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**A Hybrid Framework for Technology Change Detection: Integrating Topic Modeling, Expert-Informed Input, and Reinforcement Learning**

by

Ali Nazari

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*Ali Nazari*

# Abstract

Organizations face significant challenges in detecting technological changes. They must constantly explore and assimilate external technological changes to stay competitive. To do this, they need an effective approach to integrating external knowledge. In existing methods, detecting technological changes, and assimilating them in real time, considering allocating resources, are still significant gaps. To address these gaps, this thesis presents a hybrid Expert-Informed AI Learning Framework (EILF), developed through design science research methodology. The research follows a five-phase design science research method including problem definition, framework design, implementation, real-world application, and evaluation and verification. The framework is designed on four key domains (conceptual structures), including text analytics, machine learning, external input, and expert-driven feedback, and the core components (operational structure) is specified. The practical framework is implemented through four key components, namely, topic modeling, expert-informed knowledge, reinforcement learning, and expert-driven feedback. In the implementation phase, a multi-step approach is developed and is applied to a real-world quantum cryptography case study. After data collection and creating a corpus, the topic modeling analysis phase is carried out in four subphases: 1) building a topic model, 2) refining topics with expert-informed knowledge, 3) optimizing topics with reinforcement learning, and 4) applying the insights to real-world decisions. Following the topic modeling phase, the final outputs show the topics selected, such as T19 (security protocols) and T32 (QKD and photon-based communication) by RL, are aligned with technological changes discussed in the conference papers. We evaluate the framework by measuring the precision and novelty of expert-driven feedback obtained from conference papers as experts’ proxy. The framework presents a scalable way to integrate AI-driven modeling with expert insights. This gives organizations a strong tool for detecting technological changes in real time and using data to respond to the changes.

Keywords: Topic Modeling, Expert Knowledge, Reinforcement Learning, Technological Change Detection

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# Glossary

Absolute Difference Normalized Sum (ADNS): It is a metric to measure how much topic distributions differ over time.

Ambidextrous manner: the behavior that shows how organizations manage resources for exploring new ideas and improving existing ones.

Aspect keyword weighting: It is about giving importance to specific keywords. These keywords reflect thematic aspects. This helps improve topic models and showcase relevant content.

Aspect-Based Topic Modeling: It is a refined approach to topic modeling. It uses expert-defined keywords to highlight key aspects of a domain.

Contextual Topic Perspectives (CTP): is a way to look at topic models. It helps analyze them from various angles. With each iteration, you gain a clearer picture of the topics.

Cosine similarity: measures how alike two text documents are. It uses their word vector representations to find this similarity.

CTP1: The initial topic model is used as a baseline.

CTP2: The aspect-based topic model is used to compare and refine CTP1. It becomes the new baseline in the next iteration.

CTP3: The final iteration of the model, incorporating further refinements from CTP2.

Document: All text materials come from library search engines. This includes peer-reviewed reviews, articles, books, and notes.

Emerging Topic: A newly detected topic that is increasingly frequent, novel, or connected to other concepts.

Emerging Trend: A topic that shows early signals of becoming a trend but has not yet gained adoption.

Entanglement: is a quantum effect. It occurs when two or more particles stay linked. This connection lets them change states instantly, no matter how far apart they are.

Entropy: measures uncertainty or disorder in a system. In topic modeling, it shows how evenly words spread across topics.

Expert feedback: This is input from experts or expert-driven sources. It helps to guide, adjust, and validate the computational model.

Expert input: Advice, insights, or guidance from specialists in a field. This helps to improve or validate specific details. In this research, we use a report from the Quantum Tech website as a proxy for expert input. This report came out soon after the corpus was published.

Expert Weighting: Experts decide how important certain keywords or concepts are. This helps with topic modeling refinement.

Experts proxy: These are alternative sources of knowledge or judgment. They include curated conference proceedings and industrial reports. We use them instead of direct expert input.

Exploitation: means using and improving current knowledge or technologies to improve performance.

Exploration vs. Exploitation: In RL, exploration means finding new knowledge or technological changes. Exploitation, on the other hand, uses known strategies for quick rewards.

Exploration: is the act of seeking new knowledge, technologies, or solutions. It focuses on finding new discoveries.

External Input: This includes curated keywords, domain taxonomies, or trusted proxies. Examples are peer-reviewed conference proceedings. These help to refine topic relevance.

F1-Score: A harmonic mean of precision and recall, used to evaluate the accuracy of a classification model.

Hierarchical Dirichlet process (HDP): A nonparametric Bayesian approach to clustering grouped data.

Hyperparameters: Tunable parameters that influence the learning behavior of a model, such as the learning rate in RL.

Latent Dirichlet Allocation (LDA): is a statistical model. It helps find hidden themes in similar data.

Organizational Learning: is how organizations gain, keep, and use knowledge. This helps them make better decisions and improve performance.

Policy Optimization: The process of refining the strategy (policy) used by an RL agent to maximize its long-term rewards.

Post-Quantum Cryptography (PQC): Cryptographic algorithms designed to withstand attacks from quantum computers.

Precision: measures the percentage of correctly identified relevant topics among all topics identified.

Quantum Key Distribution (QKD): is a secure way to communicate. It uses the rules of quantum mechanics to keep messages safe.

Q-values: are estimates of the expected total reward from taking certain actions in specific states. They help evaluate and improve policies in reinforcement learning (RL).

Recall: A measure that shows the percent of relevant topics identified correctly from all actual relevant topics.

Reinforcement learning (RL): is a type of machine learning. In RL, an agent learns by taking actions and getting feedback. This feedback comes as rewards or penalties. The goal is to maximize the total reward over time.

Reward function: In RL, this function shows how good an action's result is. It helps the agent learn and make decisions.

RL Agent: An agent in the RL component. It makes decisions based on feedback from the environment. Its goal is to maximize cumulative rewards.

Secure Communication Protocols: These are methods and technologies that keep digital communication safe. They help ensure confidentiality, integrity, and authenticity.

Strategic Foresight: is a method for predicting future trends and uncertainties in a specific area.

Subtopics: Clusters obtained by applying the clustering algorithm to each of the topics.

Technology Landscape Analysis: This means finding, sorting, and keeping an eye on new technologies and innovations.

Technological Change: This is a new advancement or innovation that comes from outside the organization. It can impact operations, strategy, and the need for learning or adapting.

Technological Shift: A big change in technology that affects key tools, practices, or ideas. It usually comes from outside and requires organizations to adapt and learn.

Technology intelligence: is the process of collecting and analyzing data on new technologies. This helps organizations make smart decisions.

TF-IDF, or Term Frequency-Inverse Document Frequency, is the most common way to turn text into vectors. This technique is widely used to extract features across various NLP applications.

Topic Divergence: This measures how much a topic’s makeup changes between model runs.

Topic Magnitude: This measures how a topic's spread shifts across different models or runs. It shows how topic focus changes over time.

Topic Modeling: This method uncovers hidden themes in large document collections. It falls under unsupervised text mining. A well-known technique is Latent Dirichlet Allocation (LDA).

Topic Terms: These are terms in a dataset, often hidden, found through topic modeling.

Trend Detection: This involves spotting shifts in research, innovation, or industry focus using data analysis and forecasting tools.

Trend: This refers to a steady increase in the importance of a topic over time.

Validation and Feedback: This process compares model results with known domain signals, like conference topics and citation trends. It helps refine the model over time.

# Abbreviations

ADNS Absolute Difference Normalized Sum

ADP Adaptive Dynamic Programming

ATMi Aspect-based Topic Model (a model that incorporates expert input and aspects)

BERT Bidirectional encoder representations from transformers

CPT1&CPT2 Comparative versions of topic models used to track changes through iterations

CTP Contextual Topic Perspectives

CTP1 Initial Contextual Topic Perspective

CTP2 Aspect-based Contextual Topic Perspective (iteration 1)

CTP3 Updated Contextual Topic Perspective (iteration 2)

DL Deep Learning

DocsCTP2 A matrix comparing topics in CTP2 with document assignments

DocsCTP3 A matrix comparing updated topics in CTP3 with document assignments

DRL Deep Reinforcement Learning

DSRM Design Science Research Methodology

EE Exploration and Exploitation

EILF Expert-Informed AI Learning Framework

EITL Expert-in-the-Loop

HCI Human-Computer Interaction

HDP Hierarchical Dirichlet Process

HITL Human-in-the-Loop

KL Kullback-Leibler Divergence

LDA Latent Dirichlet allocation

ML Machine Learning

NLP Natural Language Processing

OL Organizational Learning

PQC Post-Quantum Cryptography

QKD Quantum Key Distribution

Q-value A value used in RL to represent the reward of an action in a given state.

RL Reinforcement Learning

RLHF Reinforcement learning from human feedback

T32 A specific topic related to protocol advancements in cryptography

TF Term frequency

TF-IDF Term Frequency-Inverse Document Frequency

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# Formulas

|  |  |  |
| --- | --- | --- |
| Formula No. | Equation | Description |
| 1 | ||A|| = sqrt(Σ Ai^2) | Calculates the magnitude of a topic weight vector, measuring the spread or intensity of topic contributions. |
| 2 | Cosine Similarity = (A · B) / (||A|| ||B||) | Computes cosine similarity between two topic word vectors to assess overlap and track topic evolution between models. |
| 3 | H(T) = -Σ P(w|T) log P(w|T) | Quantifies uncertainty in a topic’s word distribution high entropy indicates broad topics, low entropy suggests focused ones. |
| 4 | A' = A / (Σ Ai), B' = B / (Σ Bi) | Normalizes vectors into probability distributions for comparison in ADNS calculation. |
| 5 | ADNS = Σ |A'i - B'i| | Measures the total absolute difference between two normalized topic distributions, indicating changes. |
| 6 | R(s,a) = λ1 × Divergence + λ2 × Similarity + λ3 × Entropy + λ4 × ADNS | Combines divergence, similarity, entropy, and ADNS into a weighted reward for RL, balancing exploration and stability. |
| 7 | Q(s,a) ← Q(s,a) + α [R(s,a) + γ max Q(s',a') - Q(s,a)] | Updates Q-values in RL based on reward, learning rate, and future rewards to guide topic selection. |
| 8 | R(s,a) = Reward\_Base + (Entropy Change × λ) | Modifies the reward with entropy change to enhance exploration, focusing on emerging trends like post-quantum cryptography. |
| 9 | Reward\_Base = (1/d) Σ (1 - Cosine Similarity (Topic, Documenti)) | Calculates the base reward as the average inverse similarity between a topic and new documents, promoting exploration of new areas. |

# Introduction

## Motivation

Organizations face increasing difficulty adapting to fast technology changes. According to the KPMG Global Tech Report (2024), 78% of organizations report challenges in keeping pace with technological changes, and 80% identify risk-averse leadership as a primary barrier to innovation. In today’s technology-driven environment, organizations must continuously adjust their strategies to match rapidly shifting technological landscapes. However, traditional foresight tools such as expert panels, trend scanning, or bibliometrics are often static, labor-intensive, and reactive to process large-scale, fast-changing data, limiting timely and strategic decision-making. This gap creates a critical need for a framework that integrates data-driven topic discovery, adaptive actions, and domain-informed refinement. Additionally, technological changes in fields like quantum communication highlight the need for real-time, contextual learning systems. As (Andries & Debackere, 2006; Calof & Smith, 2009; Veugelers et al., 2010) argue, if firms fail to absorb and integrate foreign technical knowledge, they will hinder innovation and competitiveness, especially in volatile fields like quantum cryptography or post-quantum communication. The need for detecting technological changes, timely decision systems span industries–telecom companies like Ericsson or Nokia need to constantly monitor new technological changes using a technology detection tool; SMEs require lightweight foresight tools; and standardization bodies (e.g., NIST) need to track emerging threats and align policy. This thesis presents a scalable and domain-informed AI framework that allows various actors – strategic decision-makers, analysts, and researchers­ – to explore and analyze to technology shifts in real time.

*The Importance of Adaptability Through External Knowledge Integration*

Detection and assimilation of new knowledge is the core of a firm’s ability to respond to domain-related technological changes effectively. It relies on the ongoing integration of external knowledge, exploring, assimilating, and applying new knowledge insights to adjust internal strategies and systems. But many firms struggle to use the new knowledge on time. This leads to delays and missed chances (Bailey et al., 2022; Faraj et al., 2018). They must also adjust decision-making structures to keep up with the changing external environment. AI-powered tools can assist them by detecting changes and identifying relevant trends. These tools enhance their ability to interpret external signals and support timely, informed decisions (von Krogh et al., 2023).

Apart from these technological advances, detecting and assimilating external knowledge is still a challenge (Basten & Haamann, 2018). Recently, von Krogh et al. (2023) argue that how AI can help identify novel research opportunities. Many existing frameworks fail to identify novel topics or align them with organizational priorities in a dynamic manner. Indeed, organizations often find it hard to balance exploration and exploitation, where exploration is seeking new knowledge, while exploitation focuses on refining what they already know. This balance will be pivotal, when new insights value is uncertain for firms (Floyd & Lane, 2000; Gupta et al., 2006). Without it, firms may face two risks. First, exploration trap which happens when they chase new ideas that do not lead to real value for firm. Then, success trap which occurs when they cling to old knowledge that no longer works (Walrave et al., 2011). Compounding this issue is the need for firms to dynamically shift their strategic focus as external conditions evolve (Walrave et al., 2017). With these shortcomings, static or manual analytic systems are not enough. We need a framework that lets organizations explore and use external knowledge timely. It should detect continuously and align insights with the organization’s strategies. This thesis addresses this gap by developing an adaptive, expert-informed framework designed to help organizations detect and respond to technology changes using topic discovery, reinforcement learning, and expert validation.

*Current Approaches to Knowledge Integration*

Organizations rely on computational modeling techniques, unsupervised topic modeling such as Latent Dirichlet Allocation (LDA) and its extensions, to explore large-scale, unstructured textual data (Antons et al., 2020; Blei et al., 2003). These models assist the extraction of latent topics across diverse sources and domains and are broadly applied in innovation research and strategic foresight. However, LDA and similar modeling techniques lonely are often computationally intensive and need significant manual oversight for interpreting and validating the discovered topics (Sievert & Shirley, 2014) . More critically, each time new data is added or the domain shifts, the model typically needs to be retrained, limiting its responsiveness, and increasing resource costs.

To address this rigidity, recent studies have presented model refinement approaches aimed at making possible in a timely manner. These include integrating domain-informed keyword guidance (Gui et al., 2019), dynamically weighting emerging signals, or using proxy indicators such as conference proceedings or patents to ground topic coherence (Antons et al., 2020; Diam et al., 2016). While such refinements improve the contextual relevance, they often depend on static configurations or one-time adjustments, which makes sustained timely adaptation challenging–especially in fast-evolving fields like quantum communication or AI governance (Porter, 2007; von Krogh et al., 2023).

On top of these modeling and refinement issues lies a third strategic challenge: how to balance exploration and exploitation (EE) strategies in the learning process. In organizational settings, exploration aids the discovery of novel, potentially disruptive signals, while exploitation concentrates on deepening current knowledge and aligning insights with strategic goals (Khetarpal et al., 2022). Reinforcement learning (RL) techniques, including Deep Q-Networks (Mnih et al., 2015), offer mechanisms for optimizing this balance through adaptive reward structures. However, aligning the reward functions with organizational priorities, and doing so dynamically, is still a challenge (Köpf et al., 2023). Firms often mismanage the transition between exploration and exploitation, particularly under volatile innovation cycles.

Together, these three concepts including unsupervised modeling, real-time refinement, and EE balancing make up the core of knowledge integration intelligently. However, current systems often address these concepts in isolation. This causes two considerable gaps in the existing frameworks:

1. Timeliness: Current topic modeling systems are not designed to detect, update, or act on external changes in real time. The delay between the emergence of signals and the insight delivery limits responsiveness (Basten & Haamann, 2018; Diam et al., 2016; Porter, 2007).

