From Classroom to Career: Shedding Light on Graduate Employment Experiences Through The Free Energy Principle and Collective Intelligence

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Abstract

This exploratory dissertation creates and applies a **non-computational adaptation of the Free Energy Principle (FEP) and Collective Intelligence (CI)** to develop a scalable methodological framework **(the FEP–CI framework)** for analyzing science-technology-policy employment gaps. The research explores whether core concepts from FEP and CI can serve as useful principles for understanding employment system failures. Rather than claiming proven efficacy, it establishes a theoretical and conceptual foundation for future empirical and computational validation. Using the transition of students and graduates from study to workforce as a "sandbox," it frames labor policy as an opportunity to test inclusive, iterative decision-making. The study includes a comprehensive literature review evaluating academic sources on traditional employment theories, FEP and CI to identify their analytical limitations, and assess the relevance and capacity of FEP and CI to address these gaps in employment policy analysis. Based on this analysis, I developed the FEP-CI framework. To empirically test the framework, I examined employment experiences of 22 students and alumni from science-technology-policy programs using the platform-based narrative collection tool SenseMaker®.

1. Introduction

This research is motivated by the dissatisfaction with current policies and frameworks applied to complex societal challenges. The research focuses on employment policy due to its profound impact on human well-being, a fundamental determinant of quality of life, influencing financial security and physical and mental health. The employment system is at a critical juncture with rapid technological transformation, yet there's a clear scholarly deficit in novel frameworks addressing its systemic issues. This work hopes to fill this void by applying a new exploratory and methodological lens to improve this critical policy area.

1.1 Problem Statement

Policymaking is inherently complex, shaped by uncertainty, conflicting values, and persistent implementation barriers. Traditional top-down approaches frequently fail by attempting to control society, a complex adaptive system, from the outside (Rittel and Webber, 1973)(B. W. Head & Alford, 2015). Decisions are often made with incomplete information in dynamic contexts, while many issues lack consensus or clear definition, producing incremental rather than transformative change. Even well-designed policies falter due to resource constraints, political compromise, or stakeholder resistance and ongoing "wicked problems"(Rittel and Webber, 1973)(B. W. Head & Alford, 2015). "Wicked problems"are characterized by inherent complexity and resistance to traditional solutions. (Rittel and Webber, 1973)(B. W. Head & Alford, 2015). The rise of AI and other advanced technologies further intensifies these challenges, introducing algorithmic bias, privacy risks, economic disruption, and misinformation. Policymakers must therefore manage accelerating complexity while safeguarding transparency, accountability, and rights. Without a viable path forward based on ethical innovation, participatory governance, and international cooperation, technology will deepen inequality instead of serving the public good. Without proactive adaptation, labor market disruption will persist, leaving vulnerable communities behind.

1.2 Study Objective

This exploratory study examines whether FEP-CI concepts provide a robust foundation for analyzing and understanding employment problems and behaviors. This framework provides the conceptual foundation and testable hypotheses required before a full mathematical implementation. Employing an abductive methodology that integrates theory-driven and data-driven approaches, the research simultaneously tests framework applicability and identifies emergent patterns that extend theoretical understanding. Through micro-narrative collection, participants may contribute to reducing systemic uncertainty and potentially align stakeholder expectations across the employment ecosystem. The FEP-CI framework could emerge as a valuable lens for anticipatory governance, potentially offering a scalable methodological approach to address graduate underemployment and enhance job-readiness. By democratizing knowledge creation and and eventually involving all ecosystem actors will allow this model to support truly dynamic policy design

The dissertation contributes in three ways: theoretically, by applying FEP and CI concepts to understand misalignments between education and labor markets; methodologically, by creating a structured framework that integrates narrative and computational insights; and practically, by offering evidence-based recommendations to improve curriculum design and align educational preparation with employment realities and setting up the framework to be reworked computationally in future research.

1.3 Research Questions and Contributions

Primary Research Question

Can a non-computational framework grounded in the concepts of the Free Energy Principle (FEP) and Collective Intelligence (CI) reveal consistent patterns of conflict between (STEM/Policy) students and graduate's job market expectations and their actual employment experiences?

Central hypothesis

≥ 70% of students and graduates' narratives will show a negative prediction error (expectation–reality mismatches and feedback failures) indicating these are systemic problems rather than isolated individual experiences.

1.4 Alignment with the STEaPP MPA Mission and Curriculum

Applying and analyzing FEP and CI in the science-technology-policy employment ecosystem closely aligns with the core objectives of the STEaPP MPA program. This project explores integrating real-time stakeholder lived experiences to address socio-technical challenges, discussed in the program. This project develops actionable frameworks to evaluate employment policy. The approach maps onto modules such as Evidence for Decision Making, Analytical Methods for Policy, and Policy Making & Public Administration, while contributing a systems-level perspective. Methods like participatory sense-making operationalize an inclusive, dynamic, and human-centered framework, reflecting STEaPP's interdisciplinary and practice-oriented ethos(Digital Technologies and Policy MPA, 2025).

2. Literature Review

The literature review synthesizes and critically evaluates academic sources on traditional employment theories to identify their analytical limitations, and to assess the relevance and capacity of FEP and CI to address these gaps in employment policy analysis. The review further outlines the conceptual strengths and limitations of applying adaptive systems methodologies to this policy domain and specifies the core requirements such methodologies must satisfy to produce valid and meaningful data.

2.1 The Free Energy Principle

The Free Energy Principle, introduced by Karl Friston (2006; 2010; 2023), is a foundational theory in computational neuroscience that provides a unifying framework for understanding how complex adaptive systems maintain their integrity over time by minimizing prediction error, or "surprise." Friston's early work, particularly his 2010 paper in Nature Reviews Neuroscience, established FEP as a comprehensive theory of the brain, showing how biological systems resist disorder by continuously updating internal generative models. This work built on earlier mathematical formulations by Friston, Kilner, and Harrison (2006) that explained how perception and action jointly serve to minimize free energy. More recently, Friston et al. (2023) simplified and clarified the theory in "The free energy principle made simpler but not too simple," demonstrating that any system that maintains a persistent identity, whether cellular, cognitive, or social, must minimize free energy as a condition of continued existence (Friston et al., 2023). The FEP consists of several interconnected components that explain how systems maintain organization. The main components of FEP are:

- **Variational Free Energy Minimization**
  The mathematical core: $F = E[\log q(s) - \log p(s,o)]$. Systems minimize divergence between internal models (q) and external states (p) (Friston, 2010). In employment, this means reducing gaps between career expectations and market realities.
- **Predictive Processing Hierarchy**
  Prediction and error correction work hierarchically (Clark, 2013). In employment, institutional policies predict graduate outcomes, but only failures (e.g., unemployment) feed back to drive policy change.
- **Active Inference**
  Agents adapt by both updating beliefs and acting to align reality with predictions (Friston et al., 2017). Graduates may pursue extra certifications to meet employer demands.
- **Markov Blankets**
  Boundaries maintain system integrity while shaping interaction (Kirchhoff et al., 2018). In employment, credentials act as boundaries determining access to opportunities.
- **Precision Weighting**
  Systems weigh some errors more than others (Feldman & Friston, 2010). Students may assign high precision to university career advice but discount peer input, influencing adaptation.

2.2 Collective Intelligence

Collective Intelligence (CI) is the group-level capacity that emerges when people collaborate to solve problems beyond individual ability (Woolley et al., 2010; (Dellarocas, 2010)(Woolley, Aggarwal and Malone, 2015). Foundational work by Woolley et al. (2010) identified a measurable "c" factor that predicts team performance more accurately than individual intelligence. CI means that groups can often outperform individuals, not simply by pooling smart people, but through the quality of their interactions. CI emerges when members listen, share ideas, and collaborate effectively, with diverse perspectives and balanced participation driving stronger outcomes. (Janssens, Meslec and Leenders, 2022), Woolley et al. (2010) Malone, T. W., & Bernstein, M. S. (2015)found that high CI correlates with three key factors: social perceptiveness, equal conversational turn-taking, and gender diversity (mediated by social sensitivity). The main components of CI are:

- **C-Factor**: Groups exhibit measurable collective intelligence independent of individual ability, predicted by social sensitivity ($r=0.26$), conversational turn-taking equality ($r=0.41$), and female proportion ($r=0.23$) (Woolley et al., 2010).
- **Information Integration**: Effective aggregation of distributed knowledge requires structured processes such as deliberation, prediction markets, or collaborative platforms (Woolley, Aggarwal and Malone, 2015).

- **Diversity-Accuracy Trade-off**: Functional diversity outperforms individual ability in solving complex problems; diverse perspectives (e.g., international/domestic, technical/policy) enhance problem-solving in employment systems (Hong & Page, 2004).
- **Transactive Memory Systems**: Groups build shared awareness of "who knows what," enabling coordination and knowledge use across ecosystems (Wegner, 1987; Ren & Argote, 2011).
- **Collective Sensemaking**: Groups interpret ambiguous signals and co-create shared meaning, as in alumni networks shaping narratives about labor markets (Weick, 1995; Maitlis & Christianson, 2014).

2.3 Comparative Analysis of the Current Employment System Theories

Table 1: Current Employment System Analysis Approaches

Theory	**Key Authors**	**Summary**
Human Capital Theory	Becker (1964); Schultz (1961); Spence (1973); Green & Henseke (2016)	Views education as investment in productivity; assumes linear link between education, skills, and wages. Fails to explain mismatches, overqualification, and assumes perfect information.
Labor Market Signaling Theory	Spence (1973) & Arrow (1973); Collins (2019)	Education signals ability under information asymmetry. Explains credential inflation but static and ignores skill development and learning dynamics.
Job Search and Matching Theory	Mortensen & Pissarides (1994); Diamond (1982); Granovetter (1973)	Focuses on job search frictions and matching functions. Explains unemployment but lacks a learning model and ignores network effects and tech disruption.
Institutional Theory	DiMaggio & Powell (1983, 2014); Meyer & Rowan (1977)	Employment shaped by institutional norms and legitimacy. Explains inefficiencies and context, but slow to adapt and lacks micro-foundations or optimization.
Social Network Theory	Granovetter (1973); Burt (2005); Lin (2001)	Employment outcomes driven by social network position and access to weak ties. Explains inequality and network effects but ignores skill levels and assumes static networks.
Skills-Based Approaches	Autor et al. (2003); Acemoglu & Restrepo (2018)	Labor market shaped by routine vs. non-routine task matching and tech shifts. Good for tech links but ignores soft skills, learning, and future skill demands.
Complex Adaptive Systems	Arthur (2015); Beinhocker (2006)	Labor markets are dynamic, emergent systems. Captures complexity and feedback but lacks predictive power and is hard to apply to policy.
Platform Labor Models	Sundararajan (2016); Kenney & Zysman (2016)	Platforms reshape work via algorithms and networks. Captures gig economy trends but is platform-specific, overlooks worker agency, and

		lacks collective models.

