Algorithmic Selves Living in an Algorithmic Society

Designing a Transparent Job Recommendation System Interface

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ABSTRACT

This project explores how explainability in job recommendation systems affects user experience—particularly trust, autonomy, and exploratory behavior. While algorithmic recommendation systems significantly influence users' lives, their opaque nature can increase user anxiety and reduce self-efficacy. To address this issue, we designed a Chrome extension interface that uses a Large Language Model (LLM) to explain the rationale behind recommendations and allows users to interact with and modify the inputs. Users can inspect and edit the attributes involved in the recommendations, interpret results through natural language explanations, and submit feedback. Through iterative user testing and interviews, we refined the system features, confirming that LLM-based explanations offered greater intuitiveness and persuasiveness compared to traditional systems. This study demonstrates that explainability is not merely about delivering information, but can positively influence users' emotional responses and sense of agency. It serves as a starting point for expanding the role of explainability in human-centered AI design.

CCS CONCEPTS

• Human-centered computing → Human computer interaction (HCI)
• Computing methodologies → Artificial intelligence

KEYWORDS

Explainability, Job Recommendation, Human-Centered Design, Algorithmic Transparency, User Interaction

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1 INTRODUCTION

As algorithm-based systems are increasingly applied in various aspects of daily life, discussions on their trustworthiness are becoming more prominent. In particular, when these systems directly impact human lives, explainability and user autonomy from a human-centered perspective become essential.

Job recommendation systems are a representative example. These systems play a crucial role in helping job seekers explore new opportunities, yet users often receive recommendations without knowing the basis for them. When reasons for recommendations are unclear, users may not trust the system or may even feel doubt and anxiety, wondering whether they are truly qualified for the roles. Current systems that merely present a list of jobs can intensify these concerns, especially among young job seekers who are navigating uncertainty and identity formation.

This issue is closely related to the concept of the "Algorithmic Self." Users interpret what kind of person they are based on recommendations, which can shape their self-perception. However, because algorithms do not always offer fair or accurate outputs, misleading results could lead to distorted self-understanding. In situations where perfectly fair recommendations are difficult to achieve, providing explanations becomes essential not only for understanding the output but for helping users emotionally accept and critically engage with it.

This project begins from this point, aiming to structurally integrate explanation features into a job recommendation system and investigate how they affect user trust, anxiety, and exploratory behavior. Rather than relying on technical interpretability tools like SHAP or LIME—which often provide abstract or low-level explanations—this system uses a post-hoc, LLM-based explanation mechanism that allows for lightweight, flexible, and human-centered feedback. Large Language Models (LLMs) are employed not only for their capacity to generate coherent natural language but also for their ability to contextualize user-specific information and provide tailored, narrative-style explanations. From the perspective of Trustworthy AI, this approach enhances transparency and fosters user understanding by shifting the focus from model internals to communicative alignment with users' cognitive and emotional needs. By articulating the rationale behind recommendations in a conversational, adaptive format, LLMs help bridge the gap between algorithmic decision-making and human interpretability—ultimately supporting trust calibration, informed decision-making, and a greater sense of user autonomy.

By enabling users to explore why a job was recommended, how their inputs influenced the outcome, and what could change if certain conditions were modified (what-if reasoning), the system acts not only as a recommender but as a mentor-like interface. This approach positions explainability as more than a cognitive aid—it becomes a psychological and participatory interface that supports self-determined decision-making and strengthens trust in AI systems.

In doing so, this project contributes to the broader field of Trustworthy AI, particularly in the domain of user-centered post-hoc explainability, and explores how explanation design can evolve from technical transparency to emotionally grounded, value-sensitive communication.

2 RELATED WORK

As algorithmic decision-making increasingly shapes personal and professional opportunities, the importance of explainability and user interpretability becomes more than a usability issue—it becomes a question of fairness, autonomy, and dignity. In domains such as loan approvals, healthcare triage, and job matching, the outcomes of algorithmic processes are not just suggestions but deeply consequential. Scholars have increasingly called for reframing AI design as a socio-technical system that interacts with users' expectations, emotions, and identities.

In the domain of career decision-making, this interaction becomes even more sensitive, as individuals often interpret system outputs as reflections of their potential or social value. Job recommendation systems, therefore, present a uniquely important and emotionally resonant case for studying explainability. We chose this domain as our central case, with particular focus on human-centered design for explainable systems and the visibility of algorithmic assumptions. The following review summarizes key prior research that informed our work.

2.1 Understanding Algorithmic Selves through Graph-based Personalization

LinkedIn, one of the most representative platforms for job recommendations, actively utilizes Graph Neural Networks (GNNs) to infer user interests and social relationships [1]. LiGNN leverages such structural features by extracting various graph signals from users' activities and interactions, integrating them into a single vector space to perform personalized recommendations. However, this internal representation is not directly visible to users. As a result, users are unaware of how they are being interpreted or which elements are influencing the recommendations, passively accepting the outcomes created by the algorithmic self.