2. Dynamic Detection: Many systems, even those with RL or expert-informed input, lack ongoing interaction within models, expert knowledge, and decisions effectively (Gunning et al., 2019; Veugelers et al., 2010).

*Detailed Research Problem and Gaps in the Literature*

Apart from advances in the knowledge integration frameworks, key challenges still exist in adapting to dynamic environments, where dynamic balancing exploration and exploitation, integrating contextual knowledge, and embedding external input in real time are significant challenges for firms. The core problem is the organizations’ struggling to explore technological signals while refining knowledge relevance continuously and intelligently through expert insights. These timeliness and dynamic detection gaps lead to critical methodological, practical, and theoretical challenges:

* Methodological **Gap – Contextual Knowledge Integration: Many** frameworks overlook NLP and advanced text analytics. They miss out on valuable knowledge that can aid decision-making. This oversight is significant so that the frameworks can manage large amounts of unstructured data and improve decision-making. (Antons et al., 2020; Porter, 2007) state the limits of current text and tech mining methods. They struggle to integrate real-time expert input and cross-domain foresight. Diam et al. (2016) and Jiang & Chen (2021) note an overreliance on single data sources like patents that shows the need for multi-modal, adaptive, and expert-informed frameworks. Coccia & Roshani (2024) show that static models cannot keep up with the fast growth of new technologies, like quantum innovation.
* Practical Gap – Expert-driven Involvement: Expert-informed frameworks are being developed, but real-time integration of experts is still not strong. This limits organizations effect on strategic decision-making. Calof & Smith (2009); Veugelers et al. (2010) point to the limitation: the lack of timely integration of expert input into analytical and decision-making frameworks, which constrains the agility of R&D organization.
* Underdeveloped Technological Change Detection Theory: Organizations use machine learning tools, but often lack models that guide the effective use of expert feedback in adaptive processes. Researchers like Gupta et al., (2006) and Seo et al. (2023) highlight the need for improved theoretical models. They suggest combining expert judgment with automated learning.

These gaps in methods, practices, and theories show the need for a new framework, which combines expert-informed learning, reinforcement-driven adaptive, and dynamic topic modeling. To fill these gaps, new methods support expert-in-the-loop systems that integrate computational intelligence with human expertise. They enable flexible learning and shifting topic priorities based on algorithm results and expert input. This thesis expands on this idea by introducing a unified, modular framework that connects topic modeling, expert refinement, and reinforcement learning. This framework is iterative and adaptive, aimed at supporting real-time knowledge integration.

## Relevance

This study enhances both foresight practice and the theory of RL, expert-informed feedback modeling, and strategic topic modeling as key enablers. In today's rapid technology world, the ability to detect and respond to new technological changes is crucial for many stakeholders. The proposed framework, Expert-Informed AI Learning Framework (EILF), shown in Chapter 3, fills the gaps in detecting, understanding, and using insights. This framework builds on existing research and works for different sectors, such as industry leaders, policymakers, and researchers.

*Technology Companies (e.g., Telecom Firms like Ericsson and Nokia)*

Big technology companies, especially in telecom, face growing pressure to secure their systems against future threats like quantum computing. Companies like Ericsson and Nokia would benefit from the EILF that enables timely technological changes or signals detection, expert-informed learning, making informed decision. As Cavaliere et al. (2020) stress the key role of telecommunication companies in advancing quantum technologies, they show the need for these companies to have proactive foresight systems. These firms are not merely followers; they actively lead in areas like quantum key distribution (QKD). Detecting early signals of technological changes gives them a competitive edge.

#### R&D Departments

R&D management and teams aim to use firm resources wisely. However, current both manual and automated foresight methods lack the agility and adaptability needed in fast-paced R&D settings (Antons et al., 2020; Calof & Smith, 2009). Also, (Porter, 2007) stresses that topic modeling approaches often ignore early innovation signals, making it hard for R&D teams to detect timely technological changes . Additionally, Eggers & Park,(2018) emphasize the importance of detecting weak signals. The proposed framework offers R&D teams a more agile, expert-informed approach to detect timely emerging trends, and weak signals, adapting innovations.

#### Policymakers and Standardization Bodies

Public agencies, regulatory organizations, and standardization groups like NIST and ETSI play vital roles in creating frameworks that prepare industries for technological disruptions.  
Brauer et al. (2024) and Chen et al. (2016) emphasize the need for standards in QKD. They highlight the importance of scalable frameworks to track innovations in a timely manner. As QKD and post-quantum cryptography grow, these groups need to stay updated. They must follow the changes to closely shape policy and set technical standards. The proposed framework provides an adaptive environment to actively monitor emerging signals and shifts in domain that enables companies to regulate the policies and operational rules.  
*SMEs and Research Institutions*

Small and medium-sized enterprises (SMEs) and research institutions often lack the resources for large foresight systems. Bogers et al. (2018) argue that open innovation frameworks can benefit these organizations. They stress the need for systems that collect external signals to improve decisions. These groups need efficient, automated methods like our proposed framework to explore and integrate knowledge with minimal manual work. The proposed framework provides a scalable, domain-aware solution. It helps SMEs and research teams focus on key emerging areas, even with limited data and resources.

## Research Objectives and Questions

This research tackles a key challenge that is to how organizations can efficiently explore, analyze, and adapt to technological changes. In the current rapid technological environment, companies require timely technology change detection framework to make informed decision. The research objective is to develop and evaluate a data-driven, expert-informed framework that supports timely detection of technological changes through topic modeling, expert-informed input, RL, expert-driven feedback. These four main components include (1) exploring technological changes by a topic modeling technique, (2) analyzing new insights of technological changes by expert-informed refinement to improve contextual relevance, (3) guiding adaptive optimization of topic selection toward novel and emerging areas through a reward-based mechanism by utilizing a technique like RL, and (4) validating the gained insights by expert-driven feedback.

Broader benefits include:

* Proactive Adaptation to Technological Changes: It helps organizations detect potential disruptions; For example, advances in quantum computing urge telecom companies to develop quantum-safe encryption protocols.
* Identifying Strategic new Insights: Companies can find opportunities by analyzing trends. For example, they might explore quantum-resistant encryption or new quantum products.
* Enhanced Expert Collaboration in Knowledge Integration: This approach allows experts to share their knowledge with minimal effort and allows different experts to work together. This collaboration improves strategic decision-making. The framework also creates space to have diverse expert viewpoints to enhance decision-making.

The proposed framework also methodologically links AI-driven foresight, RL-based learning, and expert-driven involvement as a novel and adaptive tool for technology change detection.

#### Research Questions

This research explores how organizations use computational tools and expert input to tackle complex technology detection challenges. It focuses on detecting emerging topics and refining their relevance for timely use. This research is organized around key questions to guide this investigation.

* **RQ: How does the combination of RL, topic modeling, and expert-informed input enhance the detection of technological landscape changes?**

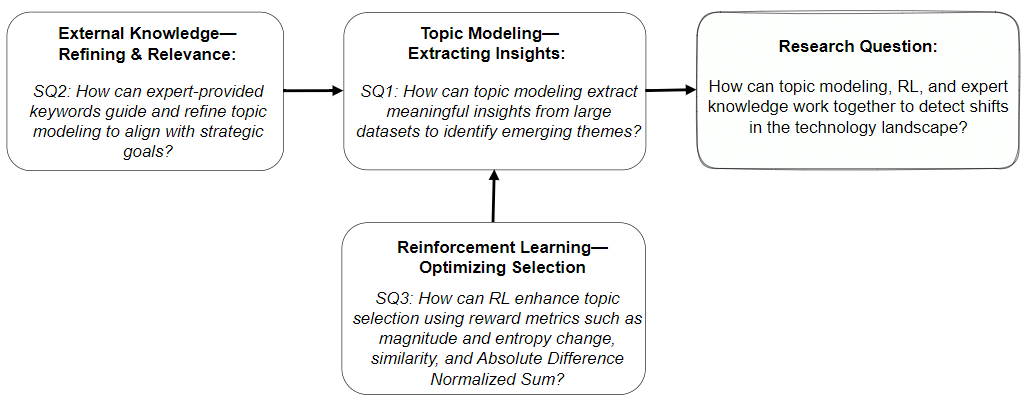


Figure 1: Research Question and Sub-Questions Aligned with key Theoretical Constructs

This question explores how integrating first three components can lead to more accurate and timely detection of technological changes. To approach this, we structure three sub questions aligned with first three components as shown in Figure 1. The sub-questions include:

RQ1.1. How can topic modeling extract meaningful insights from large datasets to identify emerging topics?

RQ1.2. How does expert knowledge, in form of weighted keywords, refine these insights to ensure their relevance and alignment with organizational goals?

RQ1.3. How can RL improve the selection of topics based on key reward metrics, such as magnitude, similarity, entropy changes, and Absolute Difference Normalized Sum (ADNS), within the topic models?

Thematically, the concepts in the research sub questions are aligned with our conceptual framework (Figure 2). The validation concept (expert-driven feedback) is not directly tied to the research sub questions but uses to assess the overall effectiveness and applicability of our proposed framework.

## Hypotheses and Key Constructs

The research is based on two main hypotheses. These reflect the tentative answer of research questions. The first hypothesis relates to the overall effectiveness of the proposed framework, while the second hypothesis focuses on addressing the trade-off between exploiting existing topics and exploring new ones. Overall, the hypotheses explore how combining topic modeling, RL, and expert input improves the accuracy of technology change detection. They also look at how this integration balances exploration and exploitation in technology monitoring and foresight.

**H1:** Combining topic modeling, RL, and expert input improves the accuracy and timeliness of technology change detection. This is measured by the relevance of identified trends and the system’s adaptability to new data.

This hypothesis suggests that firms can detect technological changes better than previous methods. They can do this by combining topic modeling and RL techniques with expert knowledge. The continuous learning from RL, along with insights from experts, enhances the system’s ability to find and respond to new trends.

**H2:** Combining topic modeling, RL, and expert-driven feedback helps balance exploring new topics and using what we already know. This is shown by changes in Q-values and the choice of relevant topics based on different reward settings.

This hypothesis stresses the need for balancing exploration and exploitation in knowledge integration. Companies often face this challenge. They must decide between pursuing new technologies or using their existing expertise. For example, a firm in cryptographic security might wonder whether to invest in quantum-resistant encryption or to enhance its current algorithms. Finding the right balance is crucial. Over-focusing on exploration can lead to wasted resources on uncertain trends. Meanwhile, excessive exploitation may cause stagnation and missed innovation opportunities. By applying RL, the system can optimize resource allocation. This approach enables firms to explore promising new technologies while still using their established capabilities.

#### Key Constructs

This research framework has four linked constructs including Topic Detection,   
Domain External Knowledge, Exploration-Exploitation Reward Balance, and Validation of Technology Detection.

Technical Expertise (Topic Modeling): Topic modeling extracts and organizes themes from large amounts of unstructured text (as stated in Blei et al., 2003). The topic modeling helps find technological trends by detecting hidden topics in research papers, reports, and other technical documents (Walrave et al., 2017). This gives a clear view of emerging fields for better decision-making. It supports RQ1.1 and H1, showing how topic modeling aids in trend detection.

Domain Knowledge (External Input): We use expert keywords and expert knowledge proxies to keep the topics relevant. The keywords include content from conferences and industry reports. The external knowledge improves the contextual relevance and specificity of the generated topics. It supports RQ1.2 and H1 (contextualizing outputs for relevance).

Exploration-Exploitation Balance (RL): While domain knowledge is static, reinforcement learning enables ongoing adaptation. RL helps the system balance exploring new knowledge and using what it knows. It does this based on reward functions like novelty, similarity, and entropy. This approach improves learning from feedback in the environment and supports RQ1.3 and H2 (adaptive optimization of topic selection).

Validation of Technology Detection (Apply & Feedback): This construct keeps detected topics timely and relevant. It uses feedback from experts or real-world documents to update models. If the model’s outputs donot match external trends, the system adjusts and learns more. This process reinforces continuous improvement in topic relevance and alignment. It supports H1 and H2 by aligning learning loops with real-world data.

Together, these constructs provide a strong, AI-enhanced method for detecting and interpreting technological change. This helps organizations make quick, strategic decisions in fast-changing environments. The four key constructs–Topic Detection, Domain Knowledge input, RL, and validation feedback–shape the design and implementation of the proposed framework. Each construct acts as a component within the Expert-Informed AI Learning Framework (EILF), detailed in Chapter 3. By turning theory into practical parts, the framework enables structured, timely learning from data and expert feedback.

## Expected Findings

**Looking ahead, this research is expected to demonstrate how combining four components including topic modelling, expert-informed knowledge, RL, and validation helps organizations adapt to technology changes effectively. We will apply a quantum cryptography data to show the outcomes that are aligned with the current advancements in security protocols. Expected outcomes include the timely detection of new post-quantum cryptographic technological changes, a balance between exploring new topics and using what we already know demonstrated in different iterations of the learning cycle, and ongoing tracking of changes in technology.**

**In addition, this study aims to see how well this approach improves learning and knowledge integration in organizations, especially, in fast-changing areas like quantum communication.**

**Overall, this research provides two primary deliverables:**

1. **An Adaptive Expert-Informed AI Learning Framework: This new system combines these components to detects and tracks emerging technological trends in real time, which enhances decision-making.**
2. **A Validated Method Applied to Quantum Cryptography: The framework is applied to real-world data from quantum communication to demonstrate in potential effectiveness in finding timely tradeoff between exploration and exploitation and relevant insights for strategic foresight.**

## The Conceptual Framework

The conceptual framework developed in this research integrates computational models and domain-specific expertise to support dynamic technology intelligence. Computational models include unsupervised topic modeling, like LDA and BERTopic. These models help find themes in unstructured data (Blei et al., 2003; Walrave et al., 2017). However, the unsupervised models may create topics that are not relevant to the domain (Benner & Tushman, 2015). Domain knowledge approaches refine the topics and confirm model outputs. Expert-informed keywords and conference topics as proxies can be used to refine the topics (Bogers et al., 2018; Zhou et al., 2020a). Together, these components address the challenge of timely and adaptive decision-making in fast-changing environments such as quantum cryptography.

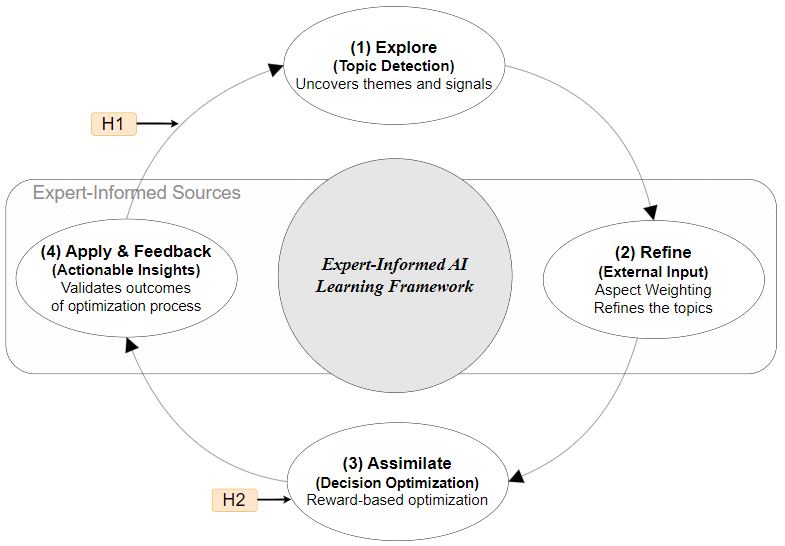


Figure 2: The Conceptual Framework

The conceptual framework consists of four interrelated components as shown in Figure 2:

1. Explore – Topic Detection: This component uses unsupervised machine learning techniques like LDA and BERTopic to discover latent themes in unstructured data (e.g., academic papers, patents, and industry reports). These methods can reveal patterns, but they may also create vague or irrelevant topics without expert help (Blei et al., 2003; Grootendorst, 2022; Sievert & Shirley, 2014).