2.3.1 Employment System Approaches Comparative Analysis Table

The comparative analysis presented in the table offers a strategic assessment of prominent labor market theories. It evaluates these frameworks against criteria that highlight the integrative strengths of the proposed Free Energy Principle-Collective Intelligence (FEP-CI) framework. The table reflects established academic critiques of preceding theories:

- **Traditional models**, such as Human Capital and Signaling theory, are depicted as limited by their focus on the individual, largely overlooking dynamic, systemic properties and, in the case of Signaling, reinforcing existing structural inequities.
- **Intermediate frameworks** like Search/Match, Institutional, and Network theories are acknowledged for their capacity to model systemic frictions and structures. However, they are simultaneously characterized as lacking the adaptability required for rapidly changing environments or failing to fully account for complex feedback mechanisms.
- **Contemporary approaches**, including skills-based hiring, platform models, and general complex systems theory, are recognized as advances but are noted for their respective limitations, such as being partial, lacking a deep theoretical foundation, or remaining too abstract without a specific agent-based framework. *Adapted from Becker (1964); Schultz (1961); Spence (1973); Arrow (1973); Mortensen & Pissarides (1994); Meyer & Rowan (1977); DiMaggio & Powell (1983); Granovetter (1973); Burt (2005); Lin (2001); Autor et al. (2003); Acemoglu & Restrepo (2020); Arthur (2015); Beinhocker (2006); Sundararajan (2016); Kenney & Zysman (2016); and the author's own synthesis.*

Table 2: Employment System Approaches Comparative Analysis

Framework	**Prediction**	**Learning**	**Collective**	**Adaptation**	**Inequality**	**Complexity**
Human Capital	LOW	LOW	NO	LOW	IGNORES	LOW
Signaling	MEDIUM	NO	NO	NO	REINFORCES	MEDIUM
Search/Match	MEDIUM	NO	NO	LOW	NEUTRAL	MEDIUM
Institutional	LOW	LOW	YES	SLOW	EXPLAINS	HIGH
Network	LOW	NO	YES	LOW	REINFORCES	HIGH
Skills-Based	MEDIUM	LOW	NO	MEDIUM	NEUTRAL	MEDIUM
Complex Systems	LOW	YES	YES	HIGH	NEUTRAL	HIGH
Platform	MEDIUM	LOW	PARTIAL	MEDIUM	INCREASES	MEDIUM
FEP-CI	**HIGH**	**HIGH**	**YES**	**HIGH**	**ADDRESSES**	**HIGH**

Table 2. Employment System Approaches Comparative Analysis. Adapted from Becker (1964); Schultz (1961); Spence (1973); Arrow (1973); Mortensen & Pissarides (1994); Meyer & Rowan (1977); DiMaggio & Powell (1983); Granovetter (1973); Burt (2005); Lin (2001); Autor et al. (2003); Acemoglu

& Restrepo (2020); Arthur (2015); Beinhocker (2006); Sundararajan (2016); Kenney & Zysman (2016); and the author's own synthesis.

2.3.2 Current Employment System Analysis Shortcomings

Traditional employment frameworks, such as Social Network Theory and Job Search and Matching Theory, are powerful tools for describing labor market behavior. They argue that market signals and rational actors will, over time, correct for inefficiencies and information problems (Mortensen & Pissarides, 1994; Diamond, 1982; Granovetter, 1973). This view suggests a reliance on equilibrium models and a deductive logic that assumes a stable system. However, these retrospective, linear frameworks have significant limitations when applied to the dynamic, non-linear realities of modern labor markets. Scholars like Bruineberg et al. (2018) contend that such models are blind to the emergent, collective dynamics and information loss inherent in complex adaptive systems. They fail to explain why dysfunctions like a skills mismatch persist, even with clear evidence of the problem.

Existing employment system frameworks face five limitations: they are retrospective rather than predictive, failing to anticipate emerging skills under rapid technological change (Mortensen & Pissarides, 1994; Diamond, 1982; Granovetter, 1973); they treat skills as static, lacking mechanisms for adaptation or meta-learning (Cappelli, 2015); they ignore collective dynamics, reducing networks and coordination to externalities; they rely on linear equilibrium models, despite labor markets being non-linear and emergent; and they misrepresent information flows, assuming perfect or uniformly imperfect information rather than uncertainty and loss. These weaknesses are amplified in today's complex labor ecosystems, where technological disruption and shifting skill demands widen gaps between education and employment. Along with systematic policy drawbacks, in science-technology-policy fields, graduates must bridge technical and policy domains, developing hybrid skills rarely taught in curricula. This leads to what Bruineberg et al. (2018) call "epistemic misalignment," a systemic disconnect between academic preparation and labor market realities.

2.4 Rationale for the Selection of FEP and CI

Building on these identified critical gaps, I hypothesize that a framework integrating principles from the (FEP) and (CI) could more effectively address these issues. The combined application of FEP and CI offers a potentially more impactful and productive and predictive model for resolving both persistent and emerging employment policy challenges. The rationale rests on their unique capacity to bridge individual adaptation and system-level learning, precisely the gap existing theories fail to address. Traditional employment theories also fail to explain why these problems persist despite clear market dysfunction. FEP offers a deeper, more structural explanation. FEP provides a predictive, non-equilibrium perspective that explains why the system behaves as it does. Institutions like universities and employers are not behaving irrationally but are rationally minimizing their own internal uncertainty, or "free energy," even if it creates a larger systemic "free energy trap" that harms students. This conceptual insight allows for the generation of testable hypotheses about these behaviors. Is there structural similarity between a biological and governing system? Is the pattern of behavior, actually, local optimization leading to global dysfunction? Which is analogous to the FEP's account of how systems minimize prediction error.Similarly, CI directly addresses the critical information flow gaps and collective dynamics that traditional theories overlook. While market forces are assumed to correct information problems, research shows that this doesn't happen in reality. CI provides conceptual tools to understand why information flows break down, illuminating a systemic lack of mechanisms to aggregate individual feedback into institutional learning.

FEP has also already been extended beyond neuroscience into social and organizational domains. Researchers such as Badcock et al. (2022) have shown how FEP can model social cooperation, institutional behavior, and belief updating within complex systems. Zhang (2024) and López-Corona et al. (2015) further demonstrate FEP's applicability to issues like algorithmic governance, resource allocation, and collective value alignment, positioning the framework as a tool for understanding systemic adaptation under uncertainty. CI is increasingly applied in workplace contexts, where equitable participation and communication predict group performance more strongly than individual ability (Riedl et al., 2021). It is understood as a dynamic process that depends on how team behaviors align with task demands (Janssens, Meslec and Leenders, 2022). Tools like the Work-Team Collective Intelligence Scale (W-TCIS) measure CI through information sharing, inclusive decision-making, and team learning. In both digital and in-person settings, structured collaboration enables teams to perform equally well (Riedl, Malone & Woolley, 2021)(Malone, T. W., & Bernstein, M. S. (2015), while AI is further amplifying CI by enhancing memory, coordination, and problem-solving (Przegalinska et al., 2024; (Woolley, Aggarwal and Malone, 2015). Related fields like team cognition and organizational learning highlight CI's role in shared mental models and scalable knowledge transfer.

2.4.1 Research Gap Identification and Opportunity

To clarify, no published studies explicitly apply FEP and CI together to employment systems or for comprehensive employment ecosystem analysis, highlighting a clear opportunity for original research. Both theories and fields of studies are relevant and have been used conceptually and at times computationally analyse social systems and groups. As previously mentioned, FEP has been applied to social systems, active inference has been explored in governance (Zhang, 2024), and CI is well-established in organizational and team contexts. Although, neither CI or FEP will be used computationally for this research, it is important to highlight, the theoretical foundations are in place: both FEP and CI have mature mathematical models, validated measures, and proven applications in fields such as neuroscience and organizational science. Both systems can be described using the same variational calculus and information-theoretic principles, as shown by applications to social coordination (Veissière et al., 2020) and institutional decision-making (Albarracin et al., 2022). Friston (2018) argues that FEP applies broadly to biological, ecological, and social systems, including labor markets and social networks. This groundwork allows for abductive analysis. This research will conduct an exploratory analysis of employment ecosystems, applying the non-computational concepts of CI and FEP to determine if these theories manifest within the system. This approach offers a novel and hopefully impactful contribution to research and employment policy creation, providing a more comprehensive and accurate model of the empirical world.

Specifically, this research and framework employs the following FEP and CI concepts, modeling workers and organizations as active inference agents who minimize surprise and adapt to market feedback and the concept of the Markov blanket, which defines an "agent" as any system demarcated from its environment by a statistical boundary. Kirchhoff et al. (2018) argue that this abstraction allows FEP to model not only biological organisms but also organizations, institutions, and networks that maintain boundaries while exchanging information with their environments. Employment systems, like neural systems, are hierarchically organized with boundaries at multiple scales, individuals within organizations, organizations within sectors, sectors within economies, each maintaining integrity through active inference (Constant et al., 2018). Systemic mismatches, such as those between graduate skills and job requirements, can be quantified as free energy and information gaps (Bruineberg et al., 2018), enabling targeted adjustments by educational institutions, employers, and graduates.

The concepts from CI that will be applied in this research include, the importance of innovation and knowledge flow across teams and the productive impact of collective hiring assessments by integrating diverse perspectives. Including the importance of openness, peering, sharing, and global action in workforce development (Tapscott & Williams, 2006, 2010). My rationale to select concepts from FEP and CI to build a new framework is based on the hypothesis that a dynamic, adaptive perspective may be better suited to analyzing interdisciplinary career pathways than conventional, static employment models. Even without mathematical formalization, FEP and CI may be able to provide diagnostic value by revealing patterns invisible to traditional analyses through collective sensemaking.

2.4.2 FEP and CI Synthesis for Employment Analysis

This table presents a synthesis of FEP and CI concepts that could be specifically applied to employment analysis.

Table 3: Mapping FEP and CI Concepts to the Employment Ecosystem Domain

FEP/CI Concept	Employment Ecosystem Translation	Description & Reference
Prediction Error	Skills Mismatch	When reality does not match expectations (Friston, 2010); in employment, this is a skills mismatch, graduates' abilities don't align with market demands (Green & Henseke, 2016; Bruineberg et al., 2018).
Markov Blankets	Professional Boundaries	Markov blankets define the boundary between agent and environment (Kirchhoff et al., 2018); in employment, this maps to professional boundaries shaping interaction with networks and opportunities.
Active Inference	Career Navigation	Agents act to minimize uncertainty (Friston et al., 2017); career navigation is the process of seeking jobs and upskilling to align with opportunities and reduce uncertainty.
Free Energy	Career Uncertainty	Minimizing free energy reduces surprise (Friston, 2010); career uncertainty is the gap between job market expectations and real outcomes.

