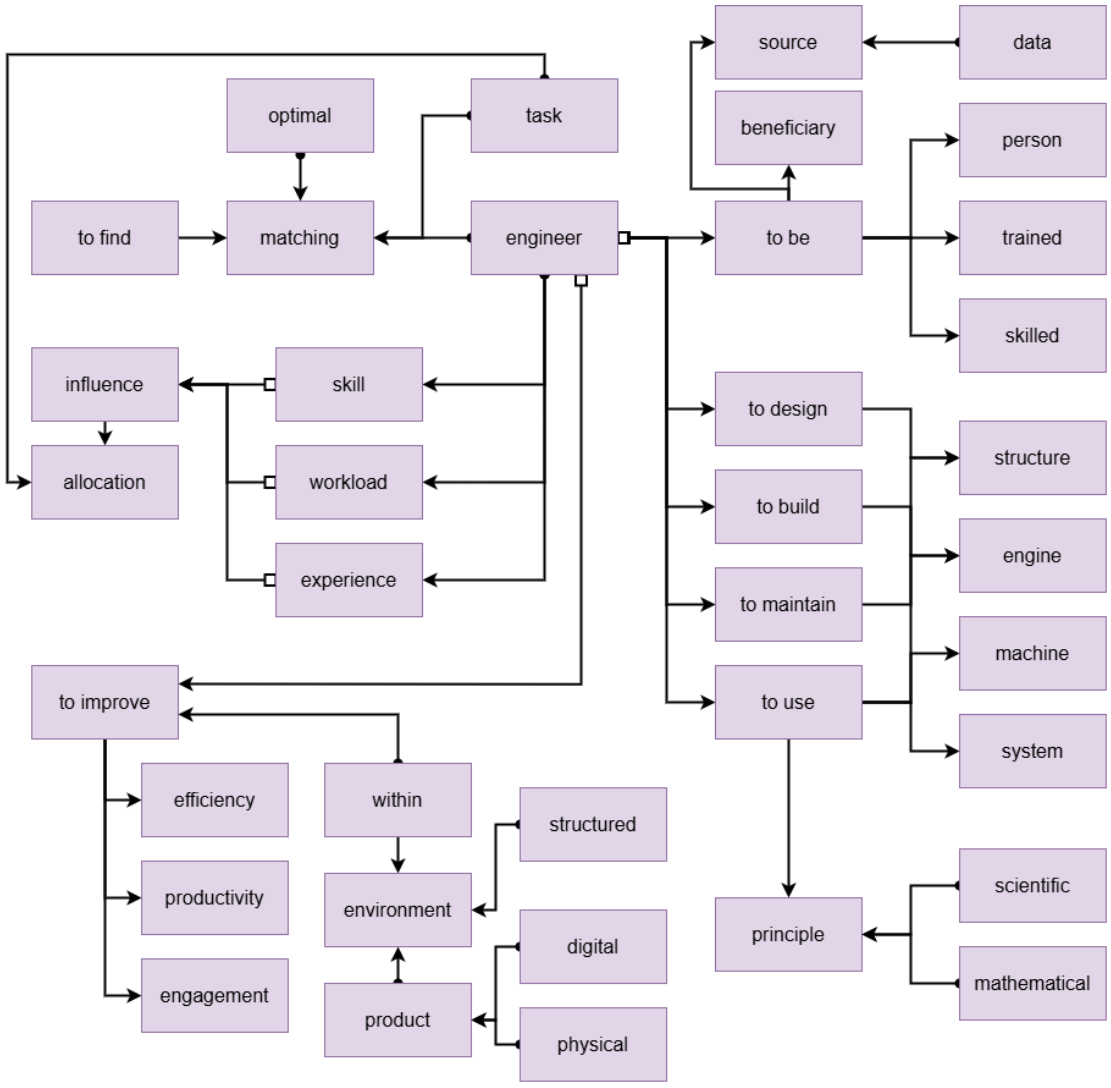

Figure 13: The partial ROM diagram extended by the answer to Question 1

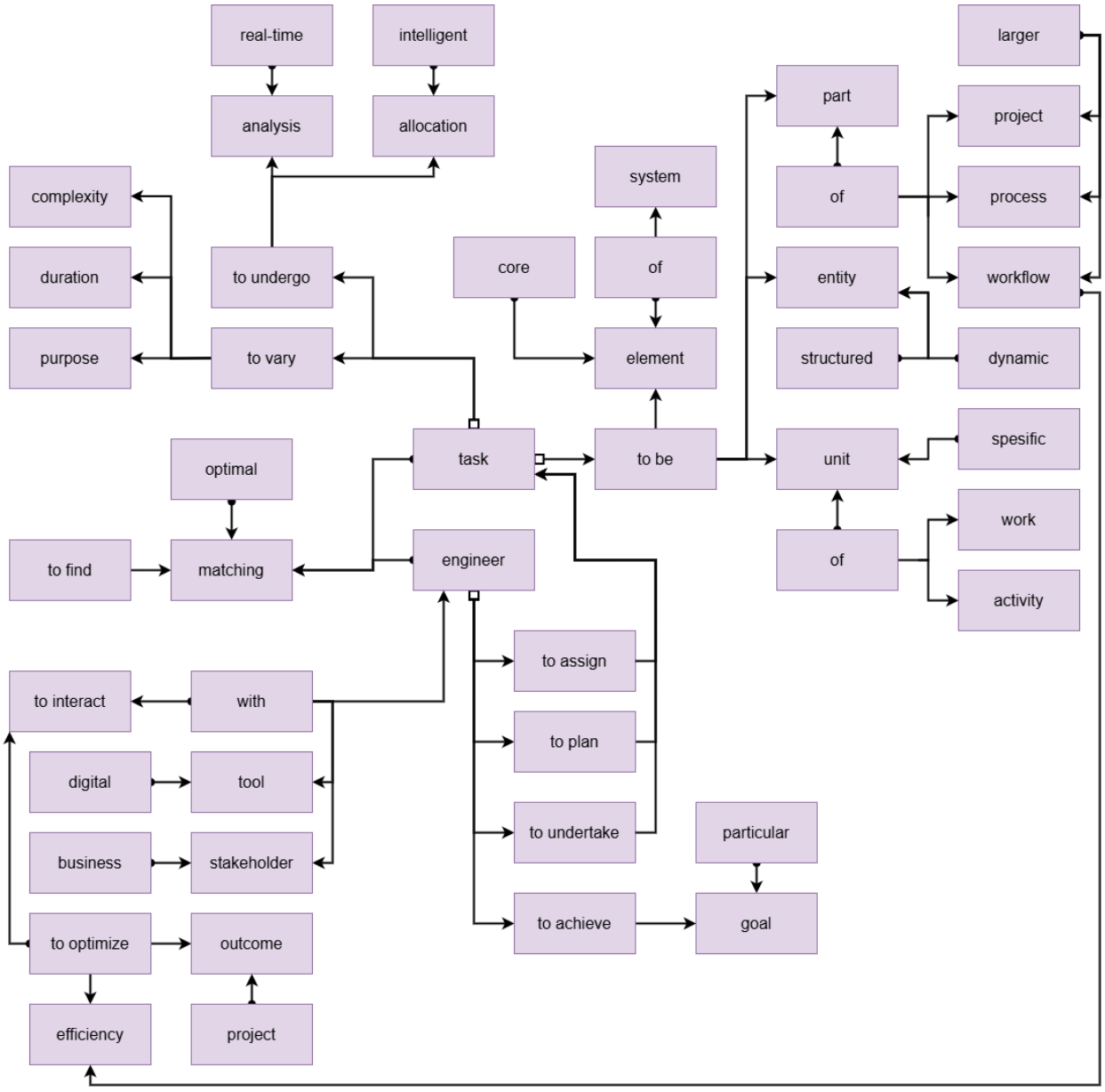