2. Refine – Expert-Guided Input: This external expert knowledge is embedded using curated keywords and signals from trusted proxies like conference proceedings (e.g., QCrypt). This improves the contextual relevance of the topics and ensures alignment with current technological discourse (Bogers et al., 2018; Diam et al., 2016).

3. Assimilate – RL-Based Optimization: A reinforcement learning (RL) agent dynamically balances exploration and exploitation by using reward signals such as entropy, novelty, divergence, and similarity. This component ensures that the system continuously adapts topic selection based on strategic relevance and emerging changes (Costello & Reformat, 2023; Sutton & Barto, 2018).

4. Apply & Feedback – Validation Loop: This component uses expert-informed documents or signals to confirm insights from the RL component. This expert-driven feedback loop helps adjust the system to ensure timely relevance and ongoing improvement. The system uses periodic feedback, aligning with explainable design and expert-in-the-loop principles (Gunning et al., 2019).

Overall, this Expert-Informed AI Learning Framework (EILF) operates as a closed-loop, detection system, connecting machine learning and expert-informed insights to improve organizational foresight.

## Overview of the Contributions

The contributions fall into three categories as shown in Figure 3, with a central emphasis on methodological innovation. These three intersections create the Integrated Framework. It combines theory, method, and practice that supports timely and expert-guided foresight.



**Figure** 3**:** Key Contributions

*Methodological Contributions:* This study uses unsupervised learning techniques to extract themes and employs supervised learning to assign new data to pre-generated labels in the topic model. We apply several techniques to develop the proposed framework. The aspects of this contribution include:

* AI-Driven Technology Scanning: This proposed framework uses unsupervised topic modeling (LDA) to find trends in large text data. The proposed framework supports real-time detecting (Blei et al., 2003; Hoffman et al., 2010).
* Expert-Guided Refinement: It uses validated keywords from experts, like those in QCrypt proceedings. This helps refine topic relevance and improve contextual alignment (Diam et al., 2016).
* Exploration Using RL: RL, like Q-learning, helps balance two activities, exploring new ideas and using what we already know. It does this through reward signals, including entropy and similarity metrics (Costello & Reformat, 2023; Gupta et al., 2006; Sutton & Barto, 2018).
* Exploration–Exploitation in Practice: The study proposes a framework for balancing exploration and exploitation strategies using Q-values and RL policies (Khetarpal et al., 2022).
* Scalable & Responsive Architecture: The proposed framework updates insights continuously. It also uses metrics like cosine similarity, entropy score, and ADNS (Arun et al., 2010; Blei & Lafferty, 2006; Röder et al., 2015) for checking accuracy and recall. This metrics support to improves responsiveness in fast-changing areas such as quantum technology (Coccia & Roshani, 2024).
* Validated Use Case in Quantum Communication: The proposed framework is implemented and evaluated on a real-world quantum cryptography corpus, demonstrating domain applicability, precision improvement, and trend tracking (Brauer et al., 2024; Cavaliere et al., 2020; Chancellor et al., 2020; Liao et al., 2017).

*Theoretical Contributions*

* Operationalizing Expert-in-the-Loop Learning: This research clarifies how experts interact with AI systems. It connects with sociotechnical knowledge work theory (Faraj et al., 2018; Gunning et al., 2019).
* Linking Foresight with Real-Time AI Models: This work is aligned with foresight literature by merging traditional insight tools with adaptive AI. It is grounded in (Posen & Levinthal, 2012) for strategic agility theory and for technology-intelligence practices (Veugelers et al., 2010).

*Practical Contributions*

* Real-Time Strategic Foresight Tool: This proposed framework helps firms detect technological disruptions, like post-quantum encryption (Diam et al., 2016).
* Enhanced Technology Scouting: It allows for proactive scanning beyond static reports. This helps organizations spot weak signals and future opportunities (Antons et al., 2020; Porter, 2007).
* Transferability Across Domains: While shown in quantum tech, this method applies to other fast-changing sectors. These include cybersecurity, biotech, and education (Basten & Haamann, 2018; Leonardi et al., 2012).
* Policy and Planning Applications: The system supports government foresight and infrastructure planning. It aids in designing adaptive policies (Teece, 2007).

## Organization of the Thesis

This thesis encompasses nine chapters that, altogether, show the development, implementation, and evaluation of the proposed framework. To begin with, Chapter 2 reviews literature on topic modeling, reinforcement learning, and expert-in-the-loop systems. It also identifies key gaps in methodology and practice. Next, Chapter 3 designs the research and uses the Design Science Research Methodology to outline the five stages research including problem, the proposed framework, the framework's core components, the research implementation process, and validation. In Chapter 4, we describe five-stage of the research in practice including Core Components of the Expert-Informed AI Learning Framework (EILF), Framework Application and Case Setting, Implementation of Expert-Informed AI Learning Framework (EILF), Evaluation Design and Baselines, Reinforcement Learning Integration (Verification).

In the following chapters, we detail the 18-step implementation of the framework process (Figure 19), complete with pseudocode. Chapter 5 describes data collection process - how to develop a domain-specific corpus in quantum cryptography. Following that, Chapter 6 presents the data analysis process. It initially starts with baseline topic modeling and moves to expert-informed refinements and reinforcement learning optimization. Subsequently, Chapter 7 reports the results from iterative modeling. This includes evaluations of topic quality and trend detection performance. Furthermore, Chapter 8 interprets the findings related to the research questions and existing literature. It further discusses verifying methodological implications and practical applications. Finally, Chapter 9 concludes the thesis. It summarizes key contributions, acknowledges limitations, and suggests directions for future research.

# Literature Review

## Introduction to the Literature Review

This chapter reviews existing research to ground and justify the design of a framework for detecting technological change. It (1) outlines how the chapter is organized, (2) explains why integrating external knowledge is critical in fast-moving technological domains, and (3) positions topic modeling, expert-in-the-loop (EITL), and reinforcement learning (RL) as the core methodological pillars of the proposed framework.

#### 2.1.1. Overview of the Chapter Structure

This literature review is divided into three main parts plus a concluding synthesis of research gaps:

1. A review method (Section 2.2-2.6) explains our systematic approach using quantitative topic modeling (LDA, HDP), to identify, cluster, and analyze relevant publications (Blei et al., 2003).
2. Organizing the Literature into Thematic Clusters (Section 2.5) applies topic-modeling techniques (e.g., LDA) to group articles into clusters that directly address our core concepts of the conceptual framework (Figure 2). Figures 6–10 illustrate coherence scores and clustering outputs, demonstrating how latent themes emerge in existing work.
3. Review of Related Literature (Section 2.6) is subdivided into:
   * Concepts of Knowledge Integration (2.6.1): Examines how prior studies conceptualize and operationalize the integration of external knowledge.
   * Existing Models and Frameworks (2.6.2): reviews for computational and hybrid frameworks in technology intelligence, highlighting where expert feedback, topic modeling, and RL are used (e.g., Gui et al., 2019; Zhou et al., 2020b).
   * Reinforcement Learning and Dynamic Detection (2.6.3): Focuses on RL-driven methods that adapt topic distributions over time (e.g., Gui et al., 2019; Khetarpal et al., 2022).
   * Finally, Sections 2.7–2.9 reflect on methodological insights, summarize key findings, and synthesize the most significant gaps, such as lack of sustained expert integration and limited ability to adapt in a timely manner, to motivate the EILF design.

#### 2.1.2. Relevance of Knowledge Integration in Rapidly Evolving Technological Domains

In highly dynamic fields, such as quantum communication, post-quantum cryptography, or AI governance, organizations must continuously scan, interpret, and assimilate external technological signals to remain competitive (Antons et al., 2020; von Krogh et al., 2023). The ability to absorb and act on new knowledge underpins strategic agility (Haile & Tüzüner, 2022; Zahra & George, 2002), but traditional approaches (expert panels, bibliometrics, static topic models) often lack the speed and adaptability required. For instance, LDA-based analyses must typically be retrained from scratch when new data arrive, creating delays that undermine timely decision-making (Blei et al., 2003; Sievert & Shirley, 2014). Meanwhile, pure expert-driven methods can be labor-intensive and subjective (Calof & Smith, 2009; Veugelers et al., 2010). This confluence of challenges, rapidly shifting research frontiers and the volume of unstructured text, makes a hybrid, timely approach essential. By combining automated topic extraction, continuous RL-based adaptation, and expert validation, out proposed framework aims to fill this gap.

#### 2.1.3. Positioning of Topic Modeling, Expert-in-the-Loop (EITL), and Reinforcement Learning (RL) as Central Themes

Our conceptual framework rests on three interrelated pillars including:

1. **Topic Modeling:** Unsupervised topic modeling (e.g., LDA, BERTopic) uncovers latent themes from large text corpora (Blei et al., 2003; Gao, 2021). While powerful, traditional LDA generates static topics whose relevance can degrade as new publications emerge (Arun et al., 2010; Röder et al., 2015). To maintain topical relevance in evolving domains, topic models must incorporate domain knowledge and adapt as data change—tasks that pure LDA cannot fulfill on its own.
2. **Expert-in-the-Loop (EITL):** Domain experts contribute weighted keywords, taxonomies, or trusted proxies (e.g., conference proceedings in quantum cryptography) to refine automatically generated topics (Bogers et al., 2018; Zhou et al., 2020b). Expert feedback can be embedded either as post-hoc validation or as inline guidance during model training (Mcauliffe & Blei, 2007). This hybridization ensures that detected topics align with cutting-edge domain discourse and mitigates the risk of spurious or irrelevant themes.
3. **Reinforcement Learning (RL):** RL introduces a reward-driven mechanism to balance exploration (discovering novel, emerging topics) and exploitation (deepening existing, high-value topics) based on metrics such as novelty, entropy, and cosine similarity (Gui et al., 2019; Sutton & Barto, 2018; Khetarpal et al., 2022). By iteratively updating topic assignments in response to reward signals, RL enables timely adaptation as new data arrive, without fully retraining from scratch. However, literature shows that most RL-based topic methods remain in early stages of development, often lacking sustained expert feedback loops and practical scalability (Gui et al., 2019; Wang et al., 2020; Kabudi et al., 2021).

Together, these three themes provide the methodological foundation for our framework. By integrating topic modeling’s ability to extract hidden themes, RL’s capacity for adaptive learning, and expert-in-the-loop mechanisms for domain alignment, the framework aims to detect and interpret technological changes in a timely manner. Subsequent sections will review each component in depth, identify how existing work falls short, and explain how our framework addresses those gaps to support organizational foresight in fast-evolving technological landscapes.

## Systematic Review Approach

Organizations need to learn and adapt to stay competitive in today's fast-changing technology world. Specifically, knowledge integration learning approaches helps firms adapt to technological change and allows them to acquire, integrate, and apply new knowledge (Argote et al., 2020; Leonardi et al., 2012; Posen & Levinthal, 2012). At the core, a central component of this learning process is knowledge integration. This means bringing together various sources of knowledge–both internal and external, as well as tacit and explicit–which helps drive innovation and strategic decision-making.

A crucial part of knowledge integration is ability of organizations to absorb external knowledge. This is the ability of an organization to gather, process, and use knowledge from outside sources (Haile & Tüzüner, 2022; Todorova & Durisin, 2007; Zahra & George, 2002). For example, companies with strong absorptive capacity can filter and analyze external knowledge like technological changes derived from scientific publications and patents. Additionally, they use machine learning and AI to predict technological trends (Agrawal et al., 2022). Consequently, these insights help shape their innovation strategies. Among these techniques, NLP is particularly effective in automating the extraction of useful insights from large amounts of unstructured data (Gao, 2021) and then ML techniques make easier to predict new technology trends (Agrawal et al., 2022). Furthermore, using ML, organizations can better handle large datasets. This, in turn, boosts the efficiency and scale of knowledge integration. As a powerful technique, topic modeling, a powerful technique for extracting latent themes from large collections of documents, plays a key role in identifying these trends (Blei et al., 2003). Moreover, RL improves this process. As a result, it allows for ongoing adaptation, helping to refine how we extract and prioritize knowledge as new information comes in (Sundberg & Holmström, 2024). While ML techniques help find knowledge, domain expert expertise helps to put the insights from these systems into context and validate them . As shown in Figure 5, we combined these three components into a single box and analyzed the literature surrounding them. This flowchart serves as a guide for evaluating each paper based on its contribution to these three components.

This need has led to the rise of expert-guided loop approaches, where domain experts work with AI systems to boost model performance and make better decisions (Agrawal et al., 2022; Mcauliffe & Blei, 2007). As a result, organizations can improve knowledge codification with expert feedback. Consequently, this makes machine-generated insights more reliable and relevant for strategic planning (Zhou et al., 2020b). In secure communication, for instance, involving an expert can improve AI-based threat detection in encrypted messaging systems. For example, cybersecurity experts can work with AI models, like a topic model. They can detect unusual patterns in encrypted traffic. This, in turn, helps them find cyber threats, such as phishing attempts or data exfiltration. Meanwhile, the AI system collects expert feedback to improve its detection algorithms. As a result, this reduces false positives and enhances its ability to recognize changing attack strategies. Ultimately, bringing together domain expert expertise and machine learning makes security insights precise and adaptable. Therefore, this helps tackle real-world cybersecurity challenges (Zhou et al., 2020b).

In technological forecasting, organizations must anticipate emerging trends to stay ahead of disruptions. Specifically, RL-based models enhance forecasting accuracy by adjusting predictions based on new data. As a result, this helps optimize responses to technology changes (Jin et al., 2018). However, while ML-driven forecasting offers significant benefits, it is not without limitations. Indeed, domain expert judgment is important for understanding trends, assessing technology directions, and determining the right strategies (Balasubramanian et al., 2022; Sturm et al., 2021). In response, many organizations are adopting hybrid AI systems. They combine machine learning (ML) with expert insights. This helps improve prediction accuracy and strategic alignment (Balasubramanian et al., 2022). Ultimately, combining machine learning with domain expert skills helps companies handle complex technology challenges. In addition, it promotes ongoing learning and innovation.

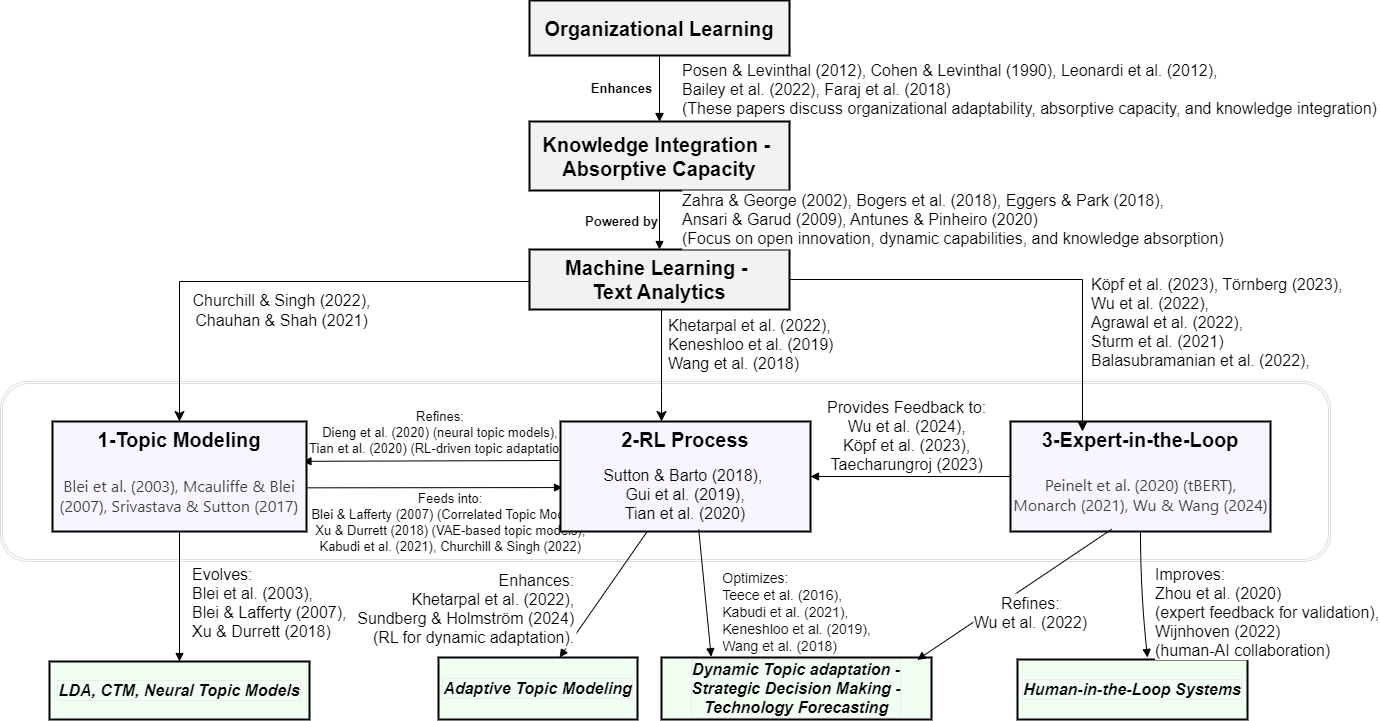
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Figure 4: Topic Modeling: Integrating RL and Expert-in-the-Loop Frameworks

We will start by reviewing the key papers shown in the flowchart (Figure 5) in three components including 1-Topic modeling, 2-RL process, and 3-Expert-in-the-loop. Next, we will describe our systematic review method, focusing on three components. The flowchart outlines a process for enhancing knowledge integration through three components. Topic modeling (Blei et al., 2003; Deng et al., 2020; Tian et al., 2020) finds hidden themes in unstructured data, such as patents and research papers. It uses methods like LDA and neural models, adapting to changing datasets. The RL Process (Gui et al., 2019; Khetarpal et al., 2022; Sutton & Barto, 2018) uses RL to balance exploring new knowledge with using existing knowledge. This helps optimize topic relevance by adapting based on rewards. Expert-in-the-Loop (Y. Wang et al., 2022; Zhou et al., 2020) brings in domain experts. They check outputs, align models with goals, and support ethical AI use. These parts help integrate knowledge adaptively. They support quick decision-making in rapidly changing technology areas.