C-factor	Team Performance in the Workplace	CI's c-factor predicts group performance better than individual IQ (Woolley et al., 2010; Riedl et al., 2021); in employment, this relates to team effectiveness.
Collective Sensemaking	Labor Market Intelligence	Interpreting and sharing group understanding (Maitlis & Christianson, 2014); in employment, this becomes market intelligence for policy and practice.
Distributed Cognition	Organizational Knowledge	Knowledge distributed across people and artifacts (Woolley, Aggarwal and Malone, 2015); in employment, this underpins how expertise and experience are shared in organizations.

3. The FEP-CI Framework

3.1 The Non Computational FEP-CI Framework Summary

The framework unfolds in three sequential layers, each building on the last to move from individual experiences to systemic
Interventions.

- **Layer 1: Individual Layer – Stakeholder Narrative Collection**
  The first layer involves collecting and analyzing rich narratives and contextual questions from system stakeholders. The focus is placed on identifying "prediction errors," or moments where employment expectations diverged from reality. These narratives provide insight into individual experiences of misalignment and adaptation within the employment system.
- **Layer 2: Collective Layer – Mapping Theory to Application**
  The second layer applies theory to practice by developing a non-computational FEP-CI framework, referred to as the "Translation Bridge." This coding system is based on core concepts from the Free Energy Principle and Collective Intelligence. By analyzing stakeholder narratives through this lens, the framework identifies recurring patterns of individual-level errors and systemic-level failures, making abstract theory actionable for policy and institutional design.
- **Layer 3: Interactive Layer – Intervention and Iteration**
  The third layer emphasizes collaboration and iteration. Findings from the analysis will be presented and discussed with stakeholders in group settings to co-develop solutions and actionable strategies. While this iterative and participatory process could not be fully implemented within the scope of this dissertation due to time constraints, it is planned as a key component of future research.

This framework provides the conceptual foundation and testable hypotheses required before a full mathematical implementation. Before attempting a complex mathematical formalization, it is necessary to first establish that FEP concepts meaningfully map onto real-world employment experiences.
This research uses the subjective experience of participants as a qualitative measure of "prediction error." You created a "Translation Bridge Model" to convert theoretical concepts into observable patterns, which allows you to generate falsifiable predictions and lay the groundwork for future research. The scientific value of this initial work lies in its systematic pattern identification and replicable procedures, which are essential prerequisites for any future computational implementation. The integration of these frameworks occurs as individual prediction errors become the learning signals for the collective; when a critical mass of agents, for instance, students in a cohort, experiences similar errors, these signals cease to be idiosyncratic and instead constitute a collective mandate for system-level model updating (Constant et al., 2018). This dynamic operates across nested scales, where individuals, teams, and entire institutions simultaneously engage in active inference to minimize free energy, with CI providing the coordination mechanism necessary to align their potentially misaligned objectives (Hesp et al., 2019).

3.2 Future Framework Development

The long-term vision for this research is to refine this framework into a robust diagnostic tool. Through continued application across larger samples and diverse contexts, the framework anticipates identifying a smaller set of recurring "canonical failures," 5-7 core patterns that consistently manifest in employment transitions.education-to-employment ecosystems. This tool would enable targeted interventions rather than generic solutions. Future work will also explore the computational formalization of these patterns to create a more precise and predictive model. This approach transforms the aggregation of individual experiences into a source of collective intelligence about system dysfunction, enabling the identification and resolution of structural problems that no single actor can perceive or solve alone.

Theoretically, this integrated approach is grounded in the understanding that system performance is optimized when both individual adaptation and collective problem-solving function effectively. At the individual level, FEP frames agent adaptation as a process of minimizing the divergence between beliefs and reality, while at the collective level, CI frameworks demonstrate that performance depends on balancing diversity, aggregation, and incentives against coordination costs (Woolley et al., 2010; Hong & Page, 2004). Therefore, a successful employment ecosystem is one that simultaneously reduces individual uncertainty through clear and accurate signals while maximizing collective intelligence through effective coordination mechanisms.

4. Methodology

My methodology followed a three-phase, mixed-methods design aimed at identifying recurring patterns of dysfunction in the education-to-employment experience.

4.1 Phase 1- Literature Review

Phase 1 began with a literature review, where I examined academic sources on traditional employment theories to evaluate their analytical limitations. This stage also involved assessing the relevance and capacity of the Free Energy Principle (FEP) and Collective Intelligence (CI) frameworks to address these shortcomings and provide a more adaptive lens for employment policy analysis.

4.2 Phase 2 - Framework Creation and Narrative Collection

Phase 2 focused on framework creation and narrative collection. I developed the framework and conducted 22 narrative surveys with STEM and policy graduates using the SenseMaker® platform, a tool designed to capture and interpret real-life experiences through narratives (EuroSense, 2025).

4.2.1 The FEP-CI Translation Bridge

The FEP-CI Translation Bridge was designed to connect micro-level narratives with macro-level patterns for intervention design, using codes that represent Free Energy Principle (FEP) and Collective Intelligence (CI) concepts applied in related contexts. At the individual level, 11 FEP-based codes were developed and organized into three categories to analyze how graduates experienced prediction error and uncertainty in the job market. These included five Prediction Error Codes, which captured moments where expectations diverged from reality; four Active Inference Codes, which revealed how individuals acted to minimize uncertainty and align perceptions with reality; and two Uncertainty State Codes, which identified the subjective experience of not knowing or feeling overwhelmed. At the system level, nine CI-based codes were constructed across three categories to uncover systemic dysfunctions that disrupt collective intelligence within the employment ecosystem. These comprised three Information Flow Codes, which analyzed how information was shared, distorted, or blocked; three Collective Learning Codes, which examined the system's capacity to integrate individual knowledge into shared understanding; and three System Feedback Codes, which detected how the system responded to and corrected for errors and mismatches. Together, the 11 FEP codes and 9 CI codes provided a total of 20 granular codes that served as the foundation for detailed narrative analysis. These were subsequently synthesized into five higher-level roll-up categories, capturing overarching systemic patterns that could guide targeted interventions.

The FEP-CI Translation Bridge is comprised of the following *a priori* codes:

FEP Concepts – Individual-Level Codes

- **Prediction Error Codes:** Defined as the mismatch between an agent's expected and observed outcomes, the minimization of which is central to adaptive behavior (Friston, 2010).
  - PE-TIM: Timing prediction error (expected vs. actual timeline).
  - PE-SKL: Skill prediction error (assumed vs. actual skills required).
  - PE-PRO: Process prediction error (expected vs. actual processes).
  - PE-NET: Network prediction error (expected vs. actual access to networks).
  - PE-VAL: Value prediction error (expected vs. actual market value of credentials).
- **Active Inference Codes:** The process by which agents act to minimize prediction error, either by updating their internal models (learning) or by acting on the world to make it conform to their models (Friston et al., 2017).
  - AI-LRN: Active inference via learning (e.g., courses, self-study).
  - AI-NET: Active inference via networking.
  - AI-PIV: Active inference via pivoting strategies.
  - AI-SIG: Active inference via signaling (e.g., credentialing, resume updates).
- **Uncertainty State Codes:** Subjective states reflecting the degree of prediction error.
  - FE-HIGH: A state of high free energy (e.g., anxiety, confusion).
  - FE-VOID: An absence of a feedback gradient to guide adaptation.
  - FE-TRAP: A state where adaptive efforts increase, rather than decrease, uncertainty.

CI Concepts – System-Level Codes

- **Information Flow Codes:** Mechanisms governing the integration of distributed knowledge within a system (Surowiecki, 2004).
  - IF-BLK: Blocked information flow.
  - IF-ASY: Information asymmetry.
  - IF-SIL: Information silos.
- **Collective Learning and Intelligence Codes:** The capacity for enhanced group problem-solving emerging from diverse and distributed inputs (Malone, T. W., & Bernstein, M. S. (2015).
  - CL-ABS: Absent mechanisms for collective learning.
  - CL-FRAG: Fragmented or incomplete collective learning.
  - CL-HOMO: Homogeneous perspectives limiting learning capacity.
- **System Feedback Codes:** Signals provided by the system to guide individual agents.
  - SF-NONE: A total absence of system feedback.
  - SF-DELAY: Delayed feedback that is no longer actionable.
  - SF-NOISE: Noisy, contradictory, or unclear feedback.

The granular codes were aggregated into five higher-level "roll-up" categories to identify overarching systemic patterns. This synthesis elevates the analysis from individual codes to a diagnosis of structural dynamics.

- **MISMATCH** (Rolls up: PE-TIM, PE-SKL, PE-PRO, PE-VAL): A systematic divergence between the expectations shaped by the system and the reality of the environment.
- **ISOLATION** (Rolls up: PE-NET, IF-BLK, IF-ASY, IF-SIL): The presence of structural barriers that prevent access to critical information and resources.
- **VOID** (Rolls up: FE-VOID, SF-NONE, CL-ABS): The absence of actionable feedback, which prevents both individual and collective learning and adaptation.
- **COMPENSATION** (Rolls up: AI-LRN, AI-NET, AI-PIV, AI-SIG): A pattern where individual agents must engage in extensive adaptive labor to compensate for systemic failures.
- **INEQUALITY** (Rolls up: CL-HOMO, IF-ASY, IF-SIL): Systemic issues related to differential access, representation, and the suppression of diverse perspectives.

4.2.2 Surveying Using the SenseMaker Platform

The sampling strategy followed the principles of thematic saturation and information power (Guest et al., 2006; Malterud et al., 2016) and included a diverse group of participants, such as current students, recent alumni within the past ten years, and individuals across varied demographics. This included approximately 30 percent international students, 20 percent part-time or working students, and tracked first-generation participants. The central narrative prompt asked: “Looking back on your transition from student to the job market, describe a specific moment when your expectations about employment didn’t match reality.”

The initial phase focuses on identifying observable phenomena within the collected narratives from a bottom-up perspective. First, self-reported challenges and experiences were extracted from each narrative in layman's terms. These were then systematically mapped to identify recurring thematic patterns across the dataset. The primary objective was to quantify the prevalence of each pattern, with a target of identifying themes present in a significant majority (i.e., ≥ 70%) of narratives to ensure they represent systemic issues rather than idiosyncratic experiences.

4.3 Phase 3 - Framework Application & Interventions

Phase 3 involved applying the FEP-CI framework to analyze narrative patterns, extract key implications, and co-develop evidence-based intervention in group discussion in which stakeholders validated findings and co-developed dual-level interventions, using the tool, estuarine mapping and participatory sense-making. Using the Kumar’s app to (using the stories) identify positive/negative constraints, actors (individuals/orgs/AI), and contextual factors, on the estuarine map (via Cynefin’s framework). Identify counterfactuals (unchangeable), volatile elements (not worth focusing on), and liminal zones where specific micro-actions can shift the system. To generate micro-actions to shift the system toward more desirable outcomes (more "good" stories, fewer "bad" ones). Future research will extend this work through participatory stakeholder discussions, incorporating estuarine mapping and the Cynefin framework to validate findings and collaboratively design interventions. This iterative process will allow for continuous testing of impact and the identification of emerging patterns (EuroSense, 2025).