Our system emphasizes the recognizability and modifiability of the algorithmically constructed self, helping users easily explore and select its elements. It builds upon tools like GNNExplainer [2], but shifts the focus from technical debugging and developer-centric analysis to a user-centered interpretation. Rather than presenting complex mathematical explanations, the system is designed so users can visually see how their information is interpreted and manipulate these components to better understand the structure.

2.2 Explainability and Human-Centered AI Design

The explanation function of AI systems serves not merely as technical elaboration but as a social and cognitive bridge between the system and the user. For instance, PEPLER, proposed by Wang et al. [3], enhances trust and persuasiveness by generating natural language explanations through personalized prompts tailored to user attributes. This approach represents a shift toward human-centered rather than technology-centered explanation.

However, explanation alone does not fully ensure user agency. Auernhammer [4] emphasizes that human-centered AI design must address not only transparency but also the embedded values, power structures, and social contexts in system design. This suggests that Human-Centered Design (HCD) must go beyond simply applying tools. Xu et al. [5] also argue that the autonomy and opacity of AI systems create new interaction challenges and advocate for HCI professionals to treat AI not as a mere technological entity but as a partner in collaboration and design. Explainability and human-centered design are thus not separate concerns but must be considered together to understand how AI systems are interpreted and accepted in users' contexts.

2.3 Value-Centered Interventions through Explainability

Existing explainable recommendation systems have mostly relied on static, text-based explanations, which fail to provide users with more than one-way information delivery. In contrast, our system visualizes the internal representations embedded in GNN-based recommendation algorithms, allowing users to reinterpret and modify the logic behind recommendations. For example, users can directly see how changes in certain elements—whether removed or emphasized—affect the final result, thereby transforming explanation into a participatory structure [3].

This approach aligns with both **Value-Sensitive Design (VSD)** and **Speculative Design**. It empowers users with interpretive and decision-making authority, enhancing the system's transparency and sensitivity through participatory engagement. Implemented as a Chrome extension, our interface reveals the interpretive structure of the system without interfering with the existing platform, enabling accessible and actionable engagement [6]. It shifts from a results-oriented to a meaning-oriented interaction for the user.

2.4 Possibility of Critical Intervention through Interface

Ko et al. [7] argue that users should go beyond simply using AI systems and engage in a practice of questioning and interpreting results. They point out that conventional explanation systems are insufficient for capturing users' skepticism, judgment, or interpretive engagement, and propose that interfaces should be redesigned to support structures for posing questions. In other words, interfaces should naturally enable users to practice **what-if reasoning**, asking questions like *"Why was this the result?"*, *"What factors influenced it?"*, or *"What if the conditions were different?"*

Our system implements this potential for critical intervention at the UI level. Users are provided with visual representations of the elements influencing recommendations and can select, modify, or remove them to adjust the outcomes. This design moves beyond simply receiving explanations—it enables users to participate in constructing the explanations themselves. Based on Ko et al.'s concept of **critical interface**, our system aims to support user interventions into AI interpretation structures, allowing them to reconfigure and co-create these logics.

One particularly compelling observation emerged when a user actively removed their major from the profile to test whether the system would still recommend similar jobs. This not only illustrated the system's sensitivity to input changes, but encouraged a deeper reflection on how much their academic background was constraining the recommendations. These moments of critical engagement exemplify the "critical interface" concept: systems that invite scrutiny and reinterpretation, not just compliance.

3 METHODOLOGY & PROCESS

This project aimed to analyze the limitations of job recommendation systems from a user-centered perspective and explore the impact of explanatory features on user trust and search experience. To this end, we defined the problem and derived improvement directions through a process of algorithm review, persona-based value alignment, iterative design experiments, and user feedback collection.

3.1 Identifying issues through algorithm review

First, we reviewed the existing recommendation system based on actual usage scenarios. While the system recommends jobs based on user input such as location, experience, and areas of interest, the results often failed to adequately reflect the user's context.

For example, when a user living in Ulsan who was about to graduate from college received recommendations based on the input information, the top of the recommendation list included a job title such as "marketing team leader in the Seoul metropolitan area requiring at least five years of experience." This was a job that required excessive experience for the user to take on immediately and physically required relocation. The user perceived this result as "the system unilaterally throwing out recommendations without considering my situation at all."

In another case, the same user was recommended for a "Nigeria-based international NGO volunteer position." This position is typically suitable for those with an interest in international organizations or social contribution fields, as well as those with foreign language skills and the ability to work overseas long-term. However, the user had no plans for overseas work, lacked confidence in English conversation, and had a major and career path unrelated to social welfare or international activities. He left feedback stating, "I can't understand why this job was recommended, and it feels like the system misjudged me." Furthermore, he added, "Maybe there aren't many jobs suitable for me?" and added that he felt the recommendation system was narrowing his possibilities.