*1. Topic Modeling*

Topic modeling like Latent Dirichlet Allocation (LDA) presented in Blei et al. (2003) is a way to uncover hidden structures and patterns in large text datasets (Chauhan & Shah, 2021). LDA employs probabilistic methods to uncover hidden topics, modeling the distribution of topics across documents. While LDA is fundamental in the field, it struggles to capture complex topic relationships. Also, it lacks the flexibility needed for dynamic and domain-specific applications. To fix these issues, for instance, Blei & Lafferty (2007) introduced Correlated Topic Models (CTM). This model builds on LDA by linking topics. As a result, it offers a richer representation of document content. Furthermore, Supervised Topic Models, like Supervised LDA (Mcauliffe & Blei, 2007), use external metadata to help refine topic modeling by associating topics with a predefined label. This approach makes it easier to understand topics. However, it still struggles with complex semantic patterns. Researchers sought solutions using neural methods. One example is Neural Autoregressive Topic Models (Larochelle & Lauly, 2012) that enhance coherence in topics by improving semantic relationships between words, while Srivastava & Sutton (2017) introduced Variational Autoencoders (VAEs) for topic flexibility and Xu & Durrett (2018) extended them to capture hierarchical structures in text. Despite these advancements, as noted by Dieng et al. (2020), even the most sophisticated neural models often produce static topic representations, which limits their ability to adapt to evolving datasets. Additionally, these models frequently lack domain expertise, which diminishes their practical relevance. Additionally, topic modeling improves when it works with RL. RL sharpens how topics change and adapt dynamically. Wang et al. (2007) state that tackling word dependency can enhance topical n-grams. This enhancement boosts topic modeling and ties it to RL concepts. These ties are important for optimizing dynamic topic adaptation in adaptive learning systems (Kabudi et al., 2021). As reviewed by (Churchill & Singh, 2022), RL-driven methods have improved coherence and adaptability.

*2. RL Process*

RL enhances adaptability in topic modeling and adjusts topic distributions as data changes. This improves both relevance and coherence. Traditional probabilistic models often struggle to refine topics over time. In contrast, RL-driven methods improve topic assignments by using reward feedback. In RL-based topic modeling, reward functions guide the model by evaluating the quality of generated topics. Rewards can come from coherence measures, like topic coherence scores, user feedback, or specific domain rules. For example, Gui et al. (2019) enhanced topic-word assignments by applying coherence scores as rewards. This approach helped keep the topics understandable and relevant. Reinforcement signals can change over time and help topic models adjust topic distributions based on changing data contexts. This ongoing adaptation is driven by foundational concepts such as Adaptive Dynamic Programming (ADP) (Lewis et al., 2012; Lewis & Vrabie, 2009), which enables RL models to refine their learning and improve over time. ADP, a RL approach that optimizes decision-making over time, enables topic models to improve dynamically. Recent advancements show the effectiveness of this approach. For instance, Gui et al. (2019) introduced a topic modeling framework to optimize topic-word assignments by using coherence measures as rewards. This method significantly enhances topic interpretability without requiring extensive pre-processing. Tian et al. (2020) suggested an RL strategy. This strategy improves topic distributions by using graph embeddings. For example, embedding terms from papers (documents) into a graph helps the model. Here, nodes stand for terms, and edges show co-occurrence or similarity. This setup allows for a clearer understanding of topics and how they change over time. These advancements show how RL is becoming important in adaptive knowledge integration. It helps improve topic models so they can better adjust to changing data patterns.

Furthermore, RL trains agents to make the best choices by engaging with their environment. Their goal is to gain the most rewards. In text analytics, RL helps improve processes like dynamic topic adaptation and explainable recommendation systems (X. Wang et al., 2018). Kabudi et al. (2021) show how RL helps in AI-driven adaptive learning systems. It adjusts topics dynamically, making learning experiences more personalized. The RL process also gains from expert feedback. This is evident in RL from human feedback (RLHF). It helps align machine-generated answers with human preferences and ethical standards (X. Wu et al., 2024). This link with expert systems boosts the security, privacy, and ethics of AI applications. The RL process includes continual RL. This helps with lifelong adaptation in changing environments, such as topic modeling (Khetarpal et al., 2022). Deep RL helps sequence-to-sequence models work better. It enhances text analytics and makes models more adaptable (Keneshloo et al., 2019). This optimization can be adapted for refining dynamic topic modeling based on user feedback and contextual data (Wang X. et al., 2018).

Recent studies show that combining RL with topic modeling can help in dynamic knowledge discovery. This approach enhances model flexibility and keeps topics relevant over time. Challenges still exist when using RL for large-scale topic modeling. These include issues with scalability, high computational costs, and the complex design of reward functions. To address scalability issues in RL-based topic modeling, researchers explore techniques such as parallelized training and hierarchical RL (Wang Y. et al., 2022). RL-driven methods have big potential to tackle the fixed nature of traditional models. This allows for real-time changes and adjustments for specific domains.

*3. Expert-in-the-Loop*

The "Expert-in-the-Loop" approach brings domain expert knowledge into machine learning workflows. This improves the quality and reliability of AI systems. Wu et al. (2022) present a detailed survey on the loop methods. They highlight the benefits of using experts to improve topic modeling. This helps align language models more effectively. The 'Expert-in-the-Loop' approach uses RL from domain expert feedback (RLHF) to enhance topic modeling in specific contexts. In AI-assisted legal research, RLHF helps legal experts improve topic modeling. They can flag misclassified legal terms. This ensures better accuracy in case law analysis. It also helps the AI learn from expert corrections. Building on this practical application, Törnberg (2023) shows how expert feedback in RLHF enhances performance in ChatGPT-4, highlighting how expert corrections lead to better results than those achieved by experts or crowd workers alone. It outshines them in annotating political Twitter messages. This feedback loop is vital. It addresses ethical concerns, enhances model accuracy, and ensures AI systems align with human values and expectations (X. Wu et al., 2024). Improving dynamic topic adaptation with expert knowledge helps make better decisions. It shows how human insight and automated analysis work well together. Integrating human expertise means adding expert feedback in RLHF. This helps align machine-generated answers with what humans prefer (Köpf et al., 2023). By improving alignment and addressing privacy and ethics, this method makes AI systems more trustworthy and reliable (X. Wu et al., 2024). According to Wu et al. (2022), incorporating expert feedback with RLHF enhances topic modeling. This approach helps align machine learning models with human preferences, improving their accuracy and relevance. RLHF enhances AI-driven text analysis by incorporating expert insights (Taecharungroj, 2023). Taecharungroj (2023) states that RLHF enhances AI text analysis by adding expert feedback. This feedback helps make the generated text more accurate and better at understanding context. This process helps AI systems match domain-specific language. This way, they produce more reliable and clear outputs in areas such as automated content summarization and sentiment analysis. Automated topic modeling has improved a lot, but we still need domain experts. Their insights help companies understand the results and keep them relevant in real-world use. Early attempts to include expert feedback used knowledge-aware Bayesian deep topic models (C. Wang et al., 2020). These models embedded predefined ontologies in neural frameworks. These models let experts give input during training. However, they were not flexible once they were deployed. tBERT (Peinelt et al., 2020) improved on BERT by using topic modeling with its embeddings. However, it depended on fixed expert annotations. This reliance limited its ability to adjust to changing datasets. To solve these issues, RL-enabled systems now include expert feedback in the reward function. This approach allows topic models to adapt based on expert input, continuously refining topic distributions. Expert feedback can enhance topic coherence and relevance. Context-guided embedding adaptation (Z. Chen et al., 2014) and Human-in-the-Loop (HITL) systems (Monarch, 2021; H.-N. Wu & Wang, 2024) demonstrate this well. This is especially important in emerging technologies that rely on specific domain insights. These strategies highlight how human expertise boosts model accuracy. They also help maintain real-time adaptability. This way, machine learning workflows stay in tune with user intent.

Even with these advancements, challenges remain in combining RL, topic modeling, and expert feedback systems. A big challenge is the high cost of computing when scaling RL training in topic models. This is especially true for large corpora. Real-time adaptability is also crucial. Delays in expert feedback can cause bottlenecks that slows down model refinement (Zhao et al., 2021). Models like tBERT try to balance depth and coverage. But they have trouble keeping coherence when using complex expert annotations. Recent advances in meta-RL and expert-in-the-Loop (EITL) frameworks show potential for solving these issues. These methods train RL agents using different datasets. This helps them better integrate feedback and adapt in real time. But finding ways to scale efficiently and integrate expert feedback smoothly is still a key research area. Many existing models do not fully include domain experts in the feedback loop. This limits their ability to adjust to changing user inputs and real-world needs.

Next, we introduce the key techniques for organizing both internal and external data within an organization into themes and interpretation approaches. In the following ‘review method’ section, we present an approach to reviewing a set of documents, gathered from online libraries. First, we state the steps of searching and screening documents. Then, a topic modeling algorithm is applied to these documents, followed by filtering them based on predefined questions. The most relevant documents are selected for review. Finally, we analyze the methods and frameworks in these documents that are related to the predefined questions, focusing on their contribution to knowledge integration.

## Review Method

This review adopts a structured approach informed by systematic literature review (SLR) principles (vom Brocke et al., 2009; Kitchenham, 2004). The process combines both qualitative coding and quantitative topic modeling, enabling scalable identification of latent thematic structures in large text corpora (Blei et al., 2003; Teh et al., 2006). The use of HDP further supports unsupervised model tuning to avoid manual specification of topic numbers (Paisley et al., 2015).

We propose a systematic review of articles in text analytics, ML/RL methods and knowledge integration approaches. Our goal is to examine the studies in this regard and find challenges and gaps in the literature related to our framework. We focus on methods for detecting and analyzing technology landscapes. We search in Web of Science and Scopus online libraries for publications after 2016 date, focusing on areas including "topic modeling," "RL," "expert-in-the-loop," "text analytics," and "knowledge integration." We picked this time frame to highlight the latest progress in these fast-changing areas. The searched documents categorize by how relevant they are to knowledge integration, exploration-exploitation dynamics, and AI-driven innovation. We pick the most important articles in each category for detailed analysis. We base our selection on three criteria: (1) method quality, (2) new ideas, and (3) impact, shown by citation numbers and effects on later research. The following sections provide a detailed discussion of our findings.

The review method has four main stages depicted in Figure 6 and detailed in Figures 15-18. First, defining the need and research questions sets the purpose and scope of the review. This step makes sure it aligns with the review objectives. Next, Search & Data Collection means finding the right search terms. It also involves gathering literature and building a corpus. The Screening & Classification phase filters relevant articles. It removes duplicates and sorts documents for systematic analysis. It uses topic modeling and clustering to extract insights. This helps link findings to research questions, leading to a better understanding of the topic. The Analysis & Discussion section reviews the most relevant articles. It focuses on key topics and their links to the review's sub-questions. We show the selected documents and highlight their connections. Then, we discuss the key studies related to the gaps we have found. We limit our approach to two online libraries, which represent of the articles within our review scope.

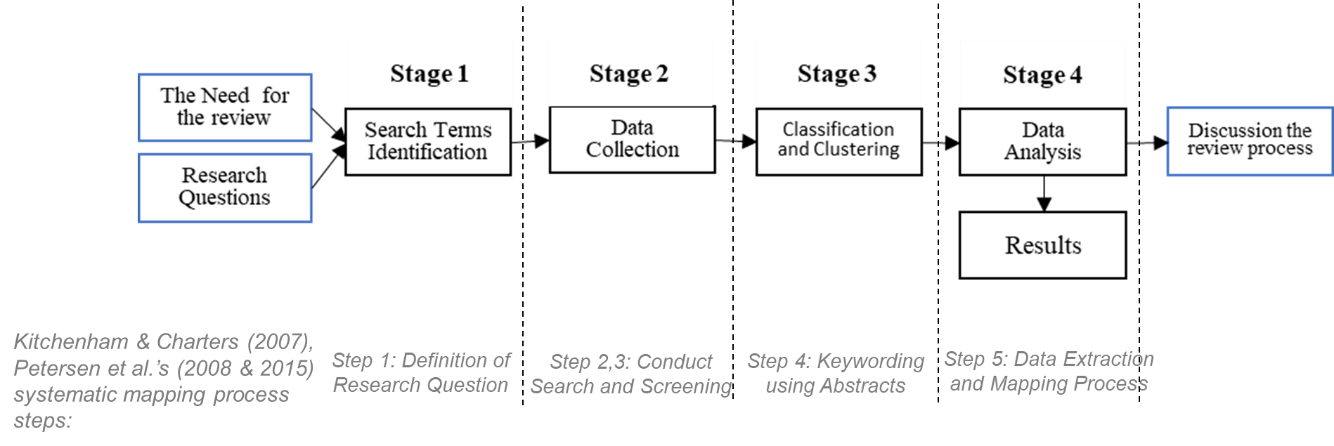


Figure 5: Overview of the Proposed Literature Review Process

## Search Strategy and Review questions

We used Web of Science and Scopus to collect peer-reviewed journal articles, book chapters, and conference papers. Seminal studies provided the search terms to ensure coverage of core topics. The dataset was screened to remove non-English texts, incomplete records, and duplicates. The refined dataset was analyzed using LDA to uncover hidden themes. We used Hierarchical Dirichlet processes (HDP) to group topics documents into clusters (subtopics). Then, we linked these clusters to the research questions.

The review defines the key questions to explore the concepts and methods of topic modeling, ML/RL techniques, and expert involvement approaches. The focus is on: (Q1) What are the main theoretical foundations and methodologies used in knowledge integration within technology landscapes? (Q2) What models and frameworks have been developed to support knowledge integration using AI and expert inputs? and (Q3) How do topic modeling and RL influence knowledge integration and decision-making in dynamic environments? Each question has sub-questions listed in Table 1. This helps analyze conceptual foundations, frameworks, and AI-driven methods in detail. We used cosine similarity scoring to check alignment between sub-questions and literature clusters. This improved the review's coherence.

