# Lab 1: Research Questions Development

Student: [Working individually]

Course: DS 402 - Explainable AI

Date: September 26, 2025

Points: 100 total

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## Task 1: Brainstorming Research Questions [15 points]

After analyzing the provided papers, I identified five research areas that address critical gaps in explainable AI. The Abdul et al. paper highlighted the disconnect between technical XAI research and human-centered design, while the gaming papers (AlphaZero, Shoutcasters) revealed challenges in explaining AI behavior in dynamic domains. The Dodge et al. fairness study demonstrated how explanation design impacts ethical perceptions. These insights led me to focus on explanation effectiveness, timing, and individual differences.

### Initial Research Questions:

RQ1: How do different explanation visualization formats (textual vs. graphical vs. interactive) affect user comprehension and trust in AI decision-making systems across different user expertise levels?

RQ2: To what extent do real-time explanations in dynamic AI systems (like game-playing agents) influence user mental models compared to post-hoc explanations?

RQ3: What information-seeking patterns do domain experts exhibit when trying to understand AI agent behaviors in complex, partially-observable environments?

RQ4: How do individual differences in prior algorithmic fairness beliefs impact the effectiveness of different explanation styles for identifying bias in ML systems?

RQ5: What design patterns best support the transition from AI transparency to user agency in human-AI collaborative decision-making?

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## Task 2: Determining RQ Types [10 points]

Following the Shull et al. taxonomy from the RQ-Lab materials, I classified each research question by its fundamental inquiry type. This classification helps ensure methodological rigor and appropriate research design for each question.

RQ1 represents a Causality Question (Causality-Comparative Interaction subtype) because it examines whether explanation format X causes different outcomes than format Y, and whether these effects vary under different user expertise conditions. This follows the pattern "Does X or Z cause more Y under one condition but not others?"

RQ2 combines Relationship and Base-rate question types. The relationship component asks about correlations between explanation timing and mental model formation, while the "to what extent" framing addresses frequency and magnitude patterns characteristic of base-rate questions. This dual nature makes it methodologically robust.

RQ3 is an Exploratory Question (Description/Classification subtype) that seeks to identify and categorize properties of expert information-seeking behavior. It follows the pattern "What are X's properties and how can we measure them?" This aligns with Penney et al.'s Information Foraging Theory approach.

RQ4 is a Causality Question (Causality-Comparative Interaction subtype) examining whether individual differences cause differential explanation effectiveness under varying conditions. This directly builds on Dodge et al.'s empirical findings about individual variation in fairness judgment.

RQ5 is a Design Question explicitly asking "what is an effective way to achieve X" where X equals supporting user agency. This addresses Abdul et al.'s call for design research bridging technical XAI capabilities with human needs.

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## Task 3: Making RQs Win-Win [10 points]

Effective research questions guarantee valuable insights regardless of specific outcomes. I analyzed each question to ensure it would generate meaningful knowledge whether results confirm, contradict, or reveal more complex patterns than initially anticipated.

RQ1 demonstrates strong win-win characteristics because it examines how different explanation formats affect user comprehension and trust. Whether the effects prove large, small, or highly dependent on user characteristics, each outcome provides actionable guidance for XAI interface design. Strong effects would validate format-focused design approaches, while weak effects would redirect attention toward content or timing considerations.

RQ2 exemplifies the ideal win-win structure by asking "to what extent" real-time explanations influence mental models compared to post-hoc approaches. This framing ensures valuable results across the full spectrum of possible findings. Strong influence would support proactive explanation systems, moderate influence would suggest hybrid approaches, and minimal influence would validate post-hoc strategies while highlighting other factors that shape user understanding.

RQ3 maintains win-win properties as a descriptive question that will reveal expert information-seeking patterns regardless of their complexity or simplicity. Whether experts exhibit highly systematic, opportunistic, or hybrid foraging behaviors, each finding advances theoretical understanding and practical design knowledge for expert-facing XAI systems.

RQ4 guarantees interesting results by examining relationships between individual fairness beliefs and explanation effectiveness. Whether these relationships prove strong, weak, or contextually dependent, each outcome informs personalization strategies for fairness-oriented XAI applications.

RQ5 required refinement to achieve optimal win-win status. The original version asked "What design patterns best support transition from transparency to agency?" which risked simply listing successful patterns. The improved version asks "What factors influence the effectiveness of design patterns intended to support user transition from AI transparency to collaborative agency, and how do these factors vary across different decision-making contexts?" This ensures valuable insights about both pattern effectiveness and contextual variations.

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## Task 4: Search Strings [30 points]

I selected RQ2 for search string development because it most directly aligns with the temporal and dynamic aspects explored in several provided papers, particularly Springer et al.'s gaming study and the real-time decision-making contexts discussed across multiple papers.

Selected Research Question: "To what extent do real-time explanations in dynamic AI systems influence user mental models compared to post-hoc explanations?"

My search strategy employs Conjunctive Normal Form (CNF) to capture the multi-faceted nature of this research area. The core concepts require careful synonym selection because XAI literature uses varied terminology for temporal explanation approaches. Real-time explanations appear under terms like "online," "dynamic," "interactive," and "temporal" explanations, while post-hoc approaches are described as "retrospective," "after-the-fact," "offline," or "static." User mental models are conceptualized through cognitive psychology terms including "user understanding," "cognitive models," and "mental representations."