4.4 Methods Approach

This research employs an abductive analytical approach, iterating between deductive and inductive reasoning. The deductive component applies established FEP and CI theories to identify predicted patterns in employment narratives (testing if concepts like prediction error and collective intelligence failures manifest empirically). The inductive component allows unexpected themes to emerge from participant data without theoretical constraints. Through iterative synthesis, moving between theory and data repeatedly, the analysis both tests existing frameworks and generates new insights. This abductive methodology is particularly appropriate for exploratory research applying FEP-CI to employment for the first time, as it maintains theoretical rigor while remaining open to empirical surprises that can refine or extend the framework.

4.5 Thresholds

To determine when participant feedback indicates a systemic issue versus isolated issues, this study adopts thresholds grounded in qualitative research standards. Negative prediction error appearing in ≥70% (**a significant majority** in descriptive reporting) of narratives indicate a significant majority or systemic issues rather than isolated individual experiences (Bryman, 2016; Creswell & Creswell, 2018). Recurrence across approximately **10–315% of narratives** is typically treated as significant, as repetition across diverse participants suggests thematic salience (Braun & Clarke, 2006). For small-N studies such as this. e (Malterud, Siersma, & Guassora, 2016) (Maxwell, 2013).

4.6 Limitations of The FEP-CI Framework

The FEP-CI framework faces several fundamental limitations that shape its contributions and boundaries. By applying complex neuroscientific concepts like FEP to social systems, there is risk of oversimplification, prediction error serves as contextual analogy rather than precise mathematical implementation. 'Free energy' cannot be directly measured in social systems (Bolis et al., 2017), requiring approximation through narrative expressions of surprise and adaptation, which adds subjectivity. (Colombo & Wright, 2017) Where FEP assumes objective calculation. Similarly, while Markov blankets statistically define system boundaries in biology, they are far less precise in social contexts. CI requires specific conditions (diversity, decentralization, aggregation) often absent in hierarchical institutions (Woolley et al, 2010) Theoretically, once the computation has been added to the conceptual framework, the framework's mathematical complexity and reliance on Bayesian inference might make it inaccessible to many policymakers. Also, cultural limitations arise from its WEIRD (Western, Educated, Industrialized, Rich, and Democratic) contexts (Henrich et al., 2010) origins, potentially missing diverse epistemologies.

Implementing this new framework can power dynamics that are often overlooked: current employment inefficiencies may benefit certain actors, such as recruitment firms or elite institutions, who profit from information gaps or exclusive networks. Historical separation between the two fields, rooted in FEP's neuroscientific origins and CI's business school lineage, reflects fundamental philosophical divides and methodological silos. Cultural bias is another concern, as both frameworks largely stem from Western traditions, which may not translate globally or capture values in non-Western societies (Henrich et al., 2010). The absence of ethics is also striking, without explicit attention to justice, equity, or inclusion, these frameworks risk optimizing exclusionary or discriminatory outcomes. Finally, the reality of implementation, entrenched interests, institutional inertia, and human resistance, complicates the practical application of even the most elegant models.

4.7 Framework Application Strategy

The FEP-CI framework implementation requires adherence to minimum methodological requirements: multi-scale data collection across individual, group, and system levels (Friston, 2010; (Woolley, Aggarwal and Malone, 2015) context-specific operationalization that validates constructs for employment rather than simply importing from cognitive science; stakeholder inclusivity ensuring diverse perspectives essential for robust collective intelligence (Henrich et al., 2010)(Hong & Page, 2004) iterative, participatory design with continuous feedback loops; robust data integration combining qualitative and quantitative approaches; transparent, reproducible protocols for scientific rigor; comprehensive ethical safeguards addressing bias and discrimination; and outcome relevance ensuring findings translate into actionable interventions. This research prioritizes small-scale validation studies that test these requirements systematically before attempting broader implementation, while embedding ethical considerations and democratic oversight throughout the development process.

Table 4: Minimum Methodological Requirements for FEP-CI-EM Applications

Requirement	**Description**	**Justification**
Multi-Scale Data Collection	Gather data at individual, group, organizational, and system-wide levels.	Captures feedback loops and emergent properties essential for FEP and CI analysis.
Context-Specific Operationalization	Define and measure FEP/CI constructs as they apply to employment (e.g., prediction error, collective sensemaking).	Ensures constructs are valid for employment research, not just imported from cognitive science or psychology.
Stakeholder Inclusivity and Diversity	Involve diverse groups (workers, employers, policymakers, educators) in data and validation.	Robust CI depends on diverse perspectives; lack of inclusivity undermines system intelligence and policy relevance.
Iterative, Participatory Design	Use participatory and adaptive methods (feedback loops, co-design, adaptive pilots).	Ensures responsiveness to evolving needs and system dynamics.
Robust Data Integration & Triangulation	Combine qualitative and quantitative data, triangulate findings.	Identifies both trends and emergent, contextualized insights for a fuller understanding of complex systems.
Transparent, Reproducible Protocols	Publish all methods, coding, and analysis frameworks for reproducibility.	Critical for scientific rigor and building interdisciplinary trust and progress.
Ethical Safeguards & Data Protection	Ensure consent, anonymization, and secure data storage; address algorithmic/systemic bias.	Protects participants, ensures compliance, and addresses risks of exclusion/discrimination.
Outcome Relevance & Actionability	Design outputs to inform interventions (curriculum, hiring, policy) and link findings to specific actions.	FEP-CI's value depends on prescriptive and actionable guidance for real-world systems.

4.8 Data Collection

4.8.1 The EuroSense/SenseMaker Platform

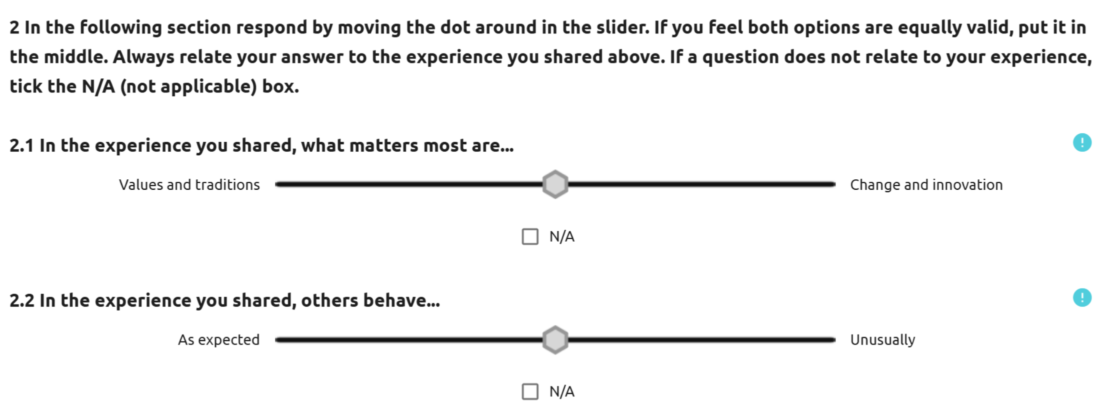
The EuroSense's SenseMaker platform was selected because it uniquely captures both individual experiences necessary for FEP analysis and collective patterns required for CI analysis simultaneously (Snowden, 2010; Van der Merwe et al., 2019). The platform allows participants to share a narrative about their experiences and then respond to questions across multiple dimensions. This process reveals prediction errors as participants interpret their own stories, with the additional questions providing context to those narratives. The core prompt asked: **"Looking back on your transition from student to the job market, describe a specific moment when your expectations about employment didn't match reality. Please share: What you expected would happen, what actually happened instead, and how you adapted or what you learned from this mismatch."**

EuroSense's narrative-based methodology provides superior alignment compared to alternatives. Traditional surveys reduce lived experience to fixed-choice answers, missing nuanced prediction errors that emerge through storytelling and failing to capture adaptive learning aspects central to FEP (Creswell & Plano Clark, 2017). Focus groups risk groupthink that obscures individual prediction errors while being time-intensive and difficult to scale (Morgan, 1996). Purely quantitative analysis fails to capture the subjective experience of core to FEP and misses collective sensemaking processes essential for CI (Seth et al., 2016; Maitlis & Christianson, 2014).

The SenseMaker platform can capture subjective models through narratives that reveal mental models, CI's need for group pattern analysis is fulfilled by the platform's aggregation capabilities (Malone et al., 2010) Malone, T. W., & Bernstein, M. S. (2015), active inference's focus on tracking adaptation is captured through story evolution (Friston et al., 2017), and Markov blanket boundary identification emerges through narrative descriptions of professional boundaries (Kirchhoff et al., 2018). The platform's self-signification feature allows participants to tag their own stories, generating structured metadata that enables both aggregation and contextual depth while empowering participant agency in meaning-making.

Figure 1: Examples of EuroSense Sensemaker Questions

Example 1:



2 In the following section respond by moving the dot around in the slider. If you feel both options are equally valid, put it in the middle. Always relate your answer to the experience you shared above. If a question does not relate to your experience, tick the N/A (not applicable) box.

2.1 In the experience you shared, what matters most are...

Values and traditions — Change and innovation

☐ N/A

2.2 In the experience you shared, others behave...

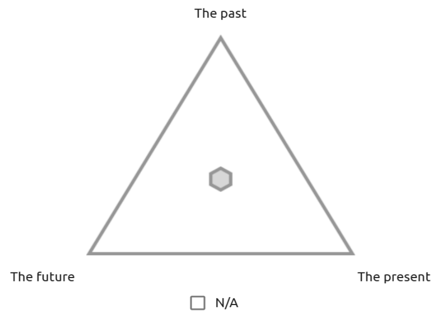
As expected — Unusually

☐ N/A

Example 2:

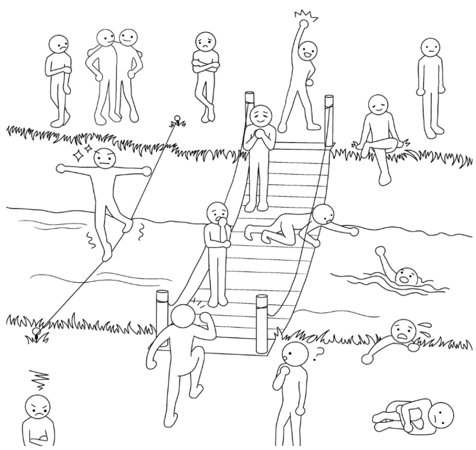
3. In the next section, move the dot around in the triangle to indicate your answer. If you think one answer is more important, put the dot closer to it. If you feel all answers are equally valid, put the dot in the middle. Always relate your answer to the experience you shared initially. If a question does not relate to your experience, tick the N/A (not applicable) box.

3.1 The experience you shared relates to...



Example 3:

4 In the experience you share, where do you see yourself and where do you see the others in the context of your experience above? Please place the dots on the corresponding figures below.



4.8.2 Sampling Strategy

The 22-participant sample reflects master's dissertation constraints and specialized program recruitment limits. Past research (Guest, Bunce, & Johnson, 2006) shows 12 interviews typically capture most qualitative themes. Malterud, Siersma, & Guassora (2016) suggest exploratory research needs fewer participants when the group is specific, the framework is strong, and interviews are focused. The sample met qualitative saturation targets and only focused on science-tech- public policy master students, while remaining within practical limits for a methodological framework and non computational application of FEP and CI concepts.

