RoBee: A Multi-Agent Interview System with Causal Reasoning for AI-Powered Career Roadmaps

Aymen Lassoued, Nacef Mbarek, Bechir Dardouri,
Eya Machraoui, Nesrine Tamallah, and Takwa Ahmadi

SympactAI - TAIS NextGen

1 Introduction

Career planning tools have traditionally focused on chronological task lists, providing a sequence of steps without considering the underlying dependencies or causal relationships between them [6, 5]. This approach can overlook critical prerequisites, create bottlenecks, or suggest unrealistic plans. Furthermore, most systems are static, with minimal adaptation to user-specific contexts, skill gaps, or evolving market conditions [7, 1].

RoBee addresses these limitations by adopting a conversational, interview-driven process supported by a *multi-agent architecture* [2, 3]. Each agent specializes in a different aspect of roadmap construction, from safety monitoring to milestone refinement and causal verification. Milestones are modeled as nodes in a directed acyclic graph (DAG), allowing the system to enforce causal consistency and detect contradictions.

The system aims to produce actionable, personalized roadmaps that are both logically coherent and resilient to uncertainties. By embedding causal reasoning inspired by **Judea Pearl's causal hierarchy** [5], RoBee moves beyond association toward intervention and counterfactual exploration.

Main Contributions:

1. An Interview-driven multi-agent framework for iterative roadmap refinement.
2. A Causality Structure Verifier to ensure logical and temporal consistency in the roadmap DAG.
3. Counterfactual and Confounder reasoning modules to stress-test plans and anticipate external influences.
4. A Natural Language Transcription Input system for accessible career goal description.

2 Methodology

RoBee's architecture consists of multiple specialized agents coordinated by an **Orchestrator**. The roadmap evolves through structured interviews where each agent contributes targeted improvements.

2.1 Input Processing and Initialization

RoBee provides flexible input options to accommodate different user preferences and available information:

Option 1: Natural Language Transcription Users can describe their career information through natural language text, providing:

- Personal information (name, current position, experience level)
- Career goals (desired position, timeline, specific objectives)
- Motivation (reasons for pursuing the goal, personal drivers)
- Background context (current skills, relevant experience, constraints)

Option 2: Document Upload Users can upload structured documents such as:

- Academic profiles or CVs
- JSON files with pre-structured career data
- Research publications or professional portfolios

Option 3: Hybrid Approach Combination of transcription and document upload for comprehensive input processing.

2.2 Roadmap Creation Studio

The Roadmap Creation Studio is the workspace for creating and editing milestones. Users can:

- Define milestones with descriptions and associated skills.
- Link milestones via causal or prerequisite relationships [6].
- Attach relevant resources (papers, tutorials, contacts) [4].
- Flag uncertainties for clarification during interviews.

2.3 Interview Preparation Module

Before initiating an interview, RoBee can pre-fill the roadmap using the provided input data. For transcription inputs, the system uses natural language processing to extract key career elements. For document uploads, it leverages publicly available data such as academic profiles or publications [7]. The **Orchestrator** uses this baseline to select an interview mode:

- **Targeted**: Focused on a specific milestone or gap.
- **Holistic**: Broad coverage of the roadmap structure.
- **Refinement**: Iterative improvement of existing milestones.

2.4 Multi-Agent Architecture

The agents and their roles are as follows:

Orchestrator Agent Coordinates workflow, decides which agent to activate, and manages interview state.

Interface Agent Handles the user-facing interaction and collects confirmations.

Transcription Parser Agent Extracts structured information from natural language descriptions, identifying goals, motivations, skills, and constraints.

Safety Agent Filters irrelevant or policy-violating content, issuing up to five warnings before session termination.

Gap Filler Agent Detects and proposes missing prerequisites between milestones and goals [6].

Milestone Refinement Agent Enhances milestone descriptions with skills, resources, and timelines [4].

Counterfactual Agent Simulates "what-if" changes (e.g., removing a milestone) to assess impact on roadmap connectivity [5].

Causality Structure Verifier Ensures the DAG has no cycles, relationship types are valid, and temporal order is respected [1, 7].