Figure 14: The partial ROM diagram extended by the answer to Question 2

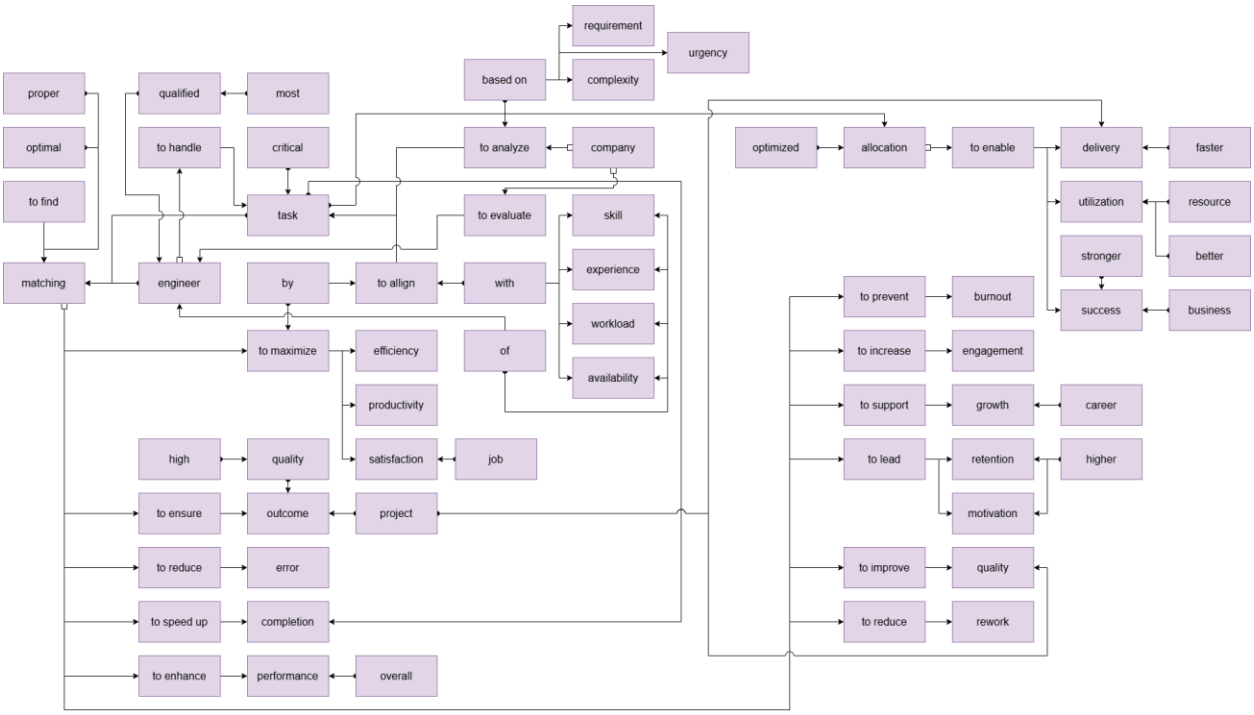

Figure 15: The partial ROM diagram extended