These cases show that when results that are disconnected from the user's expectations or realistic conditions are provided without explanation, the user feels that the system does not understand them properly. Ultimately, this led to a refusal to accept the recommendation results and acted as a major factor in hindering the user's willingness to explore the system.

3.2 Persona Setting and Value-Centered Problem Definition

To gain a deeper understanding of the limitations of recommendation systems and derive a design direction from the user's perspective, this project established two personas based on actual user feedback.

The first persona is Kim Hyun-ji (23), a college student living in Seoul who is about to graduate. Although she has no practical experience yet, she seeks a future-oriented and growth-oriented career based on her major and interests. The values important to Kim Hyun-ji were explainability and autonomy.

She desired an exploratory recommendation system that provided explanations based on her information, such as *"Why this job was recommended?"* and presented new possibilities she had not previously considered. However, the actual system provided one-sided lists based on educational background or popular jobs, resulting in her response, *"I don't understand why this job was recommended."* She could not find a reason to accept the recommendation results, and ultimately, her motivation to explore diminished.

The second persona is Lim Hyun (30), who lives in Ulsan and has been working at a small IT company for over three years. She is considering a career change to a new field. The values that are important to Lim Hyun are fairness and career shift flexibility.

He felt dissatisfied with the current system, which repeatedly recommended similar jobs based solely on his past career, and particularly felt that his graduation date and current location were acting as constraints on his ability to move into a new field. He raised the question, *"Is this really the direction I want to go in or is it just the path the system has set for me?"* and expressed discomfort that the system was actually limiting his career expansion. Based on these two personas, Value Mapping revealed the following common issues: *"The one-way structure that does not provide reasons for recommendations hinders users' willingness to explore and their trust"*

Simply listing jobs does not alleviate users' anxiety and doubts during the job search process; rather, it can make them feel that the system is limiting them. Based on this recognition, this project reset its design goals to restore user trust and expand their motivation to explore through interactive structure design centered on explainability.

3.3 Interface Design and Iterative Experimentation

Based on the value-based problem definition derived, an interface design and prototype implementation centered on explanatory functions were carried out. The initial design was a simple list of recommended results, but the functions and information structure were adjusted through iterative user interviews and usability tests. During this process, a fundamental shift in perspective occurred: while the initial goal was to provide accurate recommendations, the focus gradually shifted to the idea that "understanding the reasons behind recommendations" was more essential to building user trust.

Users who activated the extension were first guided through a step-by-step onboarding that introduced the concept of algorithmic self and how they could inspect or intervene in the recommendation process. This guided exploration helped demystify the algorithm's logic, especially for users with less technical familiarity. Additionally, the integration of a feedback input field in context—placed directly next to each recommendation—encouraged real-time reflections from users without interrupting their job search flow.

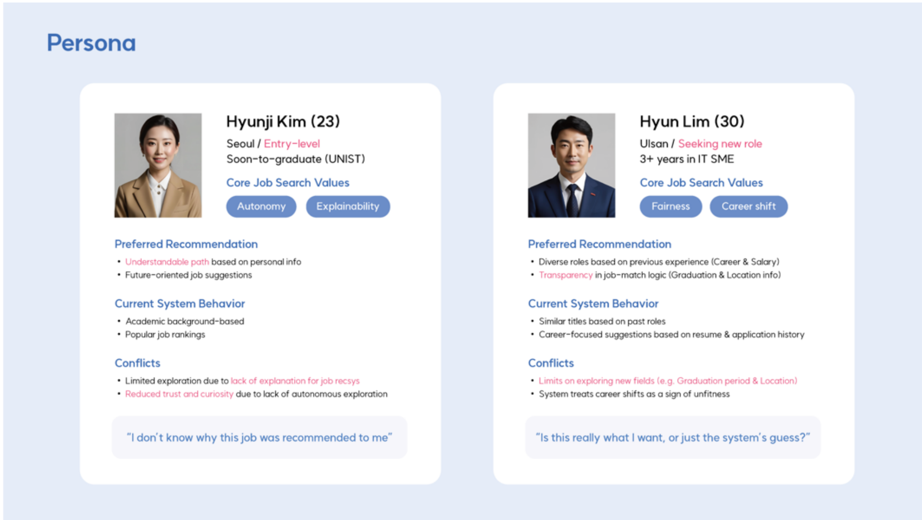

Figure 1: Persona Sheet

3.4 Implemented explanation function

The following explanation functions were structurally integrated into the final design of the system:

3.4.1 What-if Reasoning

This function allows users to actively adjust their choices by showing them a real-time simulation of how their recommendations would change if they modified their input values (e.g., desired job, location, career, etc.).
Example: Changing the region from "Ulsan" to 'Seoul' causes "Planning Position" to appear instead of "Field Operations Position," allowing users to visually recognize how the recommendation criteria have changed.