4.8.3 Participant Recruitment

Alumni and students from science, technology, and public policy master programmes, contributed narratives about their education-to-employment transitions. Participants took a 5-10 minute anonymous survey on the SenseMaker platform operated by Volt Europa with data processing by Cynefin Co (Ireland). The platform collected brief employment narratives (2-3 sentences) and contextual questions, with participants positioning experiences along dimensions like job searching vs employed and skills mismatch vs alignment using unique identifiers to ensure complete anonymity.

The contextualizing questions included experience titles, categorization (education, employment, technology, policy), and positive/negative ratings. Sliding scale questions explored tensions like "values/traditions" versus "change/innovation" and whether others behaved "as expected" versus "unusually." A triangular response tool captured three-way relationships between temporal dimensions (past/present/future), geographic scales (country/region/Europe), and democratic engagement modes (taking action/wanting politicians to act/wanting to be left alone). All narratives are immediately anonymized and become publicly accessible as part of a European citizen science project, with AI systems analyzing patterns and generating aggregated insights stored on GDPR-compliant servers. This multi-dimensional approach captured not just what happened, but how participants made sense of their experiences within broader contexts, revealing systematic prediction errors and collective intelligence failures across the cohort.

4.8.4 Participant Inclusion Criteria

All research participants were selected based on their fulfillment of the following inclusion criteria: Program structure (interdisciplinary vs. specialized), student demographics (international/domestic ratio, socioeconomic diversity), local labor market conditions, and existing career support mechanisms. The output is a context profile that documents program-specific Markov blankets, or the boundaries mediating the relationship between education and employment. Both “successful” and “struggling” trajectories were included to capture range. Diversity targets aimed for at least 30% international students (if available), 20% part-time/working students (if applicable), and tracking of first-generation university students where possible.

Table 5: Participant Inclusion Criteria and Context Profile Requirements

Category	Details	Justification / Notes
Target Sample	Participants from graduate-level Science, Technology, and Public Policy programs	Balanced between current students and alumni to capture transition trajectories
Composition	Current students: ~50% of respondents Recent alumni (≤ 10 years post-graduation): ~50% of respondents	Ensures mix of pre- and post-transition experiences

Narrative Requirement	Minimum of 12 narratives for reliable pattern identification	Aligns with saturation benchmarks in qualitative research (Guest et al., 2006)
Trajectory Coverage	Both "successful" and "struggling" pathways included	Captures full range of employment transition outcomes
Diversity Targets	- ≥30% international students (if available)- ≥20% part-time/working students- Track first-generation university students where possible	Ensures heterogeneity and broader systemic insights
Context Profile Data	- Program structure (interdisciplinary vs. specialized)- Student demographics (domestic/international, socioeconomic diversity)- Local labor market conditions- Existing career support mechanisms	Documents program-specific "Markov blankets" mediating education-to-employment boundaries
Inclusion Criteria	- Age ≥18- Current student or alumnus (≤10 years)- Ability to provide informed consent- Internet access for survey completion- English fluency	Ensures ethical eligibility and data quality
Exclusion Criteria	- Under 18- Unable to provide informed consent- Alumni >10 years post-graduation- No secure internet access	Maintains methodological and ethical integrity
Narrative Prompt	"Looking back on your transition from student to the job market, describe a specific moment when your expectations about employment didn't match reality." Participants then detail:1. What they expected would happen2. What actually happened3. How they adapted or what they learned	Captures prediction errors (FEP lens) and collective failures (CI lens)

4.9 Cross-Context Validation

Generalizability is tested through application in new contexts. Running the framework in similar programs at different institutions checks consistency within the same field. Applying it in different programs within the same institution tests whether it can transfer across domains. Finally, testing in international contexts ensures the framework is not culturally or nationally bound, and can detect prediction errors and systemic failures across varied education-to-employment ecosystems.

Lincoln and Guba (1985) proposed four criteria to establish trustworthiness in qualitative research as an alternative to traditional quantitative standards of validity and reliability. These include credibility, ensuring findings are believable and accurately represent participants' perspectives; dependability, showing the consistency of results across time and conditions; confirmability, demonstrating that results stem from participants' narratives rather than researcher bias; and transferability, providing sufficient contextual detail so readers can judge the applicability of findings to other settings. These criteria remain foundational in assessing qualitative rigor (Lincoln & Guba, 1985; Guba & Lincoln, 1994).

Cohen's Kappa (κ) is a widely used statistical measure for evaluating inter-rater reliability, especially when coding qualitative data into categories.(Cohen, 1960; Landis & Koch, 1977). Unlike raw percent agreement, Kappa adjusts for agreement expected by chance, producing a value between –1 and +1, where higher scores indicate stronger reliability. Interpretive guidelines suggest values above 0.60 indicate substantial agreement and values above 0.80 indicate near-perfect agreement (Cohen, 1960; Landis & Koch, 1977). This makes Cohen's Kappa a useful complement to Lincoln and Guba's qualitative rigor framework, particularly when research involves systematic coding of narrative or textual data.

4.9.1 Ethical Considerations

This research maintains strict ethical standards, emphasizing transparency, voluntary participation, and participant confidentiality. Data boundaries are clearly defined, with no direct transfer between EuroSense and UCL. Each institution functions as an independent data controller, and consent is handled separately for each component. All data handling complies with GDPR (Articles 9.2(a) and 9.2(f)), and participants retain full control over their involvement, including the ability to withdraw independently from either component. Data minimization and privacy are central to the design. No identifiable participant information is ever transferred to UCL. EuroSense data is stored securely on Cynefin Co servers in Ireland, while UCL data is stored on UCL OneDrive. Focus group participants would use first names only, sessions are not recorded, and all transcripts are anonymized. The study aims to produce actionable insights into employment systems while supporting both democratic participation and academic independence. Separate recruitment emails have been tailored specifically for students and alumni to ensure relevance and clarity. The consent forms provide clear, detailed information about how data will be used, participants' rights, and the procedures for withdrawing.

5. Results

5.1 Participant Demographics

The anticipated participant distribution and expected sector representation includes:

Table 6: Participant Demographics Breakdown

	Current Students	**Alumni**	**Total (by Role)**
% Sample	10	12	22

	Public	**Private**	**Non-profit**	**Academic**	**Startup**	**Total**
% Sample	3	7	4	4	4	22

5.2 Summary of Key Findings

Of the 22 total participants, 20 provided valid narratives through the SenseMaker tool, while 2 were deemed irrelevant or not applicable (NA). A striking 19 of those 20 valid narratives (95%) described negative prediction errors, indicating that this issue was nearly universal among the participants who provided relevant data. When considering the entire participant pool of 22, the data shows that 86% of all respondents experienced negative prediction errors, underscoring pervasive individual challenges and critical systemic failures. The central hypothesis was validated, as ≥ 70% of student and graduate narratives revealed negative prediction errors (i.e., mismatches between expectations and reality, and feedback failures). This finding demonstrates that these issues are systemic problems rather than isolated individual experiences. Participants averaged 3.2 system-level failures each, with narratives mapping to 2-4 interconnected breakdowns per story. This pattern emerged empirically through coding, where students typically described cascading failures: "couldn't access networking events" leading to "applied without understanding market needs" resulting in "no feedback to improve."

The (FEP-CI) framework identified five recurring systemic issues in the education-to-employment ecosystem from student narratives. The most prevalent pattern is **Mismatch**, affecting 73% of narratives, which highlights a pervasive divergence between student expectations and professional reality regarding skills and credentials. **Isolation** is a concern in 55% of narratives, revealing structural barriers to information and networking. The **Void**, affecting 45% of narratives, describes a critical absence of feedback loops that leaves individuals in high states of uncertainty. In **Compensation**, seen in 45% of narratives, individuals are forced to adapt and fill in for systemic failures. Finally, **Inequality**, present in 27% of narratives, points to disparities that undermine collective intelligence. Overall, the analysis reveals a system that fails to minimize uncertainty institutionally, shifting the burden onto individuals and creating a fragile, inequitable landscape.

5.3 SenseMaker Interpretive Questions Summary

The participants from science-technology-policy programs positioned their employment experiences as present/future-oriented challenges requiring systemic change rather than individual adaptation, with 68%

indicating others behaved "unusually" and 73% wanting personal or political action. Respondents described sharp divergences between employment expectations and reality, anticipating smooth pathways through coursework preparation and institutional networks but encountering weak support, inequitable treatment, and unpredictable organizational behaviors. Most valued innovation over tradition yet focused on past/present struggles rather than future optimism, with common feelings of isolation and marginalization highlighting gaps in belonging and connection.

From an FEP perspective, the dominance of negative experiences reveals persistent prediction errors between participants' expectations (fairness, government support) and actual outcomes (exclusion, neglect), with compromised adaptive modeling capacity indicated by past/present focus rather than future orientation (Friston, 2010). The CI lens reveals untapped systemic potential: participants' emphasis on change demonstrates collective readiness for adaptation, yet mixed institutional experiences show organizations fail to harness distributed intelligence effectively (Woolley et al., 2010). Participants recognizing struggles as common rather than isolated indicates high potential for system-level learning if distributed experiences were aggregated into collective feedback loops (Woolley, Aggarwal and Malone, 2015).

5.4 SenseMaker Narratives Analysis Summary

The initial phase of the analysis focused on identifying observable phenomena at the individual layer through a bottom-up examination of the collected narratives. This process began with a preliminary review to determine the overall percentage of narratives that contained negative self-reported issues versus those that did not. Subsequently, the content of these issues was categorized using descriptive, non-theoretical language derived directly from participant accounts. To distinguish systemic patterns from anecdotal experiences, a quantitative threshold was applied, where. These ‘Issue Titles- In Laymen Terms’ were then consolidated to see if patterns emerge at this level at subsequent theoretical coding, establishing a baseline for tracking their recurrence in future research cycles.