by the answer to Question 3

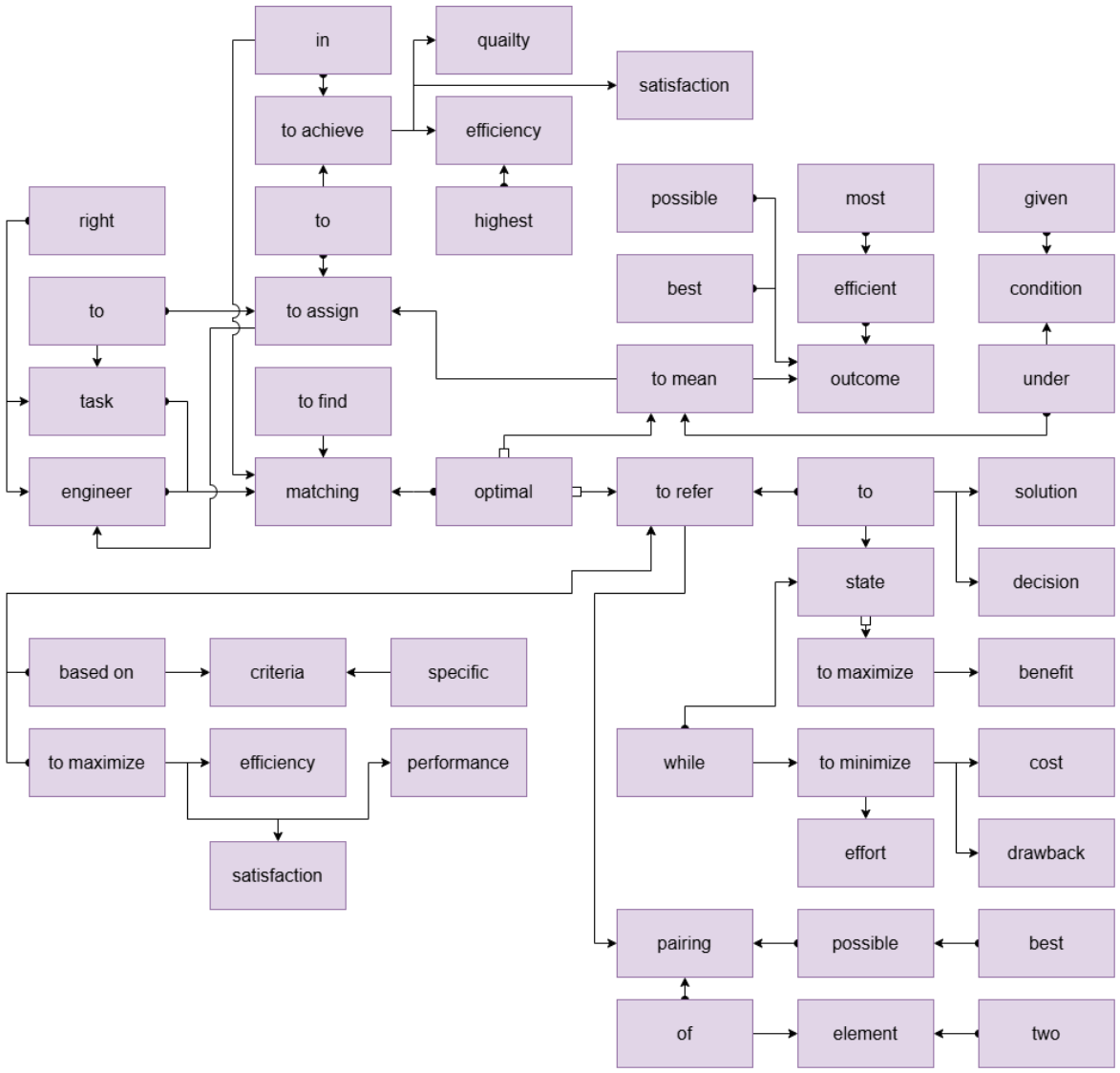

Figure 16: The partial ROM diagram extended by the answer to Question 4 - Part 1 of 8