3.4.2 Category-based Feedback

For each recommendation result, the system provides information on the conditions (e.g., major match rate, career suitability, location matching, etc.) based on which the recommendation was made.
Example: An explanation such as "This job was recommended based on the user's major (design) and project experience within the past year" is provided.

3.4.3 Job Details Provision

Rather than simply listing job titles, the system provides information such as the skills required for the job, average tenure, and profiles of users who selected similar positions, helping users make informed decisions about the job.

3.4.4 Key Findings and Implications

Key insights confirmed through this experiment are as follows: Explainability is not simply an additional feature, but a psychological safety mechanism and a core design element that helps users trust the system and make choices appropriate to their situation. In particular, in situations of high anxiety or uncertainty, a simple line of explanation can be a deciding factor in whether users continue their search.

Therefore, this project emphasizes that the structural integration of explanatory functions in a job recommendation system is not optional but essential, and suggests that the system's role in understanding user context and communicating accordingly is more important than mere technical accuracy.

4 CONCEPTUAL DESIGN

4.1 Overview of Final Concept

We designed a Chrome extension-based job recommendation interpretation interface that enables users to actively select and interpret the factors they consider important in job recommendations. This system aims to promote transparency and explainability in AI systems, while addressing users' uncertainty and mistrust through a human-centered design approach. Rather than merely delivering recommendation results, our goal was to provide users with a more interpretable and controllable experience where they can actively engage with the algorithm's reasoning.

4.2 Design Problem and Consideration

Existing job recommendation systems often fail to provide clear explanations for why a particular recommendation is made, offering **little to no room for user intervention**. This lack of transparency raises questions such as, *"Would the recommendation have been different if this factor were excluded?"*, which reveals the need for **what-if reasoning**. To address this issue, we introduced the concept of an **algorithmic self**, and designed a structure that allows users to intervene in and interpret the recommendation process. This intervention goes beyond simple attribute editing; we implemented a **visual, interactive interface** that allows users to add, remove, or inspect factors contributing to the recommendation. Each factor's contribution can be understood through **hover- or click-based explanations**.

While existing explainable AI systems mostly rely on natural language explanations, our approach **visualizes internal vector representations of a GNN-based model**, and employs a **LLM to generate structured, user-friendly explanations** based on those internal data points. This dual-layer design enhances both structural transparency and user comprehension. To minimize technical constraints and preserve user flow, we implemented the system as a **Chrome extension** that overlays on existing platforms (e.g., LinkedIn). This allows for seamless integration without disrupting users' typical browsing behavior, while introducing explainability and controllability into the existing job-seeking interface.

Table 1: Summary of Design Problem, Consideration and Feature

Design Problem	Design Consideration	Feature Design
Lack of understanding and trust in recommendations	Need to visualize internal data and reasoning	GNN vector visualization + factor-level explanations
Mismatch between algorithmic self and user interpretation	Allow user intervention and editing	Editable "algorithmic self" profile
No way to revise or provide feedback on recommendations	Enable collaborative interpretation between system and user	Natural language prompt interface
Technical constraints in modifying existing platforms	Maintain extensibility and user flow	Chrome extension overlay UI

4.3 System Architecture and Flow

We developed two key user scenarios based on real-world personas and designed the system architecture accordingly. Users activate the Chrome extension on platforms like LinkedIn, where it reads job post content and provides a checklist of user-selectable attributes relevant to the position.

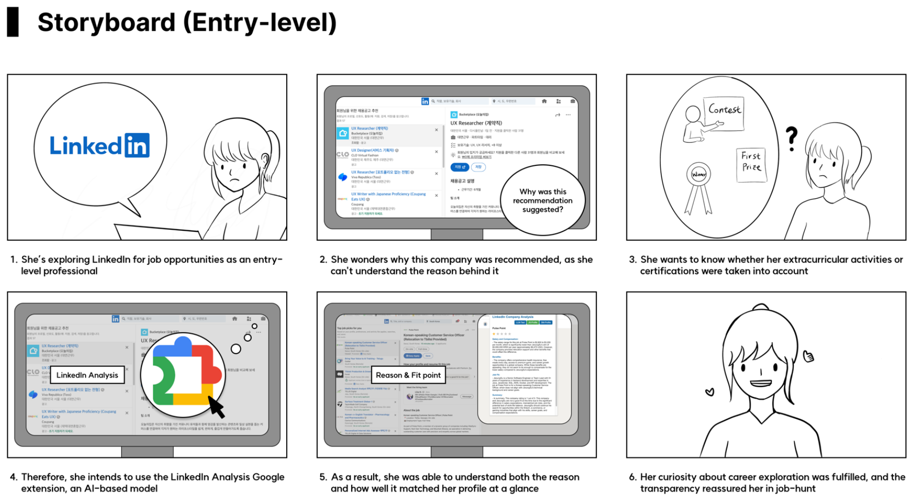

Figure 2: Storyboard of User Scenario (Entry-level)