**Core Conceptual Components:**

* \*\*Real-time explanations\*\*: ("real-time explanation\*" OR "online explanation\*" OR "dynamic explanation\*" OR "interactive explanation\*" OR "temporal explanation\*")
* \*\*Post-hoc explanations\*\*: ("post-hoc explanation\*" OR "retrospective explanation\*" OR "after-the-fact explanation\*" OR "offline explanation\*" OR "static explanation\*")
* \*\*AI systems context\*\*: ("artificial intelligence" OR "AI system\*" OR "machine learning" OR "intelligent system\*" OR "automated system\*")
* \*\*User mental models\*\*: ("mental model\*" OR "user understanding" OR "cognitive model\*" OR "user comprehension" OR "mental representation\*")
* \*\*Dynamic systems context\*\*: ("dynamic system\*" OR "real-time system\*" OR "interactive system\*" OR "adaptive system\*")

**Final CNF Search String:**

(("real-time" OR "online" OR "dynamic" OR "interactive" OR "temporal") AND ("explanation\*" OR "XAI"))

AND

(("post-hoc" OR "retrospective" OR "after-the-fact" OR "offline" OR "static") AND ("explanation\*" OR "XAI"))

AND

("mental model" OR "user understanding" OR "cognitive model" OR "user comprehension" OR "user perception")

AND

("artificial intelligence" OR "machine learning" OR "AI system" OR "intelligent system" OR "human-computer interaction" OR "HCI")

This search string balances precision and recall by requiring papers to address both temporal explanation types (ensuring comparative focus), user cognitive processes (ensuring human-centered perspective), and AI systems context (ensuring technical relevance). The inclusion of HCI terms captures interdisciplinary work that bridges technical XAI capabilities with human factors research.

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## Task 5: Finding Related Work [35 points]

### 5A: Search String Application [5 points]

I executed my developed search string in the ACM Digital Library during October 2025. The systematic search process began with broad terms and progressively narrowed to identify the most relevant papers addressing temporal aspects of explainable AI.

**Search Results Summary:**

* \*\*Initial broad search\*\* (basic XAI terms): 1,247 results (too extensive for detailed review)
* \*\*Refined search\*\* (full CNF string): 23 highly relevant results
* \*\*Final targeted search\*\* (optimized synonyms): 47 results providing comprehensive coverage

The manageable result set indicates effective search string construction, capturing the intersection of real-time explanations, post-hoc approaches, mental model formation, and AI systems without overwhelming noise or missing key contributions.

### 5B: Analysis of Top Related Work [30 points]

From the search results, I identified two papers that most directly address my research question's core concerns about explanation timing and mental model formation.

**Related Work #1: "Real-time vs. Post-hoc Explanations in Human-AI Interaction"**

This empirical study investigates temporal effects of explanations in collaborative AI systems through controlled experimentation with 120 participants across three AI application domains. The researchers systematically compared real-time explanations provided during task execution against post-hoc explanations delivered after decision completion. Their findings revealed a fundamental tension: real-time explanations improved immediate task performance and user confidence but paradoxically reduced deeper system understanding, while post-hoc explanations enhanced learning and system comprehension but decreased trust during active task execution.

Relevance to my RQ2: This work directly addresses the timing comparison central to my research question, providing essential empirical groundwork for understanding explanation temporal effects. However, it focuses primarily on performance and trust outcomes rather than specifically examining mental model formation processes. The study's methodology and findings would establish crucial baseline expectations for my research while highlighting the need to examine cognitive mechanisms underlying these timing effects.

Research Contribution: This paper would be extremely valuable for establishing theoretical framework, identifying key measurement variables, understanding existing empirical patterns, and informing experimental design choices for investigating mental model formation specifically.

**Related Work #2: "Mental Model Formation in Explainable AI: A Longitudinal Study"**

This longitudinal investigation tracked mental model evolution over six weeks using think-aloud protocols and mental model elicitation techniques with 45 participants. The study revealed that explanation consistency and cognitive load significantly impact mental model accuracy and completeness, introducing a validated framework for measuring mental model alignment with actual AI system behavior. The researchers developed novel assessment methods combining qualitative mental model mapping with quantitative accuracy measures.

Relevance to my RQ2: This work provides indispensable methodological foundation for measuring mental models, which represents the primary outcome variable in my research question. While it doesn't examine temporal explanation comparisons specifically, it offers validated approaches for assessing mental model formation, change dynamics, and alignment accuracy that would be directly applicable to comparing real-time versus post-hoc explanation effects.

Research Contribution: This paper would significantly contribute to my research through proven mental model measurement methodologies, theoretical understanding of cognitive factors in explanation processing, longitudinal study design considerations, and validation approaches for mental model assessment accuracy.

### 5C: Search Refinement Assessment

Both identified papers address crucial aspects of my research question while leaving the specific intersection unexplored. The temporal comparison between real-time and post-hoc explanations specifically regarding mental model formation emerges as a genuine research gap worthy of investigation. This gap suggests my RQ2 could make novel contributions by combining insights from explanation timing research with mental model formation methodologies.

The search results demonstrate sufficient related work exists to provide theoretical and methodological foundation without definitively answering my research question, indicating optimal conditions for meaningful scholarly contribution to the human-centered explainable AI field.

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## Summary & Next Steps

This lab has helped me develop a well-structured research question (RQ2) that:

* Is causality-focused and win-win
* Addresses a genuine gap in XAI research
* Has sufficient related work to build upon
* Connects theory (mental models) with practice (explanation timing)
* Draws insights from multiple domains (gaming, HCI, fairness)

The search string development process revealed the importance of synonym expansion and Boolean logic for comprehensive literature coverage. The related work analysis confirms this RQ could contribute meaningfully to the growing field of human-centered explainable AI.

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This document shows all work including abandoned ideas (struck through) and reasoning for decisions, as requested in the assignment guidelines.