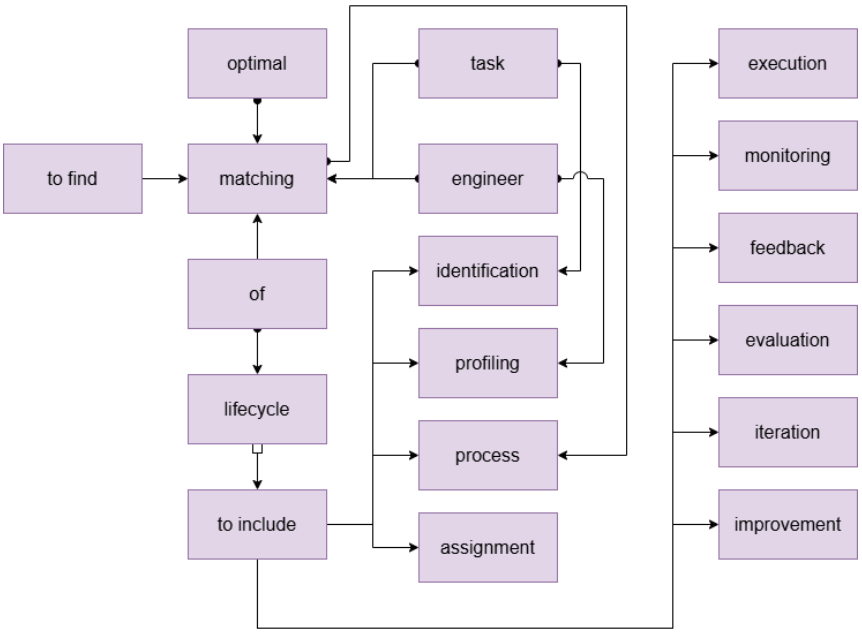

Figure 17: The partial ROM diagram extended by the answer to Question 4 - Part 2 of 8

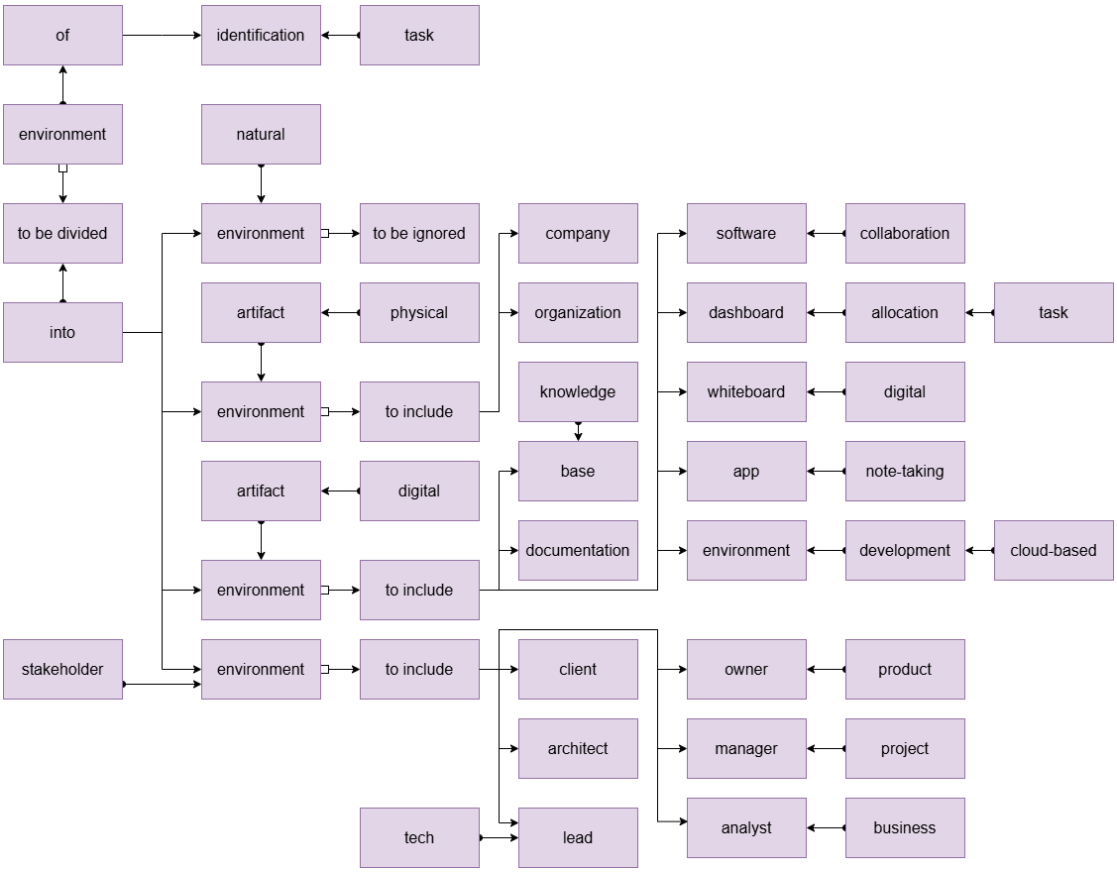

Figure 18: The partial ROM diagram extended by the answer to Question 4 - Part 3 of 8