5.4.1 Phase 1: Individual-Level Prediction Error Classification (Observable Phenomena)

Table 7: Pattern Analysis (Observable Phenomena)

#	Narrative Summary	Problem?	Issue Title (Layman’s Terms)
1	Expected to apply for jobs after dissertation; didn’t due to workload; sees job search as individual responsibility.	Yes	Poor Timing of Job Applications
2	Volunteered mentoring a disadvantaged teen; mentee succeeded in bridging the program.	No	Positive influence for future positive outcomes
3	Part-time students locked out of opportunities (no recordings, geared to international visas, not targeted networking).	Yes	Lack of Inclusion for Part-Time Students

4	Reflection on Delhi metro expansion; underfunded suburban transit, poor connectivity affecting opportunities.	Yes	Unequal Transport Priorities
5	Degree was too theoretical; employers wanted job-ready skills; had to take extra data science training.	Yes	Academic-Practical Skills Gap
6	Positive personal experience at a Berlin lake with friends.	NA	N/A
7	Observed an argument between cyclist and construction worker in Berlin traffic, equated it to a lack of consideration in these systems	Yes	Exclusion and Ongoing Inequity
8	Expected good work culture in first job; reality was mistrust and exploitation.	Yes	Toxic Workplace Culture
9	Attended research retreat; learned much, but Global South voices missing.	Yes	Lack of Diversity in Perspectives
10	Wanted deeper technical standards (STBi, GHG protocols) for career usefulness.	Yes	Missing Technical Training
11	East German narrative: chaos post-reunification, lack of guidance, toxic climate, ongoing marginalization.	Yes	Historical Exclusion and Ongoing Inequity
12	Expected UCL to facilitate alumni networking; opportunities limited and not relevant.	Yes	Weak Career Networking Support
13	(Placeholder “12312,” unclear response).	NA	N/A
14	Job hunt: many applications into void; niche market, few callbacks; coursework relevant but hard to stand out.	Yes	Applications Into the Void

15	Jobs required deeper policy/tech knowledge than coursework provided; felt underprepared; may need more courses.	Yes	Surface-Level Learning
16	Degree added little value in job applications; had to reposition experiences for CV.	Yes	Low Program Career Value
17	Only a few college courses useful; relied on self-teaching (YouTube, Udemy); weak career guidance.	Yes	Lack of Practical Training
18	Applied to jobs matching experience/education but got no replies; background not as niche as thought.	Yes	Low Job Market Demand
19	Expected more tech/digital career networking support at UCL; disappointed.	Yes	Insufficient Career Search Support
20	Observed Greek society inequality and government-controlled narratives.	Yes	Media Control & Inequality
21	Personal life: moving in with partner post-London, positive but context of hostile conditions at home.	Yes	Worries about Job opportunities
22	Master's degree boosted CV visibility, but actual job offers slow; mismatch between expectations and reality.	Yes	Degree-Job Market Mismatch

5.4.2 Phase 1: Narrative Coding

The first phase involves a detailed qualitative analysis of 22 individual narratives, 20 of which pertain to employment-related issues. Each narrative is assigned a "Layman's Issue Category" (e.g., "Academic-Practical Skills Gap," "Toxic Workplace Culture") and is then mapped to a set of specific a priori FEP/CI codes chosen from core concepts of FEP and CI most relevant to the employment system.

- **FEP Codes:** These codes address the individual's experience of uncertainty and their response to it.
  - **Prediction Error (PE):** Captures mismatches between expectations and reality (e.g., PE-SKL for a skills gap, PE-VAL for a credential's low market value).
  - **Active Inference (AI):** Describes the individual's adaptive strategies to reduce uncertainty (e.g., AI-LRN for self-directed learning, AI-PIV for a change in career strategy).

    - **Free Energy (FE):** Quantifies the individual's subjective state of uncertainty or stress (e.g., FE-HIGH for high anxiety, FE-VOID for a lack of feedback).
- **CI Codes:** These codes analyze the systemic context of the narratives.
    - **Information Flow (IF):** Identifies barriers to information sharing (e.g., IF-BLK for blocked information pathways, IF-ASY for asymmetric access to knowledge).
    - **Collective Learning (CL):** Describes the state of knowledge sharing and collaboration within the system (e.g., CL-ABS for absent mechanisms, CL-FRAG for fragmented sharing).
    - **System Feedback (SF):** Assesses the quality of feedback from the broader system (e.g., SF-NONE for a lack of feedback).

Table 8: Mapping Narrative Themes to FEP/CI Codes

Narrative	Layman Issue Category	Equivalent FEP/CI Codes	Reason
1	Poor Timing of Job Applications	PE-TIM, FE-HIGH, AI-LRN, SF-NONE	Expected later job search cycle, reality misaligned; stress reflects high free energy; learning = corrective step; no feedback from university = system failure.
2	Positive Influence for Future Positive Outcomes	AI-NET, CL-FRAG	Mentorship reduces uncertainty (active inference through networking); systemic reliance on ad hoc mentoring shows fragmented collective learning.
3	Lack of Inclusion for Part-Time Students	PE-NET, FE-TRAP, IF-BLK, CL-ABS	Expected equal access, but blocked from opportunities; repeated efforts increased uncertainty (trap); info not shared (blocked); no collective accommodation mechanisms.
4	Unequal Transport Priorities	PE-PRO, IF-SIL, CL-FRAG	Expected metro to improve connectivity, but system failed; investments siloed; fragmented planning limits collective learning.

5	Academic-Practical Skills Gap	PE-SKL, FE-HIGH, AI-LRN, IF-ASY	Employers wanted job-ready skills not provided by uni; rejection led to stress; took new course (learning); universities withheld labor market info (asymmetry).
6	N/A	None	Personal anecdote unrelated to employment.
7	Exclusion and Ongoing Inequity	PE-VAL, FE-HIGH, AI-PIV	Observation of social conflict reflects a value error in the system's design and a need for a pivot in approach.
8	Toxic Workplace Culture	PE-VAL, FE-HIGH, AI-PIV	Expected positive culture, found mistrust/exploitation; created dissatisfaction (high free energy); may trigger pivot to another workplace.
9	Lack of Diversity in Perspectives	CL-HOMO, IF-SIL, PE-VAL	Homogeneity limited CI; Global South perspectives siloed; expectation of diversity unmet (value error).
10	Missing Technical Training	PE-SKL, IF-ASY, FE-TRAP	Expected deeper standards/skills; knowledge gap reflects asymmetry; degree left students trapped needing more external training.
11	Historical Exclusion and Ongoing Inequity	PE-PRO, FE-HIGH, IF-BLK, CL-ABS	Expected post-reunification improvement but reality was uncertainty; systemic disempowerment sustained high free energy; official narratives blocked info flow; collective learning absent.

12	Weak Career Networking Support	PE-NET, FE-VOID, IF-BLK, SF-NONE	Expected strong alumni/employer links; instead faced void (no guidance); blocked information flows; job-seeking efforts received no feedback.
13	N/A	NA	Unclear Response
14	Applications Into the Void	PE-PRO, SF-NONE, AI-SIG, FE-HIGH	Hiring processes opaque; no system feedback; resorted to signaling strategies (CV, credentials); caused stress from lack of results.
15	Surface-Level Learning	PE-SKL, FE-TRAP, AI-LRN, IF-ASY	Degree too surface-level for job needs; created trap (extra costs/courses); asymmetry in course transparency; resolved by further learning.
16	Low Program Career Value	PE-SKL, IF-ASY, CL-ABS, FE-HIGH	Expected program to provide skills and career guidance, but didn't; asymmetry in advertised vs. actual content; absent collective career learning; stress from mismatch.
17	Lack of Practical Training	PE-SKL, IF-ASY, CL-ABS	Relied on self-teaching due to limited useful courses; knowledge asymmetry between education and job requirements; lack of collective learning mechanisms.
18	Low Job Market Demand	PE-VAL, FE-HIGH, SF-NONE	Believed degree/experience was highly valuable but market disagreed; lack of callbacks = no feedback; produced stress.

19	Insufficient Career Search Support	PE-NET, IF-BLK, CL-ABS	Expected more tech networking; opportunities blocked; no systemic mechanism for collective learning/career exposure.
20	Media Control & Inequality	PE-PRO, IF-SIL, CL-HOMO	Expected balance but saw manipulation; media creates silos; homogenized narratives dominate CI.
21	Worries about Job opportunities	AI-PIV, FE-HIGH	Pivoted to prioritize personal security in hostile conditions; reflects adaptation under high free energy.
22	Degree-Job Market Mismatch	PE-VAL, FE-HIGH, SF-NONE	Assumed degree would boost employability; reality: visibility but slow offers; no system feedback; produced frustration and uncertainty.

5.4.3 Phase 2: FEP-CI Translation Bridge Prediction Error Results

The second phase quantifies the qualitative findings from Table 9, providing a high-level statistical overview of the most prevalent issues. The data reveals key trends:

- **Dominant Individual Issues:** Prediction errors, particularly related to skills (PE-SKL, 25% of narratives) and credential value (PE-VAL, 20%), are the most common individual challenges. High anxiety and confusion (FE-HIGH, 50%) are the most frequently reported states of uncertainty. Individuals respond to these issues primarily through self-directed learning (AI-LRN, 15%) and strategic pivoting (AI-PIV, 15%).
- **Systemic Failures:** The data points to significant systemic failures in information flow and collective learning.
    - **Information Barriers:** Asymmetric access to information (IF-ASY, 25%) and blocked pathways (IF-BLK, 20%) are the most common information flow problems. This suggests a systemic failure of institutions (e.g., universities) to provide accurate and transparent information about job market demands.
    - **Learning Gaps:** The most prevalent collective learning issue is the absence of effective mechanisms (CL-ABS, 25%) for sharing knowledge and resources, highlighting a lack of institutional support for career development and networking.
    - **Feedback Void:** A quarter of narratives (SF-NONE, 25%) report receiving no system feedback, indicating that job application processes often fail to provide any response or guidance to applicants.

Table 9: Phase 2: FEP-CI Translation Bridge Prediction Error Results

Note: Percentages calculated from 20 coded narratives (excluding narratives 6 and 13 which were N/A). Narratives can have multiple codes, so percentages may sum to >100%.

Category	Code	Description	Occurrences	% of Narratives
FEP CONCEPTS				
Prediction Errors				
	PE-TIM	Timing mismatch	1	5%
	PE-SKL	Skills gap	5	25%
	PE-PRO	Process misunderstanding	3	15%
	PE-NET	Network access barriers	3	15%
	PE-VAL	Credential value mismatch	4	20%
	Subtotal		**16**	**80%**
Active Inference				
	AI-LRN	Self-directed learning	3	15%
	AI-NET	Network building	1	5%
	AI-PIV	Pivoting strategy	3	15%
	AI-SIG	Credential signaling	1	5%
	Subtotal		**8**	**40%**
Uncertainty States				
	FE-HIGH	High anxiety/confusion	10	50%
	FE-VOID	No feedback gradient	1	5%
	FE-TRAP	Increasing uncertainty	3	15%
	Subtotal		**14**	**70%**
CI CONCEPTS				
Information Flow				

	IF-BLK	Blocked pathways	4	20%
	IF-ASY	Asymmetric access	5	25%
	IF-SIL	Knowledge silos	3	15%
	Subtotal		**12**	**60%**
Collective Learning				
	CL-ABS	Absent mechanisms	5	25%
	CL-FRAG	Fragmented sharing	2	10%
	CL-HOMO	Homogeneous views	2	10%
	Subtotal		**9**	**45%**
System Feedback				
	SF-NONE	No feedback	5	25%
	SF-DELAY	Delayed feedback	0	0%
	SF-NOISE	Contradictory signals	0	0%
	Subtotal		**5**	**25%**

5.4.4 Synthesis of FEP-CI Systemic Patterns

Using the FEP-CI framework, the coded narratives can be rolled up into five higher-level categories: mismatch, isolation, void, compensation, and inequality. Each captures a distinct but interconnected structural issue within the education-to-employment ecosystem.