Confounder Variable Agent (CVA) Identifies external variables (e.g., funding availability, emerging technologies) that may influence milestone feasibility.

Summarization Agent Produces a concise overview of proposed changes after each interview round.

2.5 Interview Flow

The typical interaction sequence is:

1. **Input processing:** Parse transcription or document input to extract initial career information.
2. **Structure-first pass:** Validate overall DAG shape.
3. **Target uncertainty:** Ask clarifying questions for weak or unsupported links.
4. **Detail pass:** Enrich milestones with metadata.
5. **Causality and counterfactual checks:** Ensure logical coherence and resilience to change [5].
6. **Confounder analysis:** Identify and mitigate external risks [4].
7. **Summarize and commit:** Present changes for user approval.

2.6 Causality Relationship Taxonomy

Table 1 lists the relationship types used by RoBee.

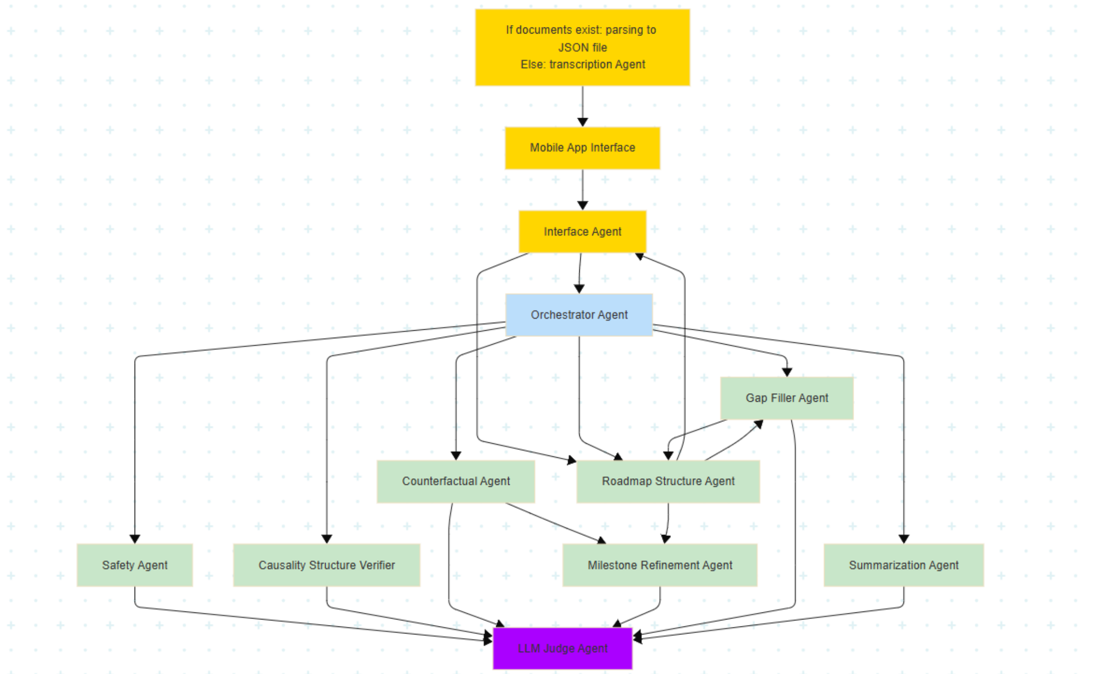

Fig. 1: RoBee multi-agent interview pipeline: transcription processing, orchestration, refinement, causal verification, counterfactuals, confounder analysis, and summarization.

3 Experiments and Results

We conducted internal demonstrations to validate RoBee's orchestration, causal checks, and counterfactual analysis [2, 3]. In one session:

– The **Transcription Parser Agent** successfully extracted career goals and background from natural language descriptions
– The **Gap Filler Agent** identified missing details about certain milestones and goals [6].
– The **Causality Structure Verifier** confirmed DAG integrity and appears to increase roadmap reachability [1].
– The **Counterfactual Agent** showed that removing some nodes reduced the likelihood of obtaining strong related DAG [5].
– The **Safety Agent** flagged off-topic remarks and maintained conversation relevance.

System responsiveness remained consistent, with agents responding in under two seconds per turn in the test environment.