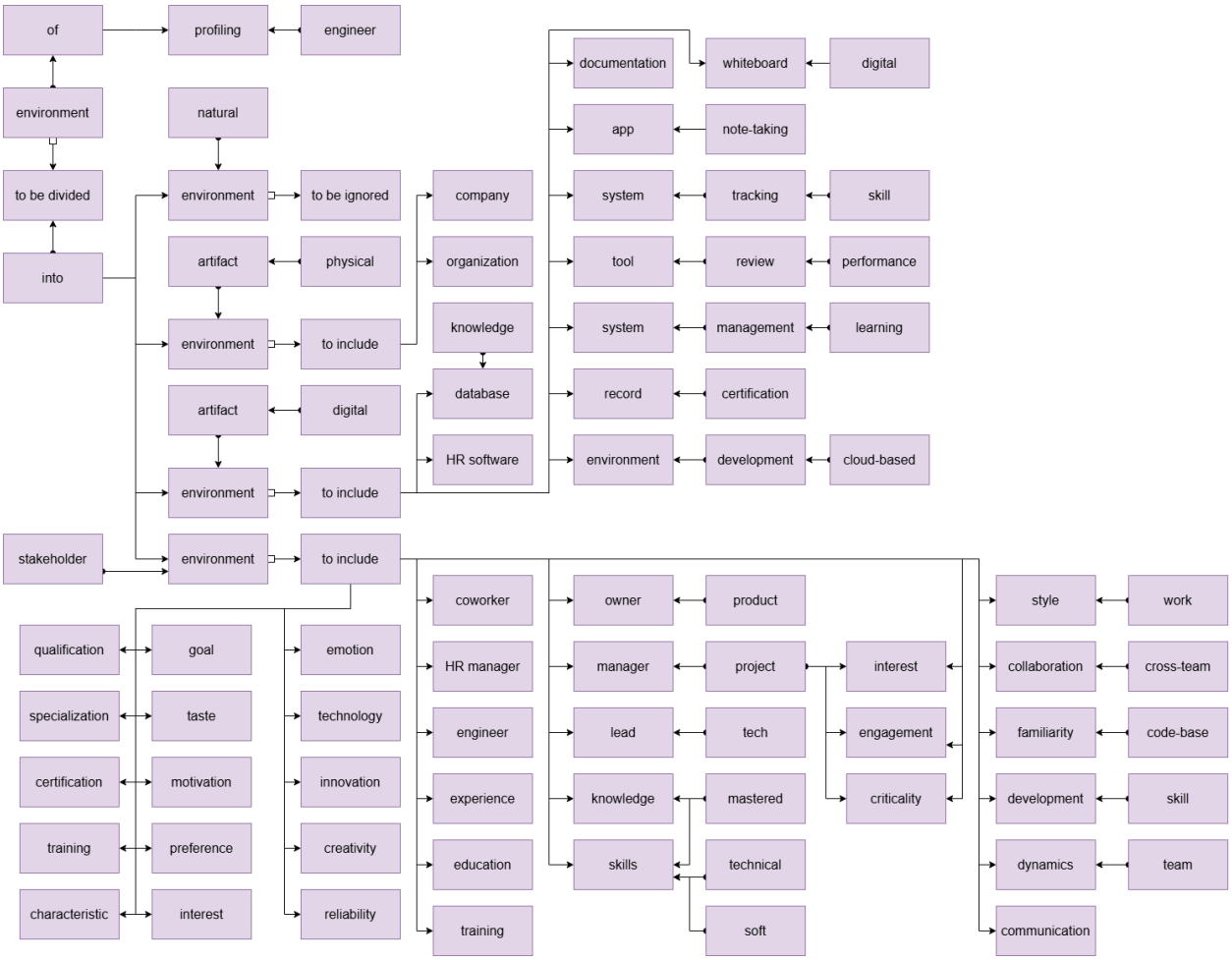

Figure 19: The partial ROM diagram extended by the answer to Question 4 - Part 4 of 8