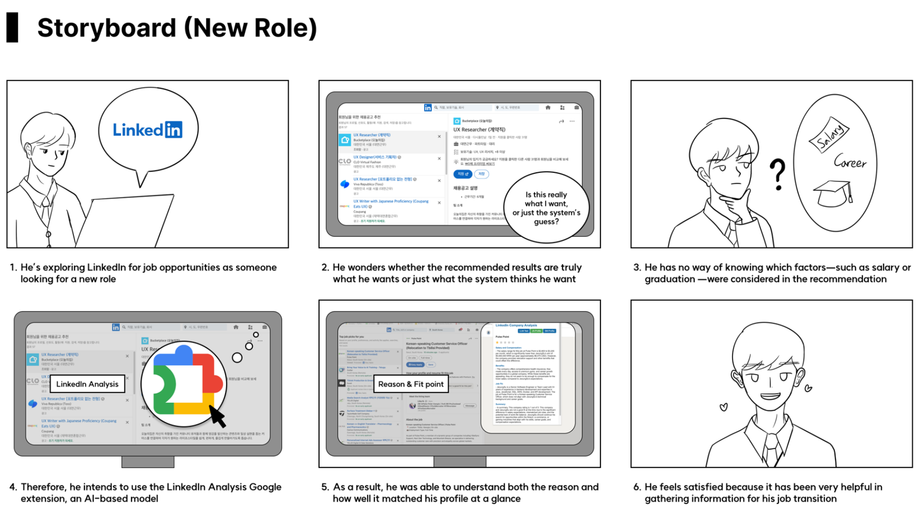

Figure 3: Storyboard of User Scenario (New Role)

After users select the attributes they care about, the system uses an LLM to generate individual factor-level scores and explanations. Company information is also analyzed by the LLM and presented as part of the result. In the future, this can be enhanced through real-time data crawling to improve the credibility and richness of explanations.

Additionally, users are encouraged to submit feedback on the recommendations. These responses are stored in a mock database and can be used to iteratively improve the system. This feedback loop not only enhances usability but also embodies a participatory design approach by including users in the refinement of the recommendation process.

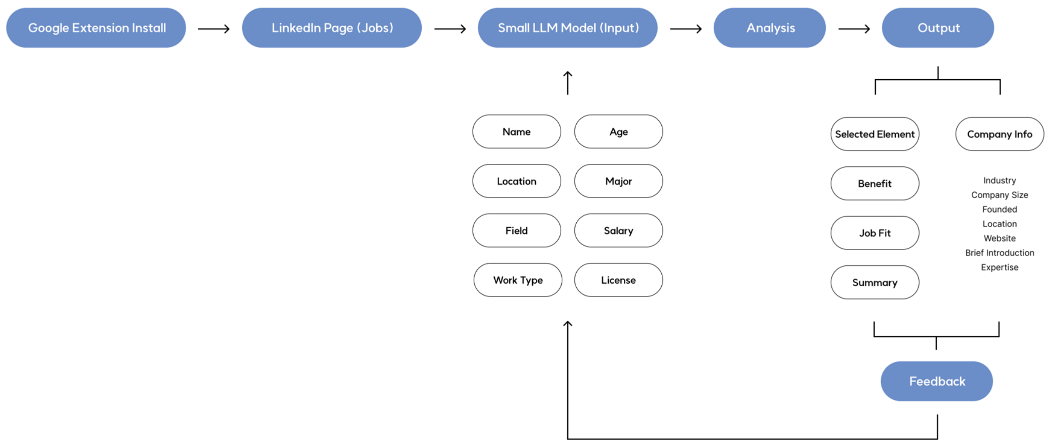

Figure 4: Flow Diagram

4.4 Transparency and Mechanism

The system enables users to intervene in three key ways. First, editing visualized recommendation components, allowing users to directly modify and understand the reasoning behind the results. Second, receiving LLM-generated explanations and scores that serve as digestible summaries of complex model outputs—functioning like a mentor providing insight. Finally, submitting direct feedback on recommendation outputs, enabling users to feel like active participants rather than passive recipients. These mechanisms encourage user engagement, build trust in the system, and support reflective decision-making grounded in interpretable AI.

4.5 Insight from Observation and Interviews

Our design process was initially motivated by recurring user concerns, particularly the question: *"Why is this job being recommended to me?"* To address this, we conducted a series of exploratory interviews and prototype walkthroughs with potential target users.

Participants generally expressed positive expectations. One participant noted that the system was *"a helpful tool to try before actually consulting a mentor,"* highlighting the system's role as a preparatory or intermediate support. Another participant appreciated its integration with existing platforms, stating, *"It's convenient that I can use this on top of platforms I already use."*

However, we also identified several critical limitations through these engagements. Some participants pointed out the system's slow response time (e.g., *"The analysis takes too long"*), while others expressed lingering skepticism toward the AI-generated feedback, saying *"I feel like I still need to verify what the AI is saying."* Another common critique was the lack of detailed breakdowns: *"I only get the overall score—it lacks fine-grained insights."*

In response to these findings, we emphasized improvements such as factor-level scoring, the ability to toggle individual attributes, and clearer feedback submission pathways. Despite these efforts, technical constraints—particularly related to processing time—remain and will require further iteration.