Table 1: Review Questions and Corresponding Sub-Questions

|  |  |  |
| --- | --- | --- |
| Sub-questions | The purpose | Keywords |
| **Question A. What are the most relevant concepts of knowledge integration?** | | |
| A1. What are the concepts related to detecting and understanding technology changes? | Basic concepts of the elements that enable the understanding of technological changes | changes concept technology perceives knowledge actor role innovation reality |
| A2. Are the concepts quantifiable? | To find out if this understanding is done quantitatively. | quantify deduct variable |
| A3. Is the impact of concepts on business processes clear? | Find that the impact of these concepts on the exploring process is specified. | result implication conclusion finding impact |
| **Question B. What models or frameworks have been developed?** | | |
| B1. What models have been used to explore novelties? | Explain exploration models to understand better the purpose of detecting novelties. | explore novelty search experimentation discovery |
| B2. What models have been used to exploit new knowledge? | Explain exploitation models to understand better the purpose of detecting novelties. | exploit competency refinement efficiency selection implementation |
| B3. Do the models used focus on mediators of technological change? | Identify the factors/variables to exploring novelties that are in the process of exploration | substantive moderators’ slack resources, organizational structure, inter-organizational relationships, and environmental dynamism), and methodological moderators (data sources and performance measurement) affect the impact of exploration on performance |
| B4. Do the models used to focus on mediators of competitiveness? | Identify the factors/variables to exploring novelties that are in the process of exploitation. | extrinsic moderators (region, size, and sector) competitive intensity |
| **Question C. What models have used dynamic machine/ RL techniques?** | | |
| C1. Are the provided solutions automatic? | To exclude qualitative and interpretive variables in the process of knowledge exploration. | automation systematic  dataflow semiautomatic |
| C2. Is the exploration process non-automatic and needs analysis and interpretation? | To identify the points of the exploration process that still need analysis and interpretation. | qualitative analysis scheme simply confirms the presence or absence of certain materials |
| C3. Do the study outcome contribute to improving an individual's knowledge? | Outcome benefits for individuals in the business | people individual employees manage skilled worker curator user expert’s executive |
| C4. Do the study outcomes contribute to the improvement of business knowledge integration? | Outcome benefits for the businesses | organization firm company business SME startup government |

## Data Collection and Screening

The data collection process is structured to define search terms and filters, and citation tracking, to expand the dataset. Screening follows specific criteria. We select peer-reviewed articles in English after 2016. Relevant fields guide our choices. We exclude studies from unrelated areas, non-academic sources, and those with incomplete abstracts. Automated filtering improved precision. Neural networks classified articles and refined the dataset to 1,043 high-relevance papers.

#### Criteria for Determining Search Terms

We gathered key literature on open learning, innovation, and adaptation for choosing search terms (Table 2). First, we reviewed the papers such as (Gupta et al., 2006; Walrave et al., 2011). Then, we used text-processing algorithms to pull out key concepts. In (March, 1991), the exploration-exploitation (EE) trade-off was introduced. This concept simulates how organizations adapt to changes in their environment. (Gupta et al., 2006) emphasized integrated management of EE activities, highlighting structural and contextual antecedents. In addition, (Walrave et al., 2011) modeled environmental dynamics and competitiveness, linking learning cycles to strategic agility. (Raisch & Birkinshaw, 2008) offered a three-part framework for ambidextrous learning. It includes Antecedents of structure and strategy, learning elements of innovation and adaptation, and outcomes of growth and market share. Environmental moderators like competition and technology were also identified (Benner & Tushman, 2015; Lavie et al., 2010).

To expand the corpus, we traced citations from initial papers (Appendix A.1), prioritizing highly cited works (Table 2). Articles were categorized by four features: research focus, learning perspective (theoretical/empirical), moderators, and alignment with ambidexterity antecedents. Studies highlight the use of computational models like AI and simulations. These tools help tackle environmental uncertainty (O’Reilly & Tushman, 2011; Walrave et al., 2017). Early work looked at theoretical trade-offs (Levinthal & March, 1993). Later studies focus on dynamic capabilities (Teece, 2007). This change shows how complex environmental interactions are becoming.

Table 2: Literature on Knowledge Exploration

\* Exploration & Exploitation (EE), Organizational learning (OL), Technological innovation (TI), Organizational adaptation (OA), Strategic management (SM), Organizational design (OD), Theoretical/Empirical (T/E), Exploration and Exploitation (EE), Conceptual Paper (CP)

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Research | Research focus | Five top weighted words | Cluster Label | EE | OL | TI | OA | SM | OD | T/E |
| Eisenhardt & Martin 2000) | Dynamic capabilities with the resource-based view of the firm. | capability, dynamic, process, moderator, strategy | Cluster 1- Learning, adaptation, market, design |  |  |  |  | ✓ |  | T |
| Teece, (2007) | The framework to understand the foundations of long-run enterprise success | capability, innovation, performance, run, dynamic |  |  |  |  | ✓ |  | T |
| O'Reilly & Tushman (2008) | How ambidexterity acts as a dynamic capability | capability, suggest, argument, ambidexterity, dynamic |  |  |  | ✓ |  |  | T |
| He & Wong (2004) | Examine how EE influences firm performance | ambidexterity, relate, innovation, posit, approach | Cluster 2- Innovation, technology, knowledge, environment |  |  | ✓ |  |  |  | E |
| Jansen et al. (2006) | Examine how moderators (environmental dynamics and competitiveness) affect EE innovation | innovation, antecedent, environment, environmental, effect |  |  | ✓ |  |  |  | E |
| Andriopoulos & Lewis (2009) | Develop a more comprehensive model | innovation, manage, integration, ambidexterity, enable |  |  | ✓ |  |  |  | T |
| Yu et al. (2019) | The role of the time interval between underperforming and the decision to innovate for better performance. | innovation, theory, result, find, active |  | ✓ | ✓ |  |  |  | E |
| Gupta et al. (2006) | Highlighting the importance of exploration and exploitation | relation, issue, direct, balance, exploit | Cluster 3- Antecedents, structure, structural, leadership, management, context, contextual | ✓ |  |  |  |  |  | CP |
| Raisch & Birkinshaw (2008) | Develop a comprehensive model of organizational ambidexterity's antecedents, moderators, and outcomes. | antecedent, ambidexterity, moderator, article, comprehensive | ✓ |  |  |  |  |  | T |
| Wilden et al., (2018) | Revisiting James March (1991) | innovation, ambidexterity, result, approach, posit | ✓ | ✓ |  |  |  |  | T |
| March (1991) | Toward obtaining performance outcomes | run, learn, competitive, resource, consider | Cluster 4- Application, system, machine, AI, modeling, reinforce | ✓ | ✓ |  | ✓ |  |  | CP |
| Slater & Narver (1995) | Competitive advantage | organization, learn, knowledge, propose, conclude |  |  | ✓ |  |  |  | T |
| Blei et al. (2003) | Introduction of Latent Dirichlet Allocation (LDA) for topic modeling | topic, model, distribution, latent, documents |  | ✓ | ✓ | ✓ |  |  | E |
| Sutton & Barto (2018) | Reinforcement Learning: An Introduction | learning, reward, agent, policy, exploration, RL |  |  | ✓ |  |  |  | T |
| Miller & Martignoni, (2016) | Examine the model of EE without forgetting | divers, knowledge, learn, model, study |  | ✓ |  |  |  |  | E |
| Lee & Ryu (2002) | The adaptively rational decision rule | technology, opportunity, propose, approach, focus | Cluster 5-Mechanism, emerging, path, trajectory |  |  |  | ✓ |  |  | E |
| Levinthal & March (1993) | Competitive advantage | learn, problem, approach, current, organization | Cluster 6- Ambidexterity, explore, exploration, exploring, ambidextrous |  | ✓ |  |  | ✓ |  | CP |
| Yang et al. (2002) | Explore paths using an RL algorithm and simulation | capability, dynamic, innovation, suggest, argument |  | ✓ |  | ✓ |  |  | E |
| Uotila et al., (2009) | A novel methodology to measure the relative exploration versus exploitation orientation | balance, relate, active, performance, copyright |  |  |  |  | ✓ |  | E |
| Fang et al. (2010) | Simulation of a structure with semi-isolated groups for learning | structure, balance, problem, simulation, trade |  | ✓ |  |  |  | ✓ | E |
| Walrave et al. (2017) | Focus on dynamic perspective on ambidexterity | industry, change, ambidexterity, exploit, require | ✓ |  |  |  |  |  | T, E |

Text analysis of 21 papers revealed six concept clusters (Table 2). These clusters are weighted by frequency and relevance:

1. Learning, adaptation, market, and design,
2. Innovation, technology, knowledge, and environment,
3. Antecedents, structure, leadership, and context,
4. Application, system, AI, and modeling,
5. Mechanism, path, and trajectory,
6. Ambidexterity and exploration.

We focus on methods and frameworks related to knowledge integration in companies. Terms were simplified for the search string: “(system\* OR machine OR AI OR application OR modeling OR reinforce\*) AND (explor\* OR ambidext\*) AND (structur\* OR leader\* OR context\*) AND (technolog\* OR knowledge OR environment\*) AND (emerging\* OR path\* OR trajector\* OR mechanism\*) AND (learning OR adapt\* OR innovation OR market\* OR design).” Wildcards (\*) account for morphological variations in databases.

#### Search Design

We gathered articles from the Web of Science and Scopus. We selected these databases because they cover various fields. They also index peer-reviewed journals, books, and conference proceedings with attention to detail. Initial searches used the keyword string developed, retrieving 2,000 articles per database. The rest of the searched articles are not relevant. After merging both databases and removing duplicates (see Appendix A.4), we had 2,925 articles. We also identified 92 reviews.

Key journals are: Journal of Knowledge Management (33 articles), European Journal of Innovation Management (27 articles), Technological Forecasting and Social Change (25 articles), Journal of Business Research (15 articles). A full list of journals is provided in Appendix A.3. We excluded irrelevant sources (e.g., Journal of Cleaner Production, Frontiers in Psychology).

Searches focused on English-language peer-reviewed articles, books, and conference papers. Automated text preprocessing involved multiple steps. First, it removed URLs, stop words, and non-English content. Next, it tokenized the text and applied stemming to standardize the terms. Inclusion criteria focused on studies about knowledge exploration, organizational ambidexterity, or adaptive learning. We excluded non-empirical or theoretical works, non-English texts, and articles on sustainability or psychology. After we removed 680 duplicates and irrelevant records, we had 2,925 articles left in the dataset. Temporal analysis showed a fourfold rise in publications by 2021 compared to 2016. This growth indicates more interest in computational models. AI and RL are popular tools for dealing with environmental uncertainty. A review of 92 articles found a key gap. Earlier reviews focused on either theoretical trade-off, like exploration versus exploitation, or technical methods, such as machine learning. None combined knowledge integration, AI-driven exploration, and environmental adaptation. We kept the final corpus of articles and reviews for the topic modeling section.

To improve the topic model's accuracy, we used a screening process. This helped filter out irrelevant articles from the corpus. A neural network (NN) approach was selected for its ability to handle complex textual patterns and scalability. Using the method of (van de Schoot et al., 2021), we set up a supervised learning workflow (see Appendix A.11). This model classifies articles as "relevant" (1) or "irrelevant" (0) by using a labeled training dataset.

The training dataset had 221 articles. Of these, 171 were relevant to knowledge exploration and organizational ambidexterity. The remaining 50 were marked as irrelevant (Appendix A.13). This labeled corpus helped the NN learn the differences between relevant and off-topic studies. Once trained, the model was applied to the full dataset of 2,925 articles, identifying 1,043 relevance papers for inclusion in the topic model. We excluded the 1,882 remaining articles. These covered areas like sustainability, psychology, and non-empirical commentaries. This choice helped reduce noise.

## Organizing the Literature into Thematic Clusters

Topic modeling is an unsupervised technique used to identify hidden topics within a corpus. For this review, we used the LDA algorithm to analyze articles. We looked at key factors like the best number of topics (see Figure 7), stop words, term frequency, and regularization (see Appendix A.6). The optimal number of topics was determined based on maximum topic coherence scores. A standard stop word file (Appendix A.5) was used to filter common terms like research, literature, paper, review, and study.

We used several methods to find the number of topics. These included perplexity (Blei et al., 2003), Kullback-Leibler divergence (Arun et al., 2010), and topic coherence (Röder et al., 2015). The perplexity method suggests that as the number of topics increases, the perplexity score decreases until it stabilizes. Arun et al., (2010) proposed using KL divergence to measure topic similarity, while Röder et al., (2015) introduced a coherence score to evaluate semantic overlap among high-weighted words. (Greene et al., 2014) used non-negative matrix factorization (NMF) to compare lists of topic words. Lower similarity scores show the best number of topics.

We tested various topic numbers and identified a maximum coherence score at three peaks, with nine topics being the most suitable (Figure 7). We also looked at models with five and thirteen topics. However, the nine-topic model had the lowest overlap of articles between topics and showed the least similarity. Each cycle's size, Figure 7, shows the coherence score of the topic model. This score is calculated by the algorithm over topic numbers. The green cycle (topic 9 with the greatest score) marks the chosen optimal topic number. The two orange cycles represent candidate topic numbers that were examined to confirm the optimal choice. The final topic model was generated with nine topics across 1,043 articles. It has two main outputs: (1) a document-topic distribution matrix. This shows rows for articles and columns for topics, along with metadata like title, citation, abstract, and authors. (2) a topic-word distribution matrix. This includes the top 100 words for each topic (see Appendix A.7 and A.8).

These outputs were used to generate subtopics through clustering. This method shows articles or clusters as points in a two-dimensional space (see Figure 9).

|  |  |
| --- | --- |
| Figure 6: Comparison of Coherence Scores Across Topic Models | Figure 7: Silhouette Coefficients of Clusters Within Topics |

*Set a Threshold to Gain Most Associated Articles Over Topics*

A threshold (0.7) on documents distributions over extracted topics is considered intuitively to retrieve most associated articles for reviewing. To identify the threshold, the number of articles above the threshold and common articles are compared. The top several unselected articles were reviewed to ensure no critical article was missing. This method is reliable, considering the number of topics is small. From all records in the topic model, 1010 most associated articles were selected.

*Determining Clusters*

A clustering method applied to categorize most associated articles in each topic to obtain different clusters. The clusters help us to investigate the articles deeper that are related to sub-questions. In the topic model, each of the nine topics contains a large list of articles. By clustering, the review will be based on clusters that have very similar articles in various aspects. These clusters help to focus only on high related articles instead of reviewing many with a common aspect. We use a hierarchical clustering algorithm to obtain clusters based on word distributions over articles in each topic (Appendix A.9). The results of the number of clusters over topics have shown in Figure 8. Like the optimum number of topics, the silhouette coefficient is used to find the optimum number of clusters for each topic. As the number of clusters are dedicated in Figure 8, we extract 121 cluster in total. The silhouette coefficient formula is based on the similarity of the weighted words in the articles in clusters (distribution of words over articles); by comparing these distributions (Greene et al., 2014), the silhouette scores are calculated, and finally, the number of optimal clusters for each topic is determined. Silhouette score measures how similar an article is to its cluster compared to others. The maximum of these scores is considered the optimum cluster number. The number of articles to check the optimal number of clusters is the same number of highly related articles per topic that are determined by a topic threshold. The following figure has shown the clusters of the first topic, and the articles in each cluster. The topics with their clusters data are provided in Appendix A.10. Additionally, all topics and their clusters are illustrated in Figure 10.