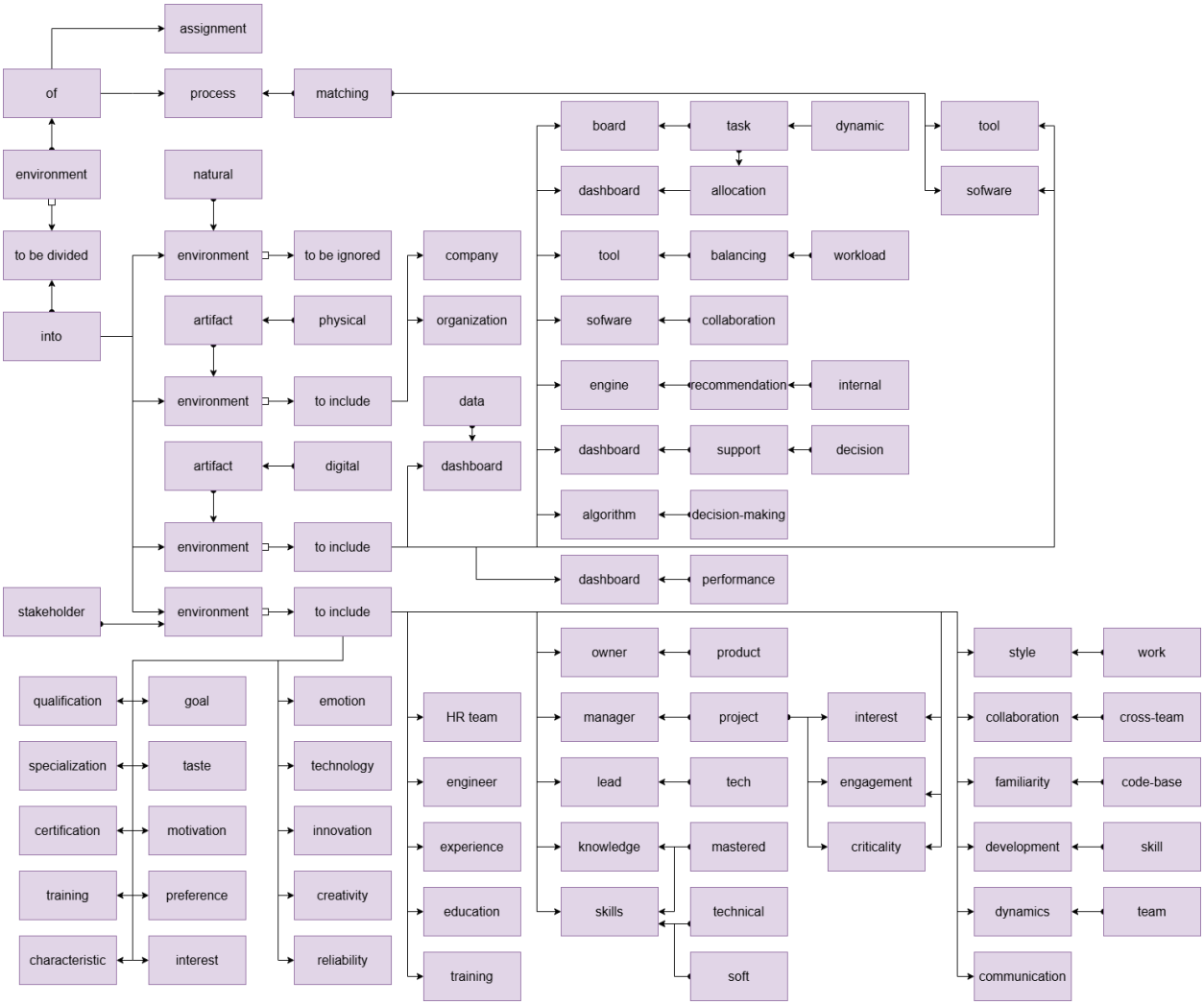

Figure 20: The partial ROM diagram extended by the answer to Question 4 - Part 5 of 8