The most prevalent pattern is **Mismatch**, appearing in nearly two-thirds of all narratives (**75%**). This reflects systematic divergences between expectations and reality across skills, processes, timelines, and credential value. Students often entered the programme with assumptions about clear career pathways, institutional support, or the intrinsic worth of their qualifications. Instead, they encountered significant prediction errors: employers expected job-ready skills not covered in coursework, processes such as recruitment unfolded in opaque and unpredictable ways, and the practical value of credentials was lower than anticipated. From a Free Energy Principle (FEP) perspective, these mismatches represent persistent failures to minimize prediction error at the institutional scale, forcing students to operate with maladaptive priors that increase uncertainty.

The second concern is **Isolation**, evident in **60%** of narratives. Students reported barriers that limited access to networks, information, or opportunities for career development. Part-time students were excluded from key workshops due to scheduling conflicts, while others experienced geographic and cultural silos in research spaces that neglected perspectives from the Global South or East Germany.

These experiences exemplify breakdowns in information flow, where collective intelligence cannot function effectively because knowledge is blocked, asymmetrically distributed, or trapped within silos. In CI terms, isolation erodes diversity of input, producing decision-making processes that are less adaptive and less representative.

A related but distinct issue is the **Void**, present in **50%** of narratives. This describes the absence of meaningful feedback loops between students and the employment system. Applications often disappeared into “the void,” with rejections rarely accompanied by explanations. Similarly, broader social systems offered little clarity to help individuals update their mental models of success. From an FEP standpoint, the void reflects conditions of high free energy without gradient: students are unable to reduce uncertainty because no corrective signals are provided. Without feedback, active inference collapses into guesswork, trapping individuals in maladaptive cycles of uncertainty.

The fourth concern, **Compensation**, highlights the strategies individuals adopt to adapt in the face of systemic shortcomings. This pattern appeared in **40%** of the narratives, where individuals described engaging in self-learning, taking additional courses, reframing CVs, or otherwise attempting to signal their employability to employers. While these actions demonstrate resilience and the ability to minimize free energy through individual active inference, they also underscore the failure of institutional scaffolding. Instead of functioning as extended cognitive systems that support adaptation, universities shift the burden of uncertainty reduction onto individuals. This may generate short-term success for some but produces inequitable outcomes overall, as only those with additional resources or initiative can compensate effectively.

Finally, **Inequality** appears in **30%** of narratives, reflecting systemic disparities in whose voices and perspectives are included in collective processes. Narratives revealed EU-centric biases in research retreats, the marginalization of East German perspectives in post-reunification discourse, and structural imbalances in media shaping political narratives in Greece. In CI terms, these cases exemplify homogeneity of input and asymmetric access to knowledge. The absence of diverse perspectives not only undermines fairness but also diminishes the collective intelligence of the system by narrowing the informational space from which adaptive solutions can emerge.

Taken together, these systemic concerns reveal an ecosystem characterized by weak feedback loops, structural barriers, and persistent mismatches between institutional design and labor market realities. Students are compelled to adapt individually, but this compensation masks deeper systemic failures that prevent collective learning. From a FEP-CI perspective, the employment ecosystem is not minimizing prediction error effectively at the institutional or societal scale. Instead, it leaves individuals in high-surprise states, while collective intelligence mechanisms remain underdeveloped. Addressing these issues requires interventions that build robust feedback loops, reduce isolation, and ensure diverse perspectives are integrated into adaptive governance of employment systems.

Table 10: Synthesis of FEP-CI Systemic Patterns

Note: Narratives can exhibit multiple systemic patterns. Percentages based on 20 coded narratives (excluding narratives 6 and 13 which were N/A).

Systemic Patterns	Definition	Narratives (IDs)	% Seen	Sub-Issues (Codes)	Examples
MISMATCH	Systematic divergence between expectations and reality	1, 3, 5, 7, 9, 10, 11, 12, 15, 16, 17, 18, 19, 20, 22	15/20 (75%)	PE-TIM (1), PE-SKL (5, 10, 15, 16, 17), PE-PRO (3, 11, 20), PE-NET (3, 12, 19), PE-VAL (7, 9, 18, 22)	Students expected degrees, support, or culture to align with job market, but encountered skill gaps, unclear processes, networking barriers, or undervalued credentials.
ISOLATION	Structural barriers preventing access to resources/info	3, 4, 5, 9, 10, 11, 12, 15, 16, 17, 19, 20	12/20 (60%)	PE-NET (3, 12, 19), IF-BLK (3, 11, 12, 19), IF-ASY (5, 10, 15, 16, 17), IF-SIL (4, 9, 20)	Part-time students excluded from sessions, missing Global South or East German perspectives, limited employer links, lack of transparency on course utility.

VOID	Absence of feedback preventing learning/adaptation	1, 3, 11, 12, 14, 16, 17, 18, 19, 22	10/20 (50%)	FE-VOID (12), SF-NONE (1, 12, 14, 18, 22), CL-ABS (3, 11, 16, 17, 19)	Applications disappear into "the void," unclear reasons for rejection, and long-term uncertainty due to lack of institutional or systemic feedback.
COMPENSATION	Individual adaptation compensating for system failures	1, 2, 5, 7, 8, 14, 15, 21	8/20 (40%)	AI-LRN (1, 5, 15), AI-NET (2), AI-PIV (7, 8, 21), AI-SIG (14)	Students pay for extra training, reframe CVs, self-teach, or pivot careers to compensate for systemic gaps.
INEQUALITY	Representation/access disparities weaken collective intelligence	2, 3, 4, 9, 11, 19, 20	7/20 (35%)	CL-HOMO (9, 20), CL-FRAG (2, 4), IF-BLK (3, 11, 19), IF-SIL (4, 9, 20)	EU-centric perspectives dominate retreats, East Germans sidelined, media shaping unequal narratives, and fragmented networking.

6. Conclusion

6.1 The "Free Energy" Trap at Multiple Scales

The narratives reveal education-to-employment transition as a multi-layer free energy minimization problem operating across three levels. At the individual layer, students must minimize surprise about professional requirements while operating with institutionally-formed priors that increase rather than decrease uncertainty. At the collective-institutional layer, universities function as autopoietic systems minimizing their own free energy (maintaining funding, rankings, enrollment). At the Interaction layer, the education-employment ecosystem lacks collective intelligence mechanisms for cross-boundary information integration, creating systematic prediction errors that cascade through generations.The persistent skills mismatch represents a multi-scale optimization problem where each institutional actor minimizes their own uncertainty while creating systematic prediction errors for others.

Through the FEP-CI framework, the analysis theorized why these mismatches are systematic and self-maintaining rather than getting corrected by market forces. The question isn't "why didn't this student learn the right skills?" but "why does the system consistently produce students without the right skills despite clear evidence this isn't working?" This is where FEP-CI framework concepts, properly applied to institutional behavior rather than individual narratives, might offer insights beyond traditional economic or sociological analysis.

6.2 Why These Mismatches Persist

From an FEP perspective and based on research into ongoing employment issues, each institution operates as a Markov blanket-bounded system minimizing its own variational free energy (Friston, 2010; Kirchhoff et al., 2018). The system maintains dysfunction through what Constant et al. (2018) describe as nested hierarchical prediction. Universities minimize uncertainty through stable curricula, predictable revenue streams, and established academic metrics. Their generative model predicts that producing "educated graduates" ensures institutional survival, and this model works for them. Updating curricula to match rapidly changing industry needs would increase internal entropy, require faculty retraining, and destabilize departmental structures (Ramstead et al., 2018). Universities train faculty to reproduce academic models, who train students in those same models, creating multi-generational prediction errors. The "publish or perish" incentive structure ensures faculty minimize their uncertainty by focusing on research rather than industry engagement (Veissière et al., 2020). Employers similarly minimize their free energy by demanding "job-ready" candidates rather than investing in training. Their prediction model assumes that credential requirements reduce hiring uncertainty, even when those credentials poorly predict performance (Albarracin et al., 2022). The cost of providing feedback to rejected candidates or communicating specific needs to universities would increase their immediate uncertainty without clear benefit to them. This creates what Bruineberg et al. (2018) might call "epistemic misalignment." Each institution's local uncertainty minimization actively generates prediction errors for others in the system.

6.3 Why Evidence Doesn't Drive Change

Despite clear evidence of dysfunction, (the analysis revealed that prediction errors were a nearly universal experience), it appears the system resists change because each actor's free energy is actually minimized by maintaining the status quo. Universities face genuinely uncertain futures if they abandon traditional academic models; they cannot predict which skills will matter in five years, so they retreat to teaching "timeless" principles (Friston et al., 2017). From research it seems, employers have discovered that maintaining high rejection rates and demanding experience creates a favorable labor market where they can select from desperate overqualified candidates, their prediction error is near zero even if graduates' is high (Van Es et al., 2021). The CI perspective shows this may not be mere coordination failure but active resistance to collective intelligence. Sharing information about skill needs, salary ranges, or hiring criteria would reduce information asymmetry advantages that currently benefit employers and elite institutions (Janssens et al., 2022). The combination of local free energy minimization and blocked collective intelligence creates an evolutionarily stable strategy - dysfunctional for students but optimal for institutions. The system consistently produces mismatched graduates not despite evidence of failure, but because this "failure" successfully minimizes uncertainty for everyone except the students themselves.

6.4 Normalized Systematic Collective Intelligence Failure

The CI framework reveals why market signals don't correct these mismatches. Woolley et al. (2010) demonstrated that collective intelligence emerges from communication equality, social perceptiveness, and diverse participation. The employment ecosystem often violates all three conditions:

1. **Communication asymmetry**: Information flows unidirectionally from institutions to students, with no return channel for error signals(Woolley, Aggarwal and Malone, 2015).
2. **Limited social perceptiveness**: Universities and employers operate with incompatible ontologies - "critical thinking" versus "deliverables," "research skills" versus "project management" (Riedl et al., 2021).
3. **Homogeneous participation**: Decision-makers in both universities and corporations share similar backgrounds, creating echo chambers that reinforce existing models rather than challenging them (Gresselle-Zaïbet et al., 2024).
4. **Fragmented CI opportunities:** Student experiences of mismatch stay isolated as individual failures rather than aggregating into system-level feedback (Sassi et al., 2022).
5. **Lack of epistemic communities:** The absence of these communities that bridge academia and industry means error signals dissipate rather than driving model updates

7. Recommendations

7.1 Interventions

Based on an analysis of 20 student narratives, this study proposes that the current education-to-employment system is in a maladaptive equilibrium, creating significant and costly prediction errors for graduates. The proposed interventions operate on both individual and collective levels to address this. At the individual level, the recommendations include Reality Calibration Sessions to establish accurate expectations, Application Labs for practical experience, and dual academic-industry feedback to refine student skills. At the collective level, the system needs to enhance collective intelligence through transparent outcome tracking, provide asynchronous networking to preserve diversity, and strengthen alumni-student connections to build a transactive memory system. These interventions are designed to force institutions to internalize the costs of free energy currently externalized to students. This can be achieved by linking university funding to graduate employment outcomes, requiring employers to provide detailed feedback, and creating real-time collective intelligence platforms that aggregate and publicize mismatches. Ultimately, this approach aims to move the system beyond simple skill alignment to one of continuous, recursive adaptation, transforming negative experiences into actionable intelligence and preventing catastrophic prediction errors at the point of graduation.