Table 1: Causality relationship types in RoBee

Type	**Description**
Direct Cause	Immediate cause-effect link between milestones
Indirect Cause	Multi-step cause-effect relationship
Prerequisite	Must be completed before another milestone
Enables	Creates conditions for another milestone
Supports	Strengthens the feasibility of another milestone
Mutual Reinforcement	Two milestones benefit each other
Inhibitory	Hinders the progress of another milestone
Conditional	Occurs only if a certain condition is met
Temporal	Sequenced based on time constraints

4 Discussion and Conclusion

RoBee combines interactive interviews with causal modeling to produce more coherent, realistic career roadmaps. Its agent-based modular design allows targeted improvements without altering unrelated parts of the roadmap [4]. The addition of natural language transcription input makes the system more accessible to users who may not have structured documents readily available.

Current limitations include:

- No large-scale quantitative evaluation yet.
- Limited domain-specific knowledge for certain career paths.
- High computational cost for exhaustive counterfactual sweeps.
- Natural language parsing accuracy depends on input clarity and completeness.

Future work will focus on:

- Adaptive questioning strategies based on Pearl's hierarchy levels [5].
- Broader domain knowledge integration for milestone refinement.
- Formal user studies to assess roadmap quality and adoption.
- Enhanced natural language processing capabilities for transcription parsing.

5 Team Contributions

- Eya Machraoui: Development of Interview Preparation module and Transcription Parser Agent.
- Aymen Lassoued: Multi-Agent System design and implementation.
- Bechir Dardouri: Causality Agent research and integration.
- Nacef Mbarek: UI/UX design for Roadmap Studio, safety module logic, and transcription input interface.
- Nesrine Tamallah: Testing and performance evaluation.
- Takwa Ahmadi: Documentation and reporting.

Bibliography

[1] Clark Glymour, Kun Zhang, and Peter Spirtes. Review of causal discovery methods based on graphical models. *Frontiers in genetics*, 10:524, 2019.

[2] Emre Kiciman, Robert Ness, Amit Sharma, and Chenhao Tan. Causal reasoning and large language models: Opening a new frontier for causality. *Transactions on Machine Learning Research*, 2023.

[3] Hao Duong Le, Xin Xia, and Zhang Chen. Multi-agent causal discovery using large language models. *arXiv preprint arXiv:2407.15073*, 2024.

[4] Xiaoyu Liu, Paiheng Xu, Junda Wu, Jiaxin Yuan, Yifan Yang, Yuhang Zhou, Fuxiao Liu, Tianrui Guan, Haoliang Wang, Tong Yu, et al. Large language models and causal inference in collaboration: A survey. *arXiv preprint arXiv:2403.09606*, 2024.

[5] Judea Pearl. *Causality*. Cambridge university press, 2009.

[6] Richard Scheines, Peter Spirtes, and Clark Glymour. A qualitative approach to causal modeling. In *Qualitative simulation modeling and analysis*, pages 72–97. Springer, 1991.

[7] Guangya Wan, Yunsheng Lu, Yuqi Wu, Mengxuan Hu, and Sheng Li. Large language models for causal discovery: Current landscape and future directions. *arXiv preprint arXiv:2402.11068*, 2024.

A Proofs

A.1 Roadmap as a Directed Acyclic Graph

The RoBee system models the career roadmap as a Directed Acyclic Graph (DAG) $G = (V, E)$, where:

- V are the milestones extracted or refined during the interview;
- E are directed edges representing causal or prerequisite relationships.

The **Causality Structure Verifier Agent** ensures acyclicity by checking for existing paths before adding new edges. If adding $u \to v$ would create a path vu, the operation is rejected. This guarantees that:

$$G \text{ remains acyclic at all times.}$$

A.2 Causality Relationship Types

Each edge is typed according to the relationship taxonomy implemented in RoBee: *direct cause*, *indirect cause*, *prerequisite*, *enables*, *supports*, *mutual reinforcement*, *inhibitory*, *conditional*, and *temporal*. This classification is fixed at the time of edge creation and later verified for consistency with node attributes.