4.6 Comparing Early and Final Concepts

Our initial prototype was limited to extracting and displaying information from job postings in LinkedIn. While it maintained an LLM-based structure, the way results were presented, the speed of the system, and the extent of user involvement differed significantly from the final version. Through simulated user interviews and iterative feedback, we gradually refined the system.

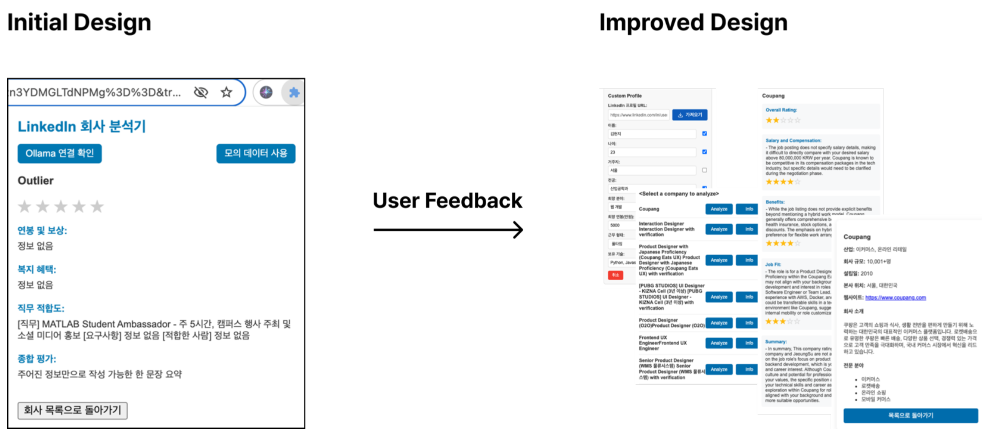

Figure 5: Initial Design and Improved Design

Table 2: Comparison for Early and Final Design

Design Aspect	Early Design	Final Design	Reason for Change
Recommendation Mechanism	Simple job-based auto-recommendation	User-driven factor selection interface	To increase transparency and user agency
Score Representation	Overall score only	Partial scores with overall average	User desired more detailed, interpretable evaluation
Feedback Function	Not available	Feedback input section storing user comments	Users wanted a way to contribute and respond
Company information	Not provided	LLM-analyzed company summaries, with future scraping potential	Users wanted company context to make informed decisions

4.6.1 A More Transparent, User-Driven Recommendation Structure

The core goal of our project was to alleviate user anxiety by introducing explainable AI. The early version provided only a basic recommendation based on job descriptions. However, we later developed a user-driven selection mechanism that allowed users to actively choose the factors they wanted to include in the recommendation. This greatly improved the system's transparency and interpretability.

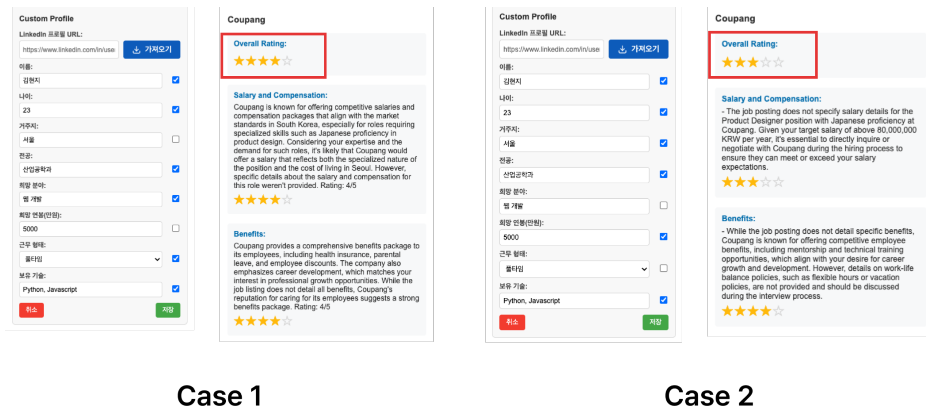

Figure 6: User-Driven Factor Recommendation

4.6.2 Partial Score

User interviews revealed a recurring issue: users found it insufficient to receive only an overall score. In response, we implemented individual scores for each evaluation attribute, with the overall rating calculated as an average. This change made the system more intuitive and aligned with user expectations compared to the original design.