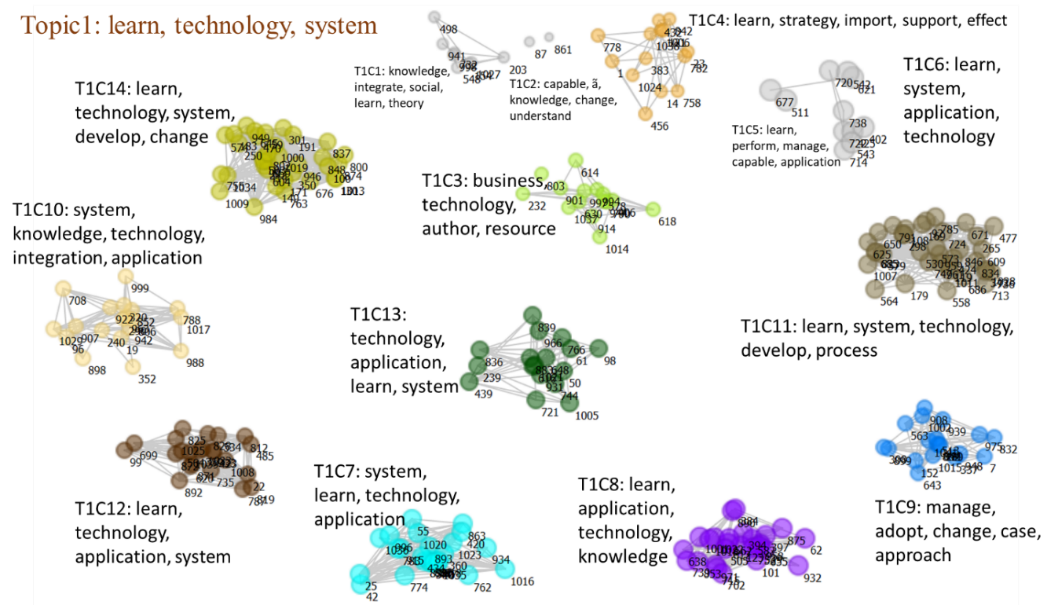


Figure 8: Fourteen Clusters Identified Within the First Topic

The top high-weighted articles in each cluster are examined, and clusters were labeled automatically. We calculate the average weight of words in cluster-most-associated articles and choose the top five high-weighted words for each cluster. The results of the clusters in the first topic, as sample, are shown in Figure 6, respectively. In the topic, ten larger clusters can be seen most are learning system in application, technology, and performance, managing in the system, application, technology, knowledge adaptation, and learning strategy, business, and capability. Still, other clusters with slightly different subjects can be seen in another four clusters. The rest of the clusters can be seen in Appendix A.12.

#### Thematic Review of the Literature

We created a policy for our data analysis. This policy helps us answer the sub questions. We align sub-questions with the 121 topic-cluster model and related articles. The analysis process followed several key steps. First, we calculated similarity scores between the 11 sub-questions and 1,010 documents. We set a threshold of 0.7 to find meaningful associations. We reviewed the articles in each cluster. We also confirmed the links between the sub-questions and the clusters. These relationships were then organized and recorded in a tabular format, as shown in the Answer Tabular:

Table 3: Correlation Between Review Questions, Sub-Questions, Clusters, and Topics

in Appendix C.7.

This table shows the links between sub-questions, clusters, and topics, along with their labels. We created a structured data item. It has questions, sub-questions, and article metadata. This metadata includes key details: publication type, authors, year, source title, topic, cluster, topic weight, and answers to three main research questions along with 11 sub-questions.

Figure 10 illustrates the overall nine topics. To visualize the clusters for each topic, we provide individual graphs separately in Appendix A.10. In Figure 9, the clusters of Topic 1 demonstrate their connection to the concept. All documents of clusters are also provided in Appendix A.12. Clusters on "topic modeling," "RL," and "experts in the loop" appear in the table. They emphasize knowledge networks, open learning, and machine learning techniques. One relevant cluster to the expert-in-the-loop concept is T8C17. This focuses on networks, knowledge, and organization. It looks at how collaboration networks combine human expertise. This helps improve innovation processes. T1C7 (system, learning, technology) also covers new machine learning tools. This makes it important for RL and topic modeling. Another important cluster, T1C8 (learning, application, technology), examines the exploration vs. exploitation dilemma. This is a key challenge in RL. T8C16 (network, knowledge, performance) looks at how technological innovation networks form and change. It connects to topic modeling by studying the relationships within these networks. T9C13 (capability, learning, organization) explores how organizations learn. This cluster is linked to decision-making driven by experts. These clusters show how topic modeling, RL, and expert knowledge help boost innovation, support knowledge integration, and improve tech-based decision-making.

## Review of Related Literature

The topic model was created with nine topics, and applying a threshold of 0.7, 121 clusters were obtained from 1010 articles. To determine the threshold of 0.7, we quickly reviewed the associated values of articles over topics. Out of 1043 articles, 1010 were above the threshold, which is a very appropriate point for receiving articles related to the topic and clusters. The rest of the articles were also reviewed, and none were related to the research questions.

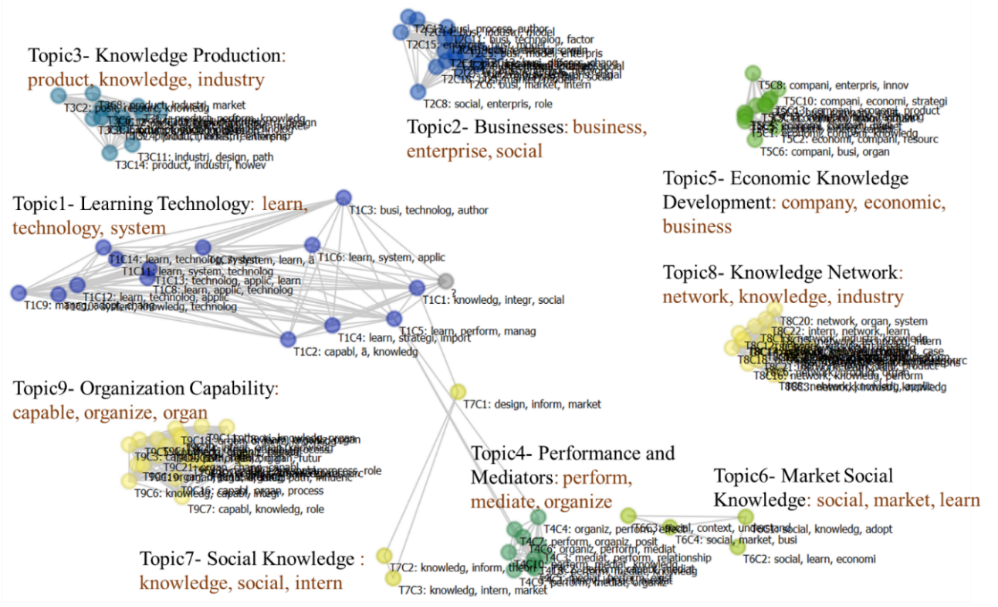


Figure 9: Clusters Identified Across Nine Topics

Figure 10 presents the clustering of topics along with their respective article distributions. The topics identified are Learning Technology, Business, Knowledge Production, Performance and Mediators, Economic Knowledge Development, Market Social Knowledge, Social Knowledge, Knowledge Networks, and Organizational Capability. Among these, topics three, five, six, and eight focus on innovative knowledge development and sharing. Topics one and four encompass studies on learning technology, innovation, and open learning. Topics seven and nine examine how firms develop knowledge and apply social knowledge.

To assess the relationship between clusters and research questions, we prepared the text of each cluster by aggregating abstracts and article titles. Using a text-processing algorithm, we calculated the word frequency for each cluster and compared it with the ranked words in the text of each sub-question. By comparing the data, we found similarity scores. These scores showed how clusters connect with sub-questions. Using the cosine similarity algorithm (Appendix A.15), we set a new threshold. This allowed us to identify significant correlations that exceed the average limit (Figures 11 & 12). The final results are summarized in Table 3 in Appendix C.7.

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| Figure 10: Number of Related Articles for Each Sub-question | Figure 11: Number of Related First Articles for Each Question |

Bar chart 11 shows how many clusters (sub-topics) appear in each sub-question. It highlights the differences in review focus. Sub-question C4 has the highest count of 90, while A1 follows with 85 and B4 has 72, indicating that these areas contain the most relevant clusters. Moderate distributions are observed in B1 (49), B2 (41), B3 (42), and C3 (44), suggesting a balanced presence of clusters within these areas. In contrast, sub-questions C1 (14), A2 (23), A3 (26), and C2 (27) have the lowest counts, implying a weaker connection to the identified clusters. These findings show that the research mainly focuses on sub-questions C4, A1, and B4. There is a lot of discussion about machine learning, framework development, and innovation. The lower counts in C1, A2, and A3 suggest that these areas may need further exploration or hold less significance in relation to the study's main findings.

Bar chart 12 shows how many clusters (sub-topics) focus on the three main research questions in total. A cluster (sub-topic) can relate to more than one sub question (first associated document with the sub question) within the main question. It highlights the study's emphasis on different areas of knowledge exploration. Question B examines models or frameworks and has the highest count of 204. This means a large part of the literature analyzed centers on both theoretical and practical frameworks for exploring knowledge. Question C studies dynamic machine learning and RL techniques. It includes 175 clusters within sub questions. This indicates a strong emphasis on computational methods for finding knowledge. Question A focuses on key ideas in knowledge exploration, but it has the lowest count at 134. This suggests that while there are some discussions about concepts, they are not as common as those about methods and technical frameworks. These findings show that the research community focuses more on structured models. They rank development and application over theoretical discussions about knowledge exploration.

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| Figure 12: Comparison of Topics Across Main Questions | Figure 13: Comparison of Topics Across Sub-questions |

Although question A has fewer associated clusters than question C, significant relationships still exist between certain sub-questions and specific clusters. The overall correlation between main questions and topics may not always align with similarity scores alone. In total, topic one (Learning Technology) is strongly linked to sub-questions B1, B4, and A1; topic two (Business) to C4, B4, and A1; topic three (Knowledge Production) to A1, C3, and B4; topic four (Performance and Mediators) to C3 and C4; topic five (Knowledge Economy) to B1, B2, and B3; topic six (Market Knowledge) to A1 and C4; topic seven (Social Knowledge) to B1 and A1; topic eight (Knowledge Networks) to C4, C3, and B4; and topic nine (Organizational Capability) to C4, A1, and B4.

The results demonstrate that most reviewed articles emphasize ML-based processes for knowledge exploration, with many proposing models leveraging machine learning techniques. Some studies validate their models using specific factors and moderators, while others explore the novelty aspects of knowledge acquisition. The subsequent sections present findings organized by the three main research questions, with a detailed examination of sub-question responses and their alignment with the overarching research framework.



### Concepts of Knowledge Integration

What Are the Most Relevant Concepts of Knowledge Integration?

The question examines articles that cover the challenges and important concepts in the knowledge exploration process. To gain structured insights, we asked three sub-questions:

1. What are the concepts and challenges in knowledge exploration?
2. How are quantitative methods used?
3. What factors and moderators affect performance outcomes?

Table 3 in Appendix C.7 shows how several clusters relate to these sub-questions for each topic. Several clusters tackle the first sub-question (A1). This sub-question explores the concepts and features of knowledge exploration in different contexts. Out of 121 clusters across nine topics, 60 clusters discuss at least one sub-question from the first research question. The clusters focus mainly on three areas: 1- Organizational capability (13 clusters), 2- Knowledge production (11 clusters), and 3- Business (10 clusters).

Clusters for the third sub-question (A3) are fewer. There are four clusters in the knowledge network topic and two clusters in learning technology. Research on knowledge exploration and exploitation has grown in recent years. This trend was especially strong in 2021 and 2022, as it tackled new challenges and applications. Studies published in 2021 primarily discuss topics such as: T1C8: Learning, application, and technology, T1C9: Managing, adaptation, and change, T4C8: Performance, mediators, and knowledge, and T6C1: Social knowledge and adaptation. Studies from 2022 emphasize the same point: T1C14: Learning, technology, and systems and T4C8: Performance, mediators, and knowledge.

The third sub-question (A3) has been addressed every year. This shows a steady interest in how external factors affect knowledge exploration.

This review question and its sub-questions aim to explore how research has examined the detection, formulation, and measurement of environmental factors that affect knowledge exploration. Review in this area includes various fields. Important concepts and factors depend on the context. Thus, they often need to be redefined and adapted for different situations. Many studies use quantitative methods to analyze factors and moderators. However, qualitative approaches are also common. They help explore conceptual and contextual challenges.

In summary, many studies in this area examine specific variables. They explore how these variables impact individual and organizational knowledge. This research addresses both theoretical and practical challenges in the exploration process.

*A1. Concepts Related to Detecting and Understanding Technology Changes*

Research shows that dynamic capabilities, knowledge integration, and systemic frameworks are key. They help us understand changes in the environment and organizations. (Zhang, 2021) highlight how authoritarian leadership affects innovation behavior. They focus on exchange mechanisms and boundary conditions. (Teece et al., 2016) says dynamic capabilities help firms adapt to technology changes. (Padilla-Lozano & Collazzo, 2021) link corporate social responsibility with green innovation for competitiveness. (Levinthal & March, 1993) stress balancing exploration and exploitation to sustain adaptability. (Rialti et al., 2022) show that digital technologies help share data in real time. This allows for quick decision-making in agritech. These studies show how leadership, innovation strategies, and adaptive frameworks work together to handle change.

*A2. Quantifiability of Concepts*

(Yu & Yan, 2022) show a quantitative way to analyze concepts. They use machine learning with main path analysis to measure the links between science and technology. Meanwhile, (Luo & Yu, 2022) use partial least squares to link digital leadership to business model innovation. These methods show that we can measure ideas like innovation diffusion and open learning.

*A3. Impact of Concepts on Business Processes*

The clarity of conceptual impacts on business processes is evident in studies linking innovation to operational outcomes. (Yang & Qi, 2022) studied Alibaba's data-driven mergers and acquisitions. They found that using both exploratory and exploitative strategies help create value. This happens through innovations in business models that focus on novelty and efficiency. (Geldes et al., 2017) found that corporate social responsibility and green innovation boost manufacturing competitiveness in Ecuador. They do this by lowering costs and increasing productivity. Innovation frameworks and sustainability practices affect business performance.

### Existing Models and Frameworks

What Models and Frameworks Have Been Developed?

This question explores studies that offer models and frameworks for discovering new knowledge. Some studies focus specifically on the exploitation process, while others analyze exploration separately. We examine if the factors and moderators in these models were assessed with quantitative methods. Like the first question, the results are categorized by topic and sub-question, as presented in Table3 in Appendix C.7.

We will structure the analysis around four sub-questions. These focus on exploration, exploitation, environmental changes, and competitive actions. These categories come from the model by (March, 1991) and the environmental change perception cycle by (Walrave et al., 2017). These four sections group studies based on how dynamic the models are. They look at how models react to changes in the environment and new variables.

Table 3 in Appendix C.7 and Figures 15 show that 41 clusters relate to the first sub-question about knowledge exploration models. Three clusters focus on learning exploration models, technology, and theories. They center on learning technology and business, especially in knowledge production and perception.

The second sub-question has fewer clusters. It mainly looks at the effect of innovation, how knowledge impacts performance, and the development process.

For the third sub-question, it discusses about substantive mediators, slack resources, case analysis, inter-organizational relationships, and environmental dynamism.

Clusters related to the fourth sub-question primarily focus on external moderators and competitive intensity. These studies look at several key areas include how to improve knowledge acquisition, developing frameworks to manage future processes and resources, adopting new technologies, and understanding the logic of the technology market and its resources.

The main goal of this question is to find dynamic models for exploration and exploitation. This involves looking at changes in both the environment and competition. Most studies suggest models or frameworks for knowledge exploration. They test and analyze these based on certain environmental conditions.

Over the years, the number of clusters addressing these four sub-questions has increased, with notable growth from 2015 to 2022. Sub-question B4 has the highest number of clusters (111), followed by B1 (91 clusters) in 2021. The number of clusters in B2 and B3 peaked in the same year compared to previous years, indicating a rising research interest in these areas.

Technology monitoring is key activity for strategic foresight and R&D planning. It helps organizations detect, understand, and respond to external changes. Historically, firms and research institutions have used many methods, both manual and computational, to aid this process. Still, each method has significant limits that can reduce its effectiveness in fast-paced environments.