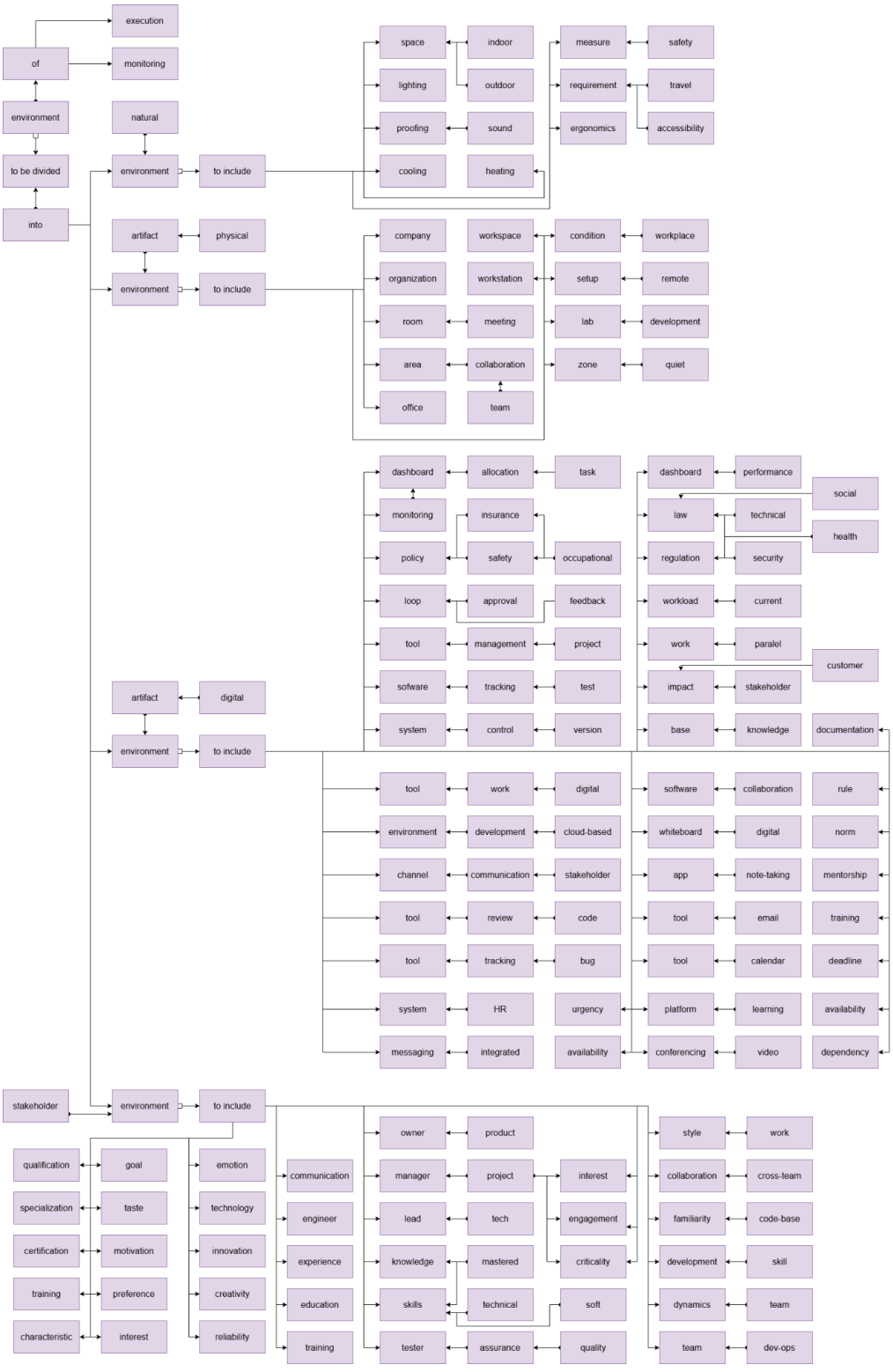

Figure 21: The partial ROM diagram extended by the answer to Question 4 - Part 6 of 8

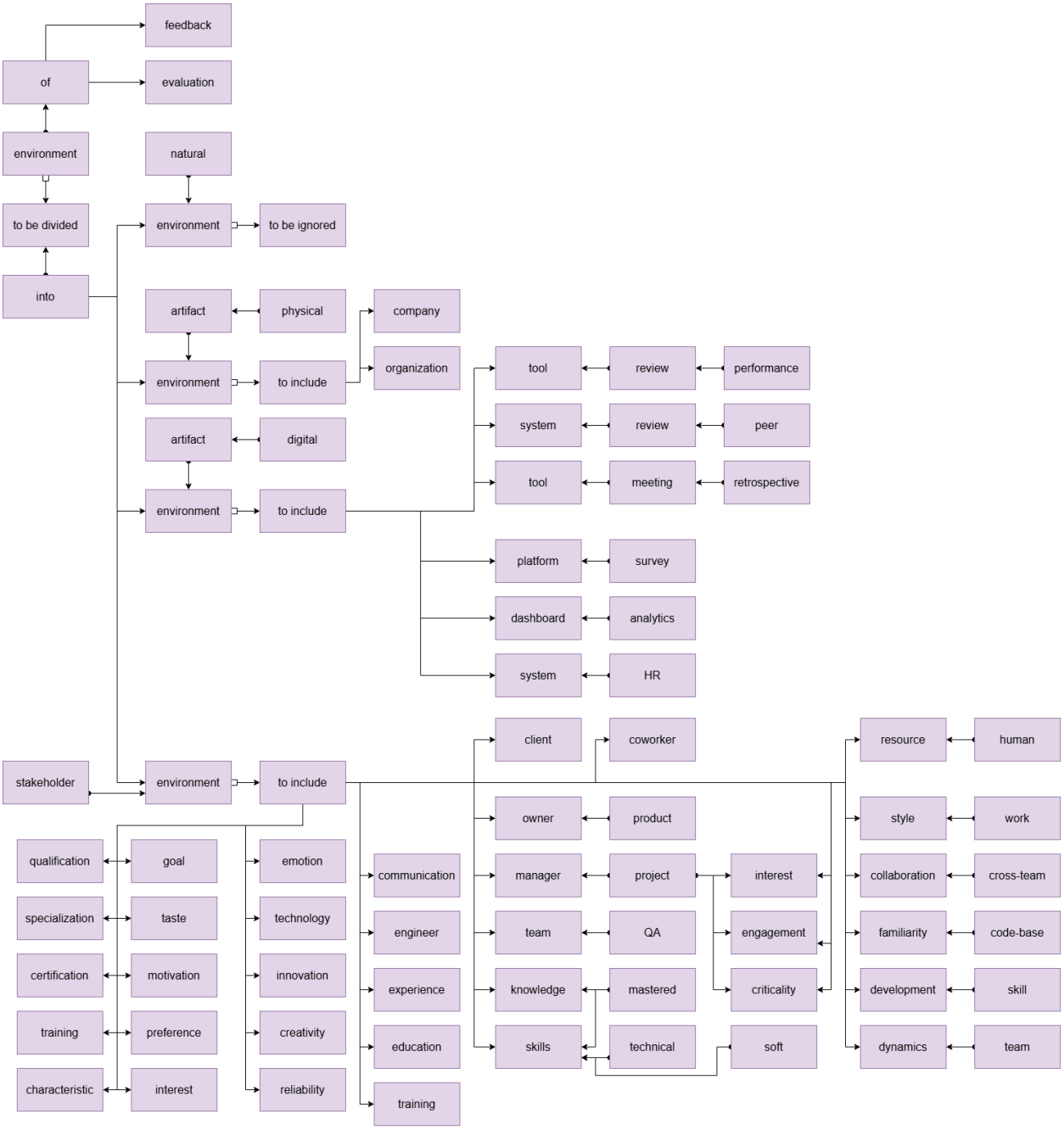

Figure 22: The partial ROM diagram extended by the answer to Question 4 - Part 7 of 8