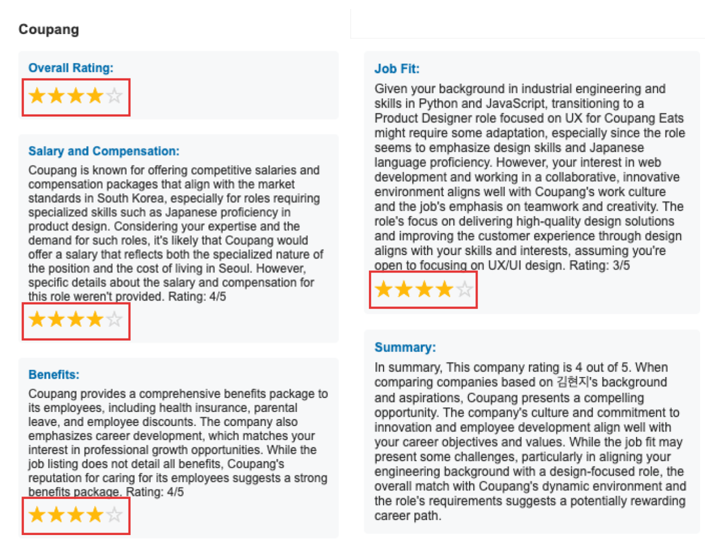

Figure 7: Partial Score

4.6.3 Feedback Input Section

During development, users expressed the need for a way to submit feedback. To address this, we added a feedback input section, allowing users to share their thoughts at any time. These submissions are stored in a mock database for future system improvements, aligning with a participatory design approach.

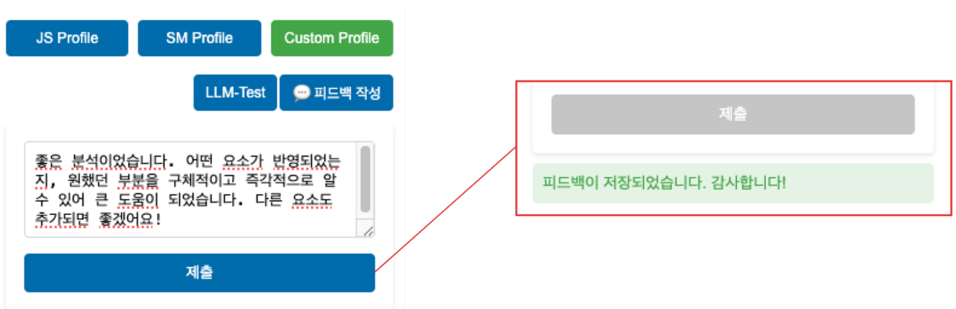

Figure 8: User Feedback

4.6.4 Company Information

Users ultimately wanted the ability to access and compare company information efficiently. The initial version lacked this functionality, but we improved the system to allow users to view **LLM-analyzed summaries of company profiles**. In the future, this feature could be enhanced with real-time data scraping or API integration, making the system feel more like a responsive mentor. In summary, our system evolved significantly through the integration of user feedback, moving from a passive recommendation tool to a **more human-centered, explainable, and interactive interface**.

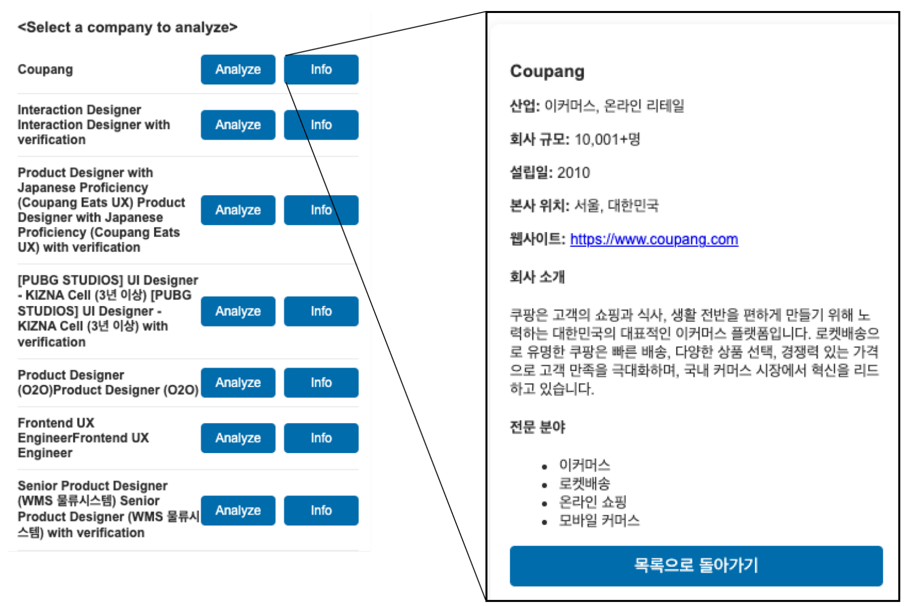

Figure 9: Company Information

5 IMPLICATIONS & REFLECTION

5.1 Impact of Explainability on User Emotions and Cognition

Career recommendations have a profound impact on individuals' paths and identities, and when the results of recommendations are opaque, users easily feel anxiety and self-doubt. In this project, integrating explainability features clarified the context and criteria of recommendations, alleviating users' psychological uncertainty and increasing their sense of self-determination and willingness to explore the future.