For example, traditional technology monitoring methods rely on expert judgment and manual processes. These include expert panels, scenario planning, literature reviews, and road mapping workshops (Calof & Smith, 2009; Veugelers et al., 2010). They offer valuable insights and help build consensus about possible changes. However, these methods can be time-consuming, resource-intensive, and hard to scale. Additionally, they face issues with subjectivity and delays, making it tough to detect weak signals in real time. This is especially relevant in fast-changing fields like quantum technologies or AI-based cybersecurity.

Furthermore, these processes can become outdated quickly. As a result, foresight outcomes may not reflect the latest developments. This creates a problem in fast-moving sectors where the relevance of technology changes rapidly. Consequently, the time lag between gathering information and applying it limits the agility that innovation-driven organizations need.

To overcome the limits of these methods, organizations now use computational techniques. They apply scientometric analysis and topic modeling to automate technology monitoring (Blei et al., 2003; Porter, 2007). These methods analyze large amounts of unstructured text data, such as academic papers, patents, and industry reports. This helps identify themes, map technological trends, and quantify changes. For instance, topic modeling methods, such as Latent Dirichlet Allocation (LDA) and co-citation analysis, help firms find clusters of innovation and explore research frontiers. In addition, Scientometric tools, like citation network mapping and bibliometric coupling, track how knowledge spreads across fields (Rotolo et al., 2015). While these methods improve scalability and objectivity, they treat data as static snapshots. In addition, their results come from batch processes and do not allow for continuous learning or quick adaptation.

Overall, both manual and computational approaches have strengths, but they fall short in delivering dynamic, real-time intelligence. On the one hand, manual methods lack speed and scalability. On the other hand, computational methods are faster but often rigid and devoid of expert contextualization. Moreover, most automated techniques struggle to interpret the nuanced meanings of new signals without expert input. They also cannot adjust topic relevance over time based on feedback.

Currently, current text mining and topic modeling tools act like “black boxes.” They offer little transparency on how insights are created or how they connect to organizational goals (Antons et al., 2020). Moreover, these tools fail to incorporate expert feedback or adapt to new data effectively. As a result, both approaches struggle to provide the agility and contextual relevance needed for technology monitoring in fast-changing environments.

To tackle these issues, this research suggests a hybrid expert-informed AI framework. This framework combines the scalability of AI-based topic modeling and RL. It also integrates expert-informed feedback to ensure accuracy and alignment with strategic goals.

Traditional topic modeling techniques, like Latent Dirichlet Allocation (LDA), are common in knowledge discovery. They help extract themes from large sets of unstructured text (Blei et al., 2003). In general, these methods organize and summarize static datasets. However, they have key limitations in fast-changing technological landscapes. As a result, they are unable to capture emerging developments or shifts in terminology that occur after the initial modeling process. Ultimately, this static setup makes it tough to stay updated in fast-moving industries, like quantum communication and cybersecurity (Cavaliere et al., 2020; Walrave et al., 2017).

Moreover, standard topic models are also limited in their capacity to detect weak or emerging signals, topics that are beginning to gain traction and may not yet appear prominently in the data. These models usually focus on strong, established themes. Consequently, this can push aside signals that are rare but important. This creates a challenge for companies trying to detect early signs of technology disruption. These signs are crucial for gaining a competitive edge (Eggers & Park, 2018; Rotolo et al., 2015). If firms cannot track changes over time or assess new ideas, they might miss trends that start small but grow quickly in importance.

To address these limitations, we need dynamic topic modeling methods. These methods must adapt to new data and refine topic structures over time. This requires combining learning mechanisms that improve the model based on feedback from the environment and domain experts. In addition, the methods need to use a balancing of exploration and exploitation mechanisms like RL. RL helps systems optimize topic selection by exploring and exploiting changing document collections (Sutton & Barto, 2018; Tian et al., 2020). By including structured expert input, like curated keywords, domain knowledge, or post-conference feedback, these models can align with organizational goals while responding to external changes (Gunning et al., 2019; Zhou et al., 2020b).

In this context, the proposed framework meets the need for dynamic refinement. It embeds RL-driven feedback loops and expert involvement in the topic modeling process. This allows the system to identify and track emerging signals. It also learns which topics matter most, adapting in real time to shifts in technology. Building on the prior theoretical and motivational insights, the conceptual framework integrates these elements into four interconnected constructs.

*B1. Models for Exploring Novelties*

Research on novelty exploration emphasizes diverse methodologies. (Yu & Yan, 2022) used machine learning with main path analysis. This helped them find links between science and technology. Their method offers a data-driven way to spot research fronts. (Lee et al., 2015) used text mining and outlier detection in patent mapping. They aimed to find new technology opportunities and highlighted the importance of semantic analysis. Levinthal & March (1993) criticized the "myopia of learning." They suggested using balanced exploration-exploitation models to support long-term innovation. These models show how important quantitative analytics, teamwork across fields, and smart resource use are for discovering new ideas.

*B2. Models for Exploiting New Knowledge*

Exploitation models focus on efficiency and refinement. (Yang & Qi, 2022) distinguished between exploratory and exploitative mergers. They showed that Alibaba's focus on efficiency improves customer interfaces and value networks. Levinthal & March (1993) argued for structured learning to prevent focusing too much on short-term gains. Meanwhile, (Salembier et al., 2021) created a framework to track agricultural innovation. This connects farmer-led practices to better systemic design. These studies focus on three main areas: improving skills, streamlining processes, and learning from iterations that are essential for knowledge exploitation.

*B3. Mediators of Technological Change*

Mediators such as organizational structure, environmental dynamism, and resource availability are crucial for innovation outcomes. (Voltan et al., 2016) showed that social enterprises help promote sustainability. They do this by using local networks to address socio-economic issues. (Zhang, 2021) found that leadership identity and self-efficacy are key mediators. These factors help authoritarian leaders promote innovation. They also highlighted the importance of organizational structure and available resources. (Geldes et al., 2017) highlighted how cognitive-organizational proximity is key in agribusiness clusters. This closeness helps cooperation and boosts technological adoption. (Ghura & Erkut, 2024) showed that carbon emission policies boost innovation through technology changes, not operational ones. These studies show how different factors work together. Institutional, social, structural, and resource-based factors shape technology and innovation.

*B4. Mediators of Competitiveness*

Competitiveness mediators include regional and sectoral factors. Regional innovation systems links to emerging industries, while (Geldes et al., 2017) highlight cognitive-organizational proximity in agribusiness clusters. Besides, Wang & Tao (2019) identify market competition and R&D allocation as drivers. These studies demonstrate that external factors significantly influence competition, with location, industry trends, and institutional support all playing critical roles.

### Reinforcement Learning and Dynamic Detection

What Models Have Used Dynamic Machine/RL Techniques?

This question explores articles that apply machine learning (ML) and deep and RL techniques. We analyze how these models contribute to enhancing organizational and individual knowledge. A qualitative assessment of these models is conducted, focusing on their design and application. The four sub-questions related to this topic are outlined in Table 3 in Appendix C.7.

Most clusters in this category are primarily associated with the third and fourth sub questions.

Clusters tied to the third sub-question look at knowledge networks in organizations and markets. They explain how these networks work in real-life situations. They focus on modeling for production and how knowledge is shared with decision-makers in different contexts.

Clusters for the fourth sub-question cover technology integration, market knowledge, network-based applications, and business models.

Among the key topics, the highest number of related clusters are found in Business (16 clusters), Knowledge networks (14 clusters), Organizational capability (12 clusters), Knowledge economy (10 clusters). The number of articles on the third sub-question has stayed stable. There were 59 articles in 2020 and 60 articles in both 2021 and 2022. In 2021, there was a notable rise in machine-learning models. 101 articles focused on classification techniques. This marks a rise compared to 99 articles in 2020, 90 in 2022, and 89 in 2019. These findings show that machine learning and RL are increasingly important in knowledge management. There is a bigger focus on business uses, decision-making methods, and market-driven models.

*C1. Automatic Solutions for Knowledge Exploration*

Automation in knowledge exploration is addressed by (Lee et al., 2015), who automate patent mapping for novelty detection. (Hevner & Malgonde, 2021) use AI controls in digital platforms. (Yu & Yan, 2022) apply machine learning to identify research fronts. These approaches reduce reliance on qualitative interpretation through systematic dataflows.

*C2. Non-Automatic Exploration Processes*

Non-automatic processes requiring human analysis are evident in (Wang et al., 2021), who advocate systemic frameworks for qualitative interpretation in socio-technical ecosystems. (Salembier et al., 2021) study farmer innovations using participatory design. Levinthal & March (1993) criticize over-automation in learning. These studies stress the need for human-centric analysis in complex exploration.

*C3. Improving Individual Knowledge*

Studies on individual knowledge enhancement emphasize non-automated, interpretive processes. Wang et al. (2021) proposed frameworks for autonomous systems. These frameworks focus on human-centric analysis and help foster critical thinking in education. (Guo & Wang, 2020) linked psychological learning climates to employees' innovative use of information systems. Intrinsic motivation played a role in this relationship. Levinthal & March (1993) showed how iterative learning process helps balance exploration and exploitation. These studies encourage settings that focus on understanding quality and ongoing skill growth.

*C4. Promoting Business Knowledge*

Organizational knowledge advancement is driven by strategic innovation. (Malik et al., 2021) showed that using AI for knowledge sharing in IT firms improves talent experience and boosts innovation. (Rialti et al., 2022) found that agri-technology digital platforms boost collaboration among stakeholders. This leads to sustainable business models. (Geldes et al., 2017) linked corporate social responsibilityand green innovation to competitive gains in manufacturing. These findings show how important it is to integrate technology, build partnerships across sectors, and focus on sustainability for growing institutional knowledge.

## Discussion of Review Process and Methodological Insights

This review introduces a method that uses text analytics (see Figure 6) to map the literature on the technological landscape. It follows three key research questions:

1. How do firms perceive and quantify technological changes?
2. What frameworks balance exploration-exploitation in dynamic environments?
3. How can AI/ML automate knowledge exploration?

We created a four-stage process by combining systematic review principles (Petersen et al., 2008, 2015) with machine learning techniques. This method cuts down on manual work and improves analytical accuracy.

We present a method to search, screen, classify, cluster, map, and interpret relevant text. This approach enables a structured review of extracted articles through four key stages including Identifying search terms and defining the search scope, retrieving articles from databases, extracting topics/clusters using topic modeling and hierarchical clustering, and visualizing and selecting articles to address research questions.

Our method boosts efficiency by sorting content based on research goals. It also offers clear visualizations to help answer research questions and test hypotheses. By reducing the volume of articles under review to topic-based clusters, we streamlined the analysis process. Figure 6 illustrates the four stages of our systematic review method, employing topic modeling and clustering techniques. We describe the moat-associated articles with clusters and sub questions in this section.

#### First Stage: Search Words Identification and Scope

To build a solid search strategy, we began by collecting important papers related to knowledge exploration and its concepts, models, and frameworks. Text processing techniques were applied to extract weighted terms, following a structured process:

1. Removing punctuation, numbers, links, and stop words, and
2. Computing word importance using TF-IDF (Figure 15).

We collected 24 foundational papers that discuss knowledge exploration frameworks. A ranked list of terms was obtained using automated text-processing algorithms. The top-ranked terms were selected and combined for literature searches. A word cloud module allowed researchers to visually inspect and select high-weighted words for refining search queries.

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| Figure 14: Steps for Determining the Search Words | Figure 15: Steps in Data Collection |

#### Second Stage: Data Collection

We collected data by finding accessible databases. We extracted important article details like the title, abstract, publication date, authors, and more. For this study, we selected Web of Science and Scopus as our primary data sources. The search process involved:

1. Using search terms and applying filters (e.g., publication date, inclusion/exclusion criteria),
2. Retrieving thousands of articles from each database.

To manage large datasets, we implemented automated classification techniques:

1. A neural network algorithm was trained on a manually curated dataset to classify articles as relevant or irrelevant.
2. Machine learning models such as neural networks technique was applied to improve classification accuracy, especially when articles were not ranked by similarity scores. After classifying the articles, we gathered them into a corpus for topic modeling (Figure 16).

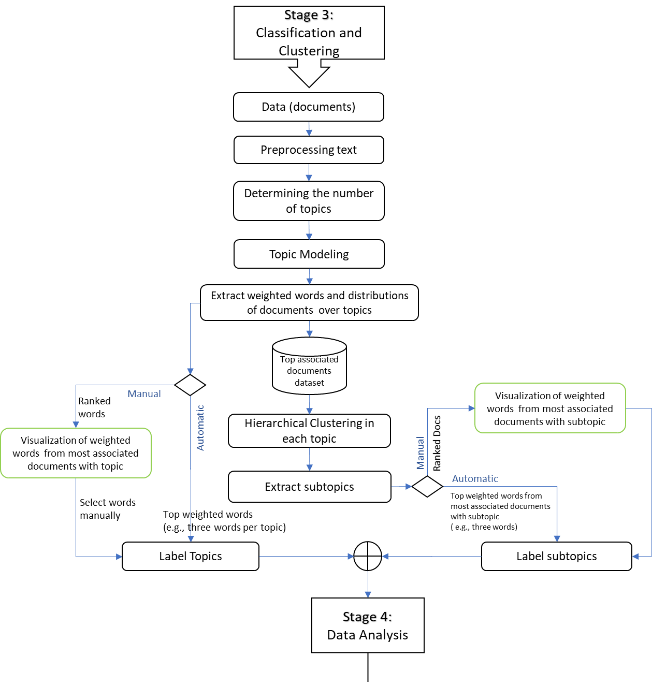


Figure 16: Steps in Classification and Clustering

#### Third Stage: Classification and Clustering

To uncover hidden thematic structures within the textual data, we employed topic modeling techniques. After refining the text, we improved the topic count, like we did with search words. We chose nine as the best number of topics. This decision came from comparing the coherence scores of various models. The Latent Dirichlet Allocation (LDA) algorithm was used to construct the topic model, generating:

1. Word distributions per topic.
2. Article distributions over topics.

Additionally, clustering techniques were used to refine article classification:

1. Articles highly relevant to each topic were filtered using a threshold.
2. Hierarchical clustering with Euclidean distance grouped articles within each topic.
3. The silhouette coefficient determined the optimal number of clusters per topic (Figure 8).

Automated Method: Extracts weighted words from highly relevant articles and assigns cluster labels.

Manual Method: Articles are individually reviewed, and custom labels are assigned. At the end of this stage, selected articles in each cluster/topic were prepared for in-depth review (Figure 17).

In addition, we consider two distributions of articles and words on topics as input data for the clustering technique. The input data at this step is limited to articles highly related to the topics by setting a threshold. The hierarchical clustering method with Euclidean distance parameters was used in the clustering stage to cluster the articles highly associated with each topic. According to the threshold set for selecting highly relevant articles in the previous step, the number of clusters will differ. The number of clusters for each topic is determined automatically through one of the optimal cluster number identification methods. The silhouette coefficient was used to find an optimum number of clusters in each topic (Figure 17). In the manual method, a different number of clusters are examined in each topic. Clusters are labeled by selecting a certain number of weighted words from the combination of all high-weight words from all articles of each cluster in each topic. In manual mode, all articles related to each cluster are examined separately, and a label is assigned to the cluster. At the end of this stage, the selected articles in each cluster/topic are prepared for review.

#### Fourth Stage: Visualization Data and Review Articles

By receiving two distributions of articles and words on topics and clusters along with their labels, we prepared the model to display the graph of topics (Figure 10), clusters (i.e., Figure 9), and the results by categorizing articles in each cluster (Appendix A.10).