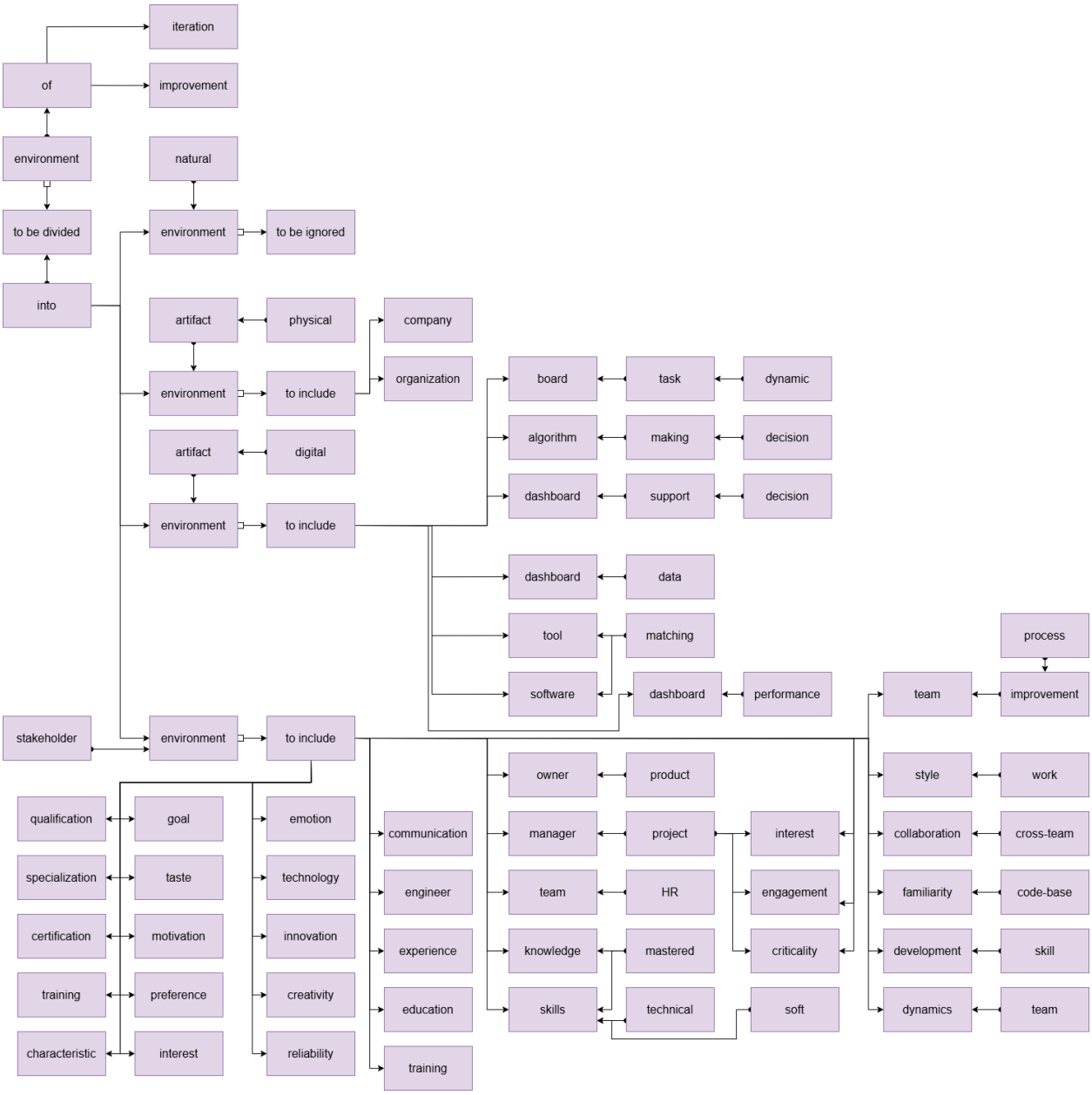

Figure 23: The partial ROM diagram extended by the answer to Question 4 - Part 8 of 8

Appendix G. The airline revenue management methods equations

$$EMSR_i(S_i) = f_i * P_i(S_i)$$

Equation 1. The formula of EMSR

(i is the fare class; S_i is the number of seats in fare class i; f_i is the average fare level of fare class i; $P_i(S_i)$ is the probability of selling S_i or more seats)

$$EMSR_H(S_L^H) = f_L$$

Equation 2. The formula to the optimal protection level for the high fare class S_L^H

(L is the low fare class; H is the high fare class; f_L is the average fare level of the low fare class; S_L^H is the number of seats protected from the low fare class and made available exclusively to the high fare class)

$$\delta_m(n, s) = \frac{1}{m} (F_s^n - F_{s-m}^n)$$

Equation 3. The formula of EMSV

(m is the number of seats requested; n is the decision period; s is the size of the seat inventory; F_s^n is the optimal total expected revenue that can be generated from decision period 1 to decision period n given the booking capacity s)