In particular, What-if Reasoning, which visually demonstrates that recommendations are generated based on user input, helped users understand and adjust how the system interprets them. This signifies a shift from merely displaying results to a structure where users actively participate as interpretive agents alongside the system. One participant described the system as *"a lightweight exploration tool that can be used before asking a real mentor,"* demonstrating that explainability can serve as a foundation for psychological acceptance beyond cognitive understanding.

5.2 Transition from Technology-centric Explanation to Human-centric Communication

Previous explainability studies have focused on technology-centric approaches, such as GNNExplainer [2], which debug model structures or visualize internal operations. However, this project goes beyond that, redefining the explanation function as communication that considers the social relationship and emotional context between users and systems.

This is based on the recognition that, as Auernhammer [4] argues, explanations should not merely be about "providing information" but should serve as a communication tool that mediates the power, value, and trust relationships between the system and the user. Additionally, by leveraging LLM-based natural language explanations, as in PEPLER [3], we were able to provide users with feedback that is emotionally persuasive beyond cognitive explanations.

This approach aligns with the HCI context, as proposed by Xu et al. [5], which considers AI as a "designable partner" and promotes collaborative interaction with users. Ultimately, explainability has expanded from a "function that enables understanding" to a "structure that enables acceptance."

Explainability is more than just showing how a system makes decisions—it also gives users a chance to understand how they are being seen by the system. In services like job recommendations, where the outcome can feel personal, users often interpret the results as a reflection of who they are or what they're capable of.

In our system, features like editable inputs and What-if simulations allowed users to explore how the system was interpreting them and what would happen if that interpretation changed. Rather than simply accepting the results, users could experience moments like, *"So this is how I'm being viewed,"* or *"If I adjust this, something different is recommended."* This made the interaction more active and personal. In this way, explainability becomes more than just a technical function—it becomes a kind of conversation between the user and the system, helping people reflect on and even reshape how they're represented by algorithms.

5.3 Contribution to User-centered Human-centered AI Design

This system was designed to allow users to directly view and modify the attributes that serve as the basis for recommendations, transforming the existing one-way recommendation structure into a two-way participatory structure. Users could participate as active agents who construct and modify their own "algorithmic self" rather than passively accepting it.

Users can participate as subjects who can confirm how the system interprets them and directly intervene in or modify that interpretation. This structure differs from text-based explanation systems that simply list results, as it is a participatory design approach centered on the user's values and context. This reflects an attempt to understand explainability from the perspectives of Value-Sensitive Design and Speculative Design as a value-centered interaction process rather than a technical function.

By implementing a method that provides explanations within the context without compromising existing platforms through the Chrome extension format, non-intrusive and practical interventions became possible within users' everyday browsing environments.

5.4 Design Tensions and Future Considerations

However, explainability did not always have positive effects. Some users felt that the system took too long to analyze information and present results, and even after reviewing the results, they still found it difficult to clearly understand which elements were problematic. Such responses suggest that while explanation features serve the role of providing information, they can sometimes exacerbate users' cognitive load due to excessive information volume or unclear expressions. Therefore, it is necessary to refine information design strategies that minimize user fatigue while effectively conveying core messages.

Additionally, while LLM-based explanations offer flexibility, their limitations include ambiguous criteria for evaluating accuracy and reliability. In the future, it will be necessary to establish a systematic evaluation framework that incorporates not only qualitative user feedback but also quantitative and psychological indicators (e.g., reduced anxiety, perceived autonomy).

Finally, while this system was designed as a Chrome extension, offering high accessibility and integration, technical challenges and usability considerations remain in terms of scalability for large-scale recommendation platforms.

6 CONCLUSION

This project structurally integrated explanation features into a job recommendation system to enhance user trust, autonomy, and exploratory behavior. Designed to go beyond mere information display, the interface helped users emotionally engage with recommendations and support self-determined decisions—highlighting the potential for explainability as a psychological design element.

The use of LLMs and iterative feedback processes contributed meaningfully to building a user-friendly system within limited resources. Features like the feedback box and job info views were directly shaped by user input, demonstrating the feasibility of human-centered design. However, due to resource constraints, synthetic data explanations could not be fully implemented, limiting quantitative analysis of diversity and reliability. Future work should address this with improved data-driven modeling and scenario design.

In sum, this project marks an experimental starting point for investigating how explainability in job recommendation systems may influence emotional reception and self-efficacy. We hope future studies will further examine the link between user affect and explanation-centered AI design, expanding the potential of human-centered AI.

Building on this foundation, we envision that such explainable systems could be extended beyond job recommendation into domains such as educational guidance, career counseling, or personalized learning pathways. By transforming explainability into a narrative and dialogic structure, future systems may evolve into interactive mentors—supporting not only informed choices but also self-reflection and identity development over time.

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