Table 11: Intervention Implementation and Evaluation

Intervention	**Mechanism (Individual ↔ System)**	**Details**	**Metrics for Evaluation and Policy Impact**
Reality Calibration Sessions	Exposes students early to real job market signals; updates institutional advice with lived graduate outcomes.	Starting in term one, bring recent graduates (6–12 months post-graduation) to share unfiltered job search experiences, including rejection rates, skill gaps discovered, and successful strategies. Provides early prediction error signals.	• Reduction in timing-related prediction errors (students apply earlier). • Improved awareness of rejection rates/skills. • Student survey evidence of greater preparedness.
Hybrid Assignment Structures	Aligns student practice with real industry needs; creates dual academic–industry feedback loops.	The policy solution here is the **Network Commons Protocol**, which mandates alumni introductions, embeds structured network-sharing into curricula, and uses digital platforms to monitor and address inequities in professional access. By fostering shared information infrastructures, systems can counteract isolation and create conditions where diverse inputs circulate and inform collective decision-making.	• Employer satisfaction with student outputs. • Student confidence in applied/hybrid skills. • Evidence of curriculum–industry alignment.
Collective Intelligence Platforms	The platform's core mechanism transforms individual prediction errors into a collective intelligence signal that allows other students to proactively update their beliefs, thereby	Building Collective Intelligence Platforms such as EuroSense, where students can contribute and access narrative-based feedback loops on career pathways. Additionally, real-time labor market dashboards and employer-student feedback systems would provide signals to reduce uncertainty	• Increase in application-to-interview ratios. • Reduced reports of “application void” frustration. • Aggregated insights on employer trends.

	reducing systemic uncertainty.	and enable continuous recalibration.	
Asynchronous Networking Infrastructure	Expands access to networking resources for part-time and working students; systemically reduces barriers to distributed intelligence.	Record all career events with speaker consent obtained upfront, creating an accessible repository for students unable to attend live.	• Uptake of recorded resources by part-time/working students. • Higher inclusivity ratings in student surveys. • Broader participation in networking activities.
Transparent Outcome Tracking	Provides individuals with realistic benchmarks; institutions gain data to recalibrate program design.	Publish anonymous but detailed placement data showing application-to-offer ratios by sector, required training, and time-to-employment.	• Improved student calibration of expectations (survey data). • Use of outcome data in institutional planning. • Reduction in skill/timing mismatches over time.

7.2 Ethics & Equity and Justice

An important extension of the exploratory FEP–CI framework is the incorporation of ethical guardrails to ensure it does not reinforce inequities or reproduce systemic biases.

- **Equity calibration:** Ensure that prediction error detection incorporates demographic disaggregation (e.g., are errors more severe for international, part-time, or first-gen students?).
- **Justice in intervention design:** Require that interventions benefit the most disadvantaged groups first, not just "average" students.
- **Participatory validation:** Stakeholders (students, alumni, employers) review findings to prevent elite or institutional capture.
- **Ethical AI/data use:** If future computational models are developed, ensure consent, anonymization, and fairness testing (bias audits).

8. Discussion

8.1 Contribution to Knowledge

This research demonstrates the potential value of applying Free Energy Principle and Collective Intelligence frameworks to understand employment system dysfunction, while acknowledging its exploratory and novel nature. The analysis of 20 science-technology-policy student and alumni narratives revealed systematic patterns: persistent prediction errors between academic preparation and market realities, institutional structures that increase rather than reduce uncertainty, and absent collective intelligence mechanisms that prevent system-wide learning from individual struggles. This dissertation's primary contribution lies not in proving FEP-CI's superiority but in demonstrating its potential as a diagnostic and intervention-design tool. The Translation Bridge Model offers a systematic method for converting theoretical insights into practical recommendations without requiring full mathematical implementation. The framework's value emerges from its ability to reveal patterns invisible to traditional analyses: the compound disadvantage effect where prediction errors and network exclusion create self-reinforcing cycles, and the collective learning failures where valuable insights from struggling students never reach the broader system.

The FEP–CI framework could potentially advance employment analysis beyond legacy models by integrating continuous individual adaptation with system-wide learning. A key advantage is the framework's ability to bridge agency and structure: individuals actively adjust their strategies, while institutional patterns emerge through collective interaction, conceptualized via mechanisms such as nested Markov blankets. This supports a future methodological and computational predictive and adaptive responses to labor market volatility, addressing shortcomings of static, equilibrium-based theories.The potential paradigm shift lies in reframing employment systems as continuously adaptive rather than descriptive and static. By embedding prediction, feedback, and collective learning into three layers of analysis, FEP–CI could offer a pathway to more resilient and responsive employment ecosystems. This framework addresses the issue of "no definitive formulation" by reframing the problem as one of active inference: instead of seeking a single, static definition, the system continuously updates its model of the problem space through interaction and feedback. This "active" and adaptive approach also mitigates "complexity blindness," as the framework is inherently designed to manage the dynamic, interconnected nature of complex adaptive systems. Furthermore, the FEP's emphasis on minimizing prediction errors provides a mechanism for addressing the "information gaps" and the lack of a "clear set of solutions." Instead of a static checklist, the system iteratively tests hypotheses and refines its understanding, with each "solution" being a form of predictive action rather than a definitive, irreversible intervention. By treating symptoms as prediction errors, the framework also offers a way to trace a wicked problem back to its underlying "Symptoms of other problems," allowing for more holistic and integrated interventions that adapt to the unique, changing context of each problem (B. W. Head & Alford, 2015). Internationally, the FEP–CI framework could also support cooperation on employment adaptation under AI and automation, with shared databases and platforms enabling countries to pool foresight and anticipate disruptions. Employment policy restructured as a learning system, continuously sensing, analyzing, and adapting, could create fairer, faster, and more ecological-centered labor markets.

8.2 Limitations

This master's dissertation faces practical constraints that affect its scope. The sample of 22 participants enables qualitative pattern identification but not statistical generalization, making findings exploratory rather than definitive. Additionally, the research lacks quantitative FEP modeling to formalize prediction errors and adaptation patterns, instead relying on narrative-based methods appropriate for exploratory theoretical work at the master's level. The current framework's value lies in opening new theoretical pathways for employment analysis. Demonstrating FEP-CI integration feasibility, generating hypotheses for future testing, and offering a vocabulary for discussing employment challenges that moves beyond individual deficit models toward systemic understanding.

8.3 Future Research

8.3.1 Questions

Applying the Free Energy Principle to employment raises several critical questions for future research. A major challenge is how to quantify a graduate's "surprise" without oversimplifying their complex experiences. Longitudinal studies are needed to see if collective intelligence can truly reduce unemployment over time. It's also essential to investigate the ethical implications of these systems, ensuring they don't reinforce existing inequities. Researchers must also understand how cultural factors influence career decisions, as strategies that work for one group might not for another. Future research should compare the FEP-CI framework's effectiveness against traditional models, evaluate if FEP-CI-informed interventions are more successful than standard career services, and confirm its validity across different cultures and economic conditions.

8.3.2 Toward a Hybrid Math and Meaning Approach

The current exploratory framework should expand research into using computational implementation. Using tools such as PyMDP, RxInfer, or SPM could calculate variational free energy and generate precise predictions about individual trajectories through multi-agent active inference simulations. Strategic integration of mathematical FEP applications could quantify inequality in ways policymakers cannot dismiss, combining "math and meaning." This dual approach would make employment discrimination mathematically undeniable to policymakers who might dismiss narratives as anecdotal, while ensuring the human impact remains central rather than obscured by equations. Specifically, funding would support developing computational models that could calculate prediction error magnitudes across demographic groups, creating evidence that is both statistically rigorous and humanly meaningful.

8.3.3 Proposed Next-Steps

Future research should incorporate broader stakeholder perspectives, employers, policymakers, career services, and workforce development experts, to build comprehensive, multi-perspective analysis of employment misalignments. The FEP-CI Framework, also requires testing across diverse contexts and longitudinal validation.

- **Data structures:** longitudinal cohort datasets linking course enrollment, job applications, interviews, and outcomes. This would allow prediction-error modeling over time.

- **Computational methods:**

    - PyMDP or RxInfer for active inference simulations at individual level.
    - Agent-based modeling to simulate network flows and CI breakdowns.
    - Bayesian hierarchical models to quantify prediction error distributions across sub-groups.

- **Hybrid pipeline:** narrative data provides qualitative priors → priors parameterize computational models → models generate quantitative predictions → predictions tested against new cohorts.

8.4 The Contemporary Relevance of the FEP–CI Framework

As artificial intelligence accelerates labor market change, frameworks that capture both individual adaptation and collective system evolution become critical. This research suggests the FEP–CI approach could provide such a framework, though further testing is needed. The stakes may have never been higher than at this moment in time. Humanity could be facing a "Fourth Industrial Revolution," with estimates that AI could automate 40% of jobs within 15–20 years (Acemoglu & Restrepo, 2020). Yet governments and universities still operate on outdated models, creating cascading uncertainty or what this dissertation calls "collective free energy overflow," where attempts to reduce uncertainty (education, retraining, career changes) paradoxically often increases it. "Governance systems therefore need to function as an infrastructure for uncertainty reduction. Instead of measuring GDP or employment statistics alone, societies could also track "Collective Free Energy," or the uncertainty citizens face about work, healthcare, and stability. Policies should be judged on whether they lower this uncertainty. As AI development accelerates at digital speed, the cost of institutions that amplify uncertainty rather than reduce it becomes existential. The students sending applications "into the void" are not isolated cases but early warning signals of a broader prediction error crisis. The choice is not between technological progress and human welfare, but between governance systems that minimize collective surprise through adaptive, transparent support, and those that entrench rigidity and self-preservation while leaving citizens in states of life changing uncertainty. Action is required now to safeguard the wellbeing of present neighbors and future generations against a looming crisis.

9. Appendices

Appendix 1: Dissertation Author (Allegra Grunberg's) Original Concepts:

1. **The FEP-CI Integrated Framework** - A novel synthesis combining FEP and CI for employment analysis
2. **The Translation Bridge Model** - A novel method for converting theoretical concepts into practical employment interventions
3. **The specific operationalization** of FEP concepts (like prediction error) in employment contexts
4. **The three-level integration approach within the FEP-CI Framework** (Individual, Collective, Interaction layers)
5. **The methodological requirements table** for applying FEP-CI to employment
6. **The comparative analysis table** showing how FEP-CI addresses gaps in existing theories

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