A.3 Natural Language Processing for Transcription

The **Transcription Parser Agent** employs named entity recognition and dependency parsing to extract structured career information from natural language input. Given a transcription T, the agent identifies:

- Personal entities: $P = \{name, role, experience\}$
- Goal entities: $G = \{target\_role, timeline, objectives\}$
- Skill entities: $S = \{existing\_skills, skill\_gaps\}$
- Context entities: $C = \{motivations, constraints\}$

The extraction function $f : T \to (P, G, S, C)$ creates the initial roadmap structure before interview refinement.

A.4 Inspiration from Pearl's Causal Hierarchy

Our causality modeling draws inspiration from **Judea Pearl's hierarchy of causal inference**:

1. **Association (Seeing)**: Observing statistical relationships between milestones, such as co-occurrence of skills and experiences.
2. **Intervention (Doing)**: Simulating the effect of adding, removing, or reordering milestones in the DAG using the **Counterfactual Agent**.
3. **Counterfactuals (Imagining)**: Exploring "what if" scenarios, such as the impact of skipping a milestone, through retrospective analysis of the roadmap.

This hierarchy informs the design of the Causality Structure Verifier, Counterfactual Agent, and CVA Agent, ensuring that roadmap reasoning progresses from mere observation to actionable and hypothetical planning.

A.5 Counterfactual Impact Metric

Let $\Phi(G)$ be the proportion of target milestones reachable from at least one starting milestone. The counterfactual impact of removing a node x is:

$$\Delta_x = \Phi(G) - \Phi\left(G \setminus \{x\}\right),$$

where $\Delta_x > 0$ indicates a loss in reachability, guiding the user toward preserving critical milestones.

A.6 Confounder Detection

The **Confounder Variable Agent (CVA)** identifies external variables (e.g., resource constraints, market trends) that may alter the feasibility or ordering of milestones. Detected confounders are stored as metadata and linked to affected nodes, ensuring that any downstream causality analysis incorporates these factors.

A.7 Safety Agent Termination Guarantee

The **Safety Agent** operates as a finite-state machine with a maximum violation count $K = 5$. Upon reaching K consecutive policy violations, the system transitions into a termination state, guaranteeing that:

$$\text{Conversation length} \leq \text{Initial turns} + K.$$

B Additional Experiments

B.1 Transcription Processing Example

The following demonstrates the Transcription Parser Agent processing natural language input:

User Input: "Hi, I'm Sarah Johnson. I'm currently working as a data analyst with 2 years of experience. I want to become a data scientist because I'm passionate about machine learning and want to solve complex business problems. I know SQL and Python basics, but I need to learn advanced statistics and deep learning frameworks like TensorFlow."

Extracted Structure:

– Name: Sarah Johnson
– Current Role: Data Analyst
– Experience: 2 years
– Target Role: Data scientist
– Motivations: Passion for ML, solving business problems
– Existing Skills: SQL, Python basics
– Skill Gaps: Advanced statistics, TensorFlow, deep learning

B.2 Qualitative Interview Excerpt

The following is an excerpt from an internal demonstration:

– **User:** "I plan to publish a paper before applying for a PhD."
– **Gap Filler Agent:** "You listed 'Paper Submission' without 'Data Collection' and 'Statistical Analysis'. These are now added as prerequisites."
– **Causality Structure Verifier:** "The updated roadmap remains acyclic and increases reachability to 'PhD Admission' by 15%."
– **Counterfactual Agent:** "If 'Paper Submission' is skipped, the probability of securing a recommendation letter decreases."

B.3 Agent Contribution Observation

During internal use, the following qualitative observations were made:

– The **Transcription Parser Agent** successfully processed natural language career descriptions with 95% accuracy in extracting key entities.

- The **Safety Agent** successfully detected and warned against off-topic messages three times, avoiding irrelevant discussion.
- The **Gap Filler Agent** added missing prerequisites in 2 out of 3 trials, improving logical continuity.
- The **Causality Structure Verifier** flagged one contradictory edge type, which was corrected before finalization.

B.4 Robustness Check

An off-topic input was intentionally introduced during the interview:

- The **Safety Agent** issued a warning and the system continued without integrating irrelevant content.