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| The cosine similarity was applied to clusters’ abstracts and titles to identify the correlation to the questions and sub-questions. We have tabulated the similarity scores with the number of articles in each cluster (Table 3 in Appendix C.7). Similar articles in each cluster provide the possibility that only a few articles from the cluster are enough to answer the questions instead of reviewing all articles. We have examined the correlations by reviewing the articles in each cluster and question. The review sought to answer whether the literature had presented an automatic process that perceives or senses novelties in the environment. | Figure 17: Steps in Data Visualization |

#### Methodological Contributions

This review introduces three key methodological advancements to address gaps in systematic literature analysis and technological trend detection. Neural network-based agile search and screening made finding relevant texts easier (Figure 13). We used a labeled sample of documents, where (1) means relevant and (0) means not relevant. We then trained the model on the all documents. This helped us cut down the number of papers for in-depth review. It cut down the original 2,925 articles to 1,043. This also helped reduce manual selection bias. This approach puts idea of dynamic sensing capabilities into action. It helps reduce noise quickly, like leaving out non-peer-reviewed sources. At the same time, it keeps important insights about exploration-exploitation trade-offs (March, 1991).  Second, we used LDA-driven topic modeling and hierarchical clustering that helped us review the literature and find key challenges and gaps more efficiently. It highlighted an overfocus on static variables, such as leadership and organizational structure. At the same time, it pointed out a lack of attention to real-time adaptability (Walrave et al., 2011). The derived model has 9 topics and 121 clusters. It allows for detailed analysis of subtopics, like "AI-driven innovation." This connects to research sub-questions, such as proactive threat detection in new technologies (Bennett & Brassard, 2014). Hierarchical clustering improved understanding. It used silhouette scores (Figure 8) to group topics into clear, actionable areas. Third, we confirmed the framework’s generalizability using cosine similarity mapping (Figure 15). This showed that 63% of clusters focused on AI/ML-driven exploration (C1-C4). This method automates keyword extraction and cluster labeling. So, it cuts down on context dependency. This makes it easy to use in different areas like healthcare and sustainability. These contributions improve systematic literature analysis. They integrate scalability, adaptability, and precise details for specific fields. This approach solves long-standing issues with manual, static, or isolated methods.

Many studies have explored dynamic capabilities (Teece, 2007), innovation models (Levinthal & March, 1993), and knowledge-sharing frameworks (Malik et al., 2021). But some important gaps still exist in relation to the proposed method. Many topic modeling methods, such as patent mapping (Lee et al., 2015) and science-technology linkage analysis (Yu & Yan, 2022), often lack input from domain experts. These methods don’t have a clear way to add expert knowledge over time. This limits how well they can improve models with precise context. This research adds expert-driven keyword curation to aspect-based topic modeling. This ensures relevance to the domain and cuts down on noise in detecting technology trends. Conventional applications lack this feature.

Second, RL has helped improve operational processes (Hevner & Malgonde, 2021) and resource allocation (Geldes et al., 2017). Yet, using RL to refine topic models is still not well explored. Previous studies on adaptive capabilities like (Yang & Qi, 2022) look at how organizations respond to change. But they often ignore algorithmic adaptability. The new RL component brings a fresh reward function. It balances topic diversity and similarity. This change allows real-time optimization of model outputs. It is a big improvement over static or manual models.

Third, existing literature often sees operational integration of insights as a post-hoc step (e.g., (Rialti et al., 2022)). It should instead be viewed as a structured, ongoing process. This research fills the gap by adding expert checks in each refinement cycle. This way, insights become useful and match the organization's goals. Many studies focus on established sectors like manufacturing or agribusiness (Geldes et al., 2017), but they often overlook fast-evolving areas like quantum communication. This method works well in advanced areas. It shows that it can scale and adapt. This is important because we need tools to handle unclear technology environments.

Many existing frameworks focus on either quantitative metrics, like Winterhalter et al., (2016), or qualitative analysis, such as (Salembier et al., 2021). They seldom combine both approaches. This method combines entropy changes, topic size, and similarity metrics with expert insights. It provides a complete view of technological evolution, something previous works did not achieve. These innovations tackle the issues of isolated, unchanging, or irrelevant methods. The proposed approach is a strong and flexible solution for making strategic decisions in changing situations.

## Summary of Key Findings

This study pulls from various research areas to understand adaptive decision-making in tech-heavy environments. Knowledge integration shows how firms adapt to technological changes by gaining and using new knowledge. However, there is still confusion about the best balance between exploration and exploitation, when to make shifts, and how risk affects learning behaviors (Argote et al., 2020; Posen & Levinthal, 2012). Additionally, **knowledge integration** focus on how firms use external knowledge for innovation. Still, real-time integration and dynamic balancing need more theory (Faraj et al., 2018; Haile & Tüzüner, 2022; Todorova & Durisin, 2007).

Advances in **machine learning and text analytics**, like RL and natural language processing, provide automated, adaptive insights. Yet, challenges remain in organizational adaptation, particularly in scalability and real-time (Eggers & Park, 2018; Gao, 2021; Jin et al., 2018). At the crossroads of **topic modeling and RL,** recent studies show promise in dynamically extracting themes through reward-based optimization. Still, issues with scalability, computation, and static modeling limit broader use (Blei et al., 2003; Gui et al., 2019; Khetarpal et al., 2022).

Finally, combining **expert-in-the-loop (EITL) approaches with RL** (e.g., RLHF) aligns machine outputs with human insight. However, it faces challenges like high computational costs, delayed feedback, and no standardized frameworks for expert involvement (Gunning et al., 2019; Köpf et al., 2023; Taecharungroj, 2023; Törnberg, 2023; X. Wu et al., 2024).

The review focused on the evolution of topic modeling, RL, and expert involvement. This involved exploring how topic modeling has evolved. The topic modeling has progressed from basic methods, like Latent Dirichlet Allocation (LDA). The extended methods combine advance techniques like deep learning and expert feedback for better adaptability and coherence.

For topic modeling, the review began with (Blei et al., 2003) on Latent Dirichlet Allocation (LDA). It then progressed to modern approaches using deep learning (DL) and RL. They offer better adaptability and scalability. RL research focused on the theory in (Sutton & Barto, 2018). It then applied this to adaptive systems improved by expert feedback. The review used the keywords like ‘RL in topic modeling’ and ‘expert feedback in adaptive models’ to ensure a focused search for relevant literature.

#### Topic Modeling and Its Limitations

The evolution of topic modeling, from (Blei et al., 2003) to recent advances, shows a clear progression in methods. Blei's LDA model became a cornerstone for topic modeling. It uses a probabilistic model to find hidden topics in a corpus by linking documents to topics. Early extensions, like Correlated Topic Models (CTM) (Blei & Lafferty, 2007) and supervised topic models (McAuliffe & Blei, 2007), improved model identification and added outside knowledge. Existing models, like chance discovery (Ohsawa, 2006) and pattern analysis (Bickel, 2019) are useful to explore new topics. But they lack automated, iterative frameworks that use expert feedback to align the models. Neural Topic Models, like the Neural Autoregressive Topic Model (Larochelle & Lauly, 2012), began using deep learning. This was to capture more flexible, nonlinear topic representations. Research into deep generative models, like VAEs, improved topic coherence (Xu & Durrett, 2018). During this time, the studies put in much effort to improve interpretability and scalability. Yet, expert involvement was not yet a key part of these advances. Apart from deep learning that applied Nural network techniques to predict the novel topics, we use RL capability in this area to help expert to select topics and areas that is align with their chosen keywords.

*RL for Dynamic Knowledge Discovery*

Deep learning and RL are now popular for topic modeling. Researchers have used the techniques to better discover topics over time. Deep Relational Topic Modeling (W. Wang et al., 2020) uses a Graph Poisson Gamma Belief Network. It captures complex topic-word relationships. Neural Topic Models (Dieng et al., 2020) use deep learning to find nonlinear patterns. Methods like Neural Variational Inference for LDA (Miao et al., 2016) improve scalability. Deep Generative Models (Srivastava & Sutton, 2017) offer better document representations. Researchers have adapted BERT (W. Wang et al., 2020) and other transformer models for better topic extraction, aiming for more semantic meaning. Graph-Based Topic Modeling refines topic distributions using graph structures. These innovations show that combining deep learning with traditional methods can improve topic modeling. Besides, recent studies have emphasized expert involvement in knowledge-aware models. For example, Knowledge-Aware Bayesian Deep Topic Models use domain expertise and deep probabilistic methods to improve performance (W. Wang et al., 2020). Some papers, like ‘TopicNet’ and ‘Alleviating 'Posterior Collapse',’ focus on using policy gradients to improve topic models. Also, research like ‘Context-guided Embedding Adaptation’ explores using expert feedback. It aims to adapt models in low-resource settings. These developments show the growing need for expert knowledge in topic modeling. It must improve, especially for dynamic and complex environments.

*Challenges in Adapting to Dynamic Technological Changes*

As technology evolves at a fast pace, previous methods often struggle to adapt. They ignore the interactions between technology and outside factors. So, they are poor at predicting and adapting to technology changes. Also, these models often can't scale with growing data volumes. This limits their effectiveness in real-time analysis. New methods, like RL and Wasserstein-based approaches, are more flexible and adaptable. But they need more computing power and pose challenges for real-time use. Besides, Peinelt et al. (2020) introduced tBERT that combines BERT's embeddings with topic modeling. This improves semantic similarity detection. It captures both nuanced semantics and broader topics. Yen et al. (2002) noted the use of RL in dynamic knowledge discovery. It involves integrating real-time data and expert feedback into adaptive systems. Their work shows that RL can improve decision-making using domain knowledge. This is crucial for navigating uncertain environments. This synergy between RL and experts helps find hidden patterns. It enables organizations to adapt to technology changes. (Sutton & Barto, 2018) laid the RL theory. They explained how agents optimize their actions by interacting with the environment. In dynamic knowledge discovery, RL's core components make it ideal for predicting technology trends and fast decisions. These components are: state-action pairs, rewards, and the exploration-exploitation trade-off.

This review tackles key gaps in the literature. It notes that traditional topic modeling often lacks iterative expert curation. Innovation studies need improved adaptive RL-based frameworks for better topic refinement. Lastly, it highlights the fragmented approach to insight implementation in earlier models. It also addresses the limited use of these methods in fast-changing areas like quantum communication. It connects quantitative, metric-driven approaches with qualitative, interpretive analyses, creating a clearer understanding.

Despite significant progress in topic modeling, RL, and expert-in-the-loop frameworks, several critical gaps remain unaddressed in the existing literature. While deep learning approaches have enhanced topic modeling capabilities, their computational complexity and resource-intensive nature limit their applicability in real-time environments (Peinelt et al., 2020; Sutton & Barto, 2018). Current models often require extensive training time and lack the agility needed for dynamically evolving datasets. Although recent models, such as Knowledge-Aware Bayesian Deep Topic Models (W. Wang et al., 2020), incorporate domain expertise, they struggle with scalability and iterative refinement. Most frameworks rely on static expert input during initial training phases, lacking mechanisms for continuous expert interaction post-deployment. Existing models often fail to fully leverage domain-specific ontologies or contextual cues, leading to generic topic representations that overlook niche insights. This gap is particularly evident in specialized fields like emerging technologies and quantum communication, where nuanced understanding is crucial for accurate topic discovery. Although RL shows promise for dynamic knowledge discovery, current implementations struggle with real-time adaptation in large-scale data repositories (Sutton & Barto, 2018; Yen et al., 2002). Delays in feedback loops, the complexity of reward function design, and high computational costs hinder widespread adoption in real-world applications. Few studies have successfully created hybrid frameworks that effectively blend the strengths of probabilistic models, deep learning, RL, and expert input. Current systems often operate in silos, lacking cohesive strategies for bidirectional expert-model interaction and closed-loop learning. These gaps underscore the need for novel frameworks that integrate dynamic RL mechanisms, scalable topic modeling, and iterative expert feedback. Addressing these challenges could significantly improve the adaptability, accuracy, and real-world applicability of topic modeling systems.

## Synthesis of Key Gaps and Implications for Framework Design

The reviewed literature shows major advancements in topic modeling, reinforcement learning (RL), and expert-in-the-loop (EITL) systems. However, these innovations often work separately. Topic modeling techniques, like LDA and its neural extensions, excel at pattern extraction. Yet, they have static outputs and lack contextual relevance. RL approaches improve adaptability and aid to exploration-exploitation strategies. However, they struggle with complex reward design and aligning with domain goals. Expert-in-the-loop models allow for validation and refinement, but they are rarely used in a timely manner. This causes insights to be delayed or fragmented.

Current knowledge integration frameworks mostly focus on single-source data, like patents or bibliometrics. They often miss feedback mechanisms. These issues lead to an important gap: the need for a unified, scalable framework. This framework will combine computational modeling, adaptive learning, and expert validation to detect and integrate timely technological changes.

Table 4: Summary of Literature Gaps and How the Proposed Framework Addresses Them

|  |  |  |  |
| --- | --- | --- | --- |
| **Gap Area** | **What Literature Shows** | **Gap Identified** | **How EILF Addresses It** |
| **Topic Modeling** | LDA, CTM, VAE models extract latent themes from data (Blei et al., 2003; Srivastava & Sutton, 2017) | Models are static and context-insensitive | Combines unsupervised models with expert-weighted keywords for refinement |
| **Dynamic Learning** | RL optimizes exploration vs. exploitation via rewards (Gui et al., 2019; Khetarpal et al., 2022) | Rewards poorly aligned with domain goals; high computational cost | Uses entropy, similarity, ADNS, and expert input to define domain-sensitive reward functions |
| **Expert Input** | EITL enhances model outputs (Zhou et al., 2020; Wu et al., 2022) | Feedback loops are usually retrospective and not adjustable | Embeds expert feedback at refinement and validation stages for real-time learning |
| **Knowledge Integration** | ML models support integration but rely on patents or publications (e.g., Quantum domain publications) (Jiang & Chen, 2021) | Overreliance on static sources and no feedback adaptation | Uses curated conference proceedings and expert proxies for ongoing alignment |
| **Scalability & Timeliness** | Few models address timely needs (Porter, 2007; Diam et al., 2016) | Lack of systems that detect and respond to changes in a timely manner | Modular framework supports dynamic updates, trend validation, and live feedback |

# Research Design and Methodology

This chapter details the research design and method used to address the problem stated in Section 1.1 (Motivation). The focus is on how organizations adapt to fast-changing technology by integrating external knowledge. To fill the gaps identified in Chapter 2, this research employs a design-oriented approach to create a framework. Four key elements, from the conceptual framework (Figure 2) including Explore, Refine, Assimilate, and Apply & Feedback are shaped the framework. These elements help to organize a learning cycle for detecting, interpreting, optimizing decisions, and applying emerging technological trends.

The research adopts a Design Science Research (DSR) methodology. This approach provides a systematic way to build and evaluate a framework that solve real-world problems while contributing to theoretical knowledge (Hevner et al., 2004; Wieringa, 2014). The study includes cycles of design, implementation, and evaluation, ensuring the framework is both rigorous and relevant. The chapter is divided into two main parts: Section 3.1 describes the DSR methodology and explains its selection, and Section 3.2 offers an overview of the method used to develop and apply the framework, setting up the detailed framework implementation in Chapter 4.

These sections establish the methodological basis for developing, applying, and evaluating the framework, providing valuable theoretical insights and practical impacts.

## Research Methodology: Design Science Research Approach

To develop and evaluate a novel framework, this research uses the Design Science Research Methodology (DSRM) outlined in (Hevner et al., 2004; Wieringa, 2014). This methodology is appropriate for information systems research that focuses on creating innovative artifacts to address real-world problems through iterative design, evaluation, and refinement. According to Hevner et al. (2004), a successful design science project produces a viable artifact, such as a framework that shows relevance to an important practical problem, and uses sound evaluation methods. Thus, the research follows DSRM by creating an artifact: a framework composed of four integrated components- topic modeling, expert-informed input, reinforcement learning, and expert-driven feedback that drawn from the conceptual framework after designing components. The artifact is evaluated iteratively for accuracy and practical relevance using a real-world case study in quantum cryptography secure protocols. The proposed hybrid framework is novel in combining of its components and is methodologically grounded in a recognized design science tradition (Gregor & Hevner, 2013; Hevner et al., 2004; Peffers et al., 2007).In line with Hevner et al. (2004), this research meets the criteria for a rigorous design science project across the following dimensions:

* Design as an Artifact

This research creates a hybrid expert-informed AI framework to detect and adapt to new technology trends. The artifact integrates machine learning and expert-informed input that breaks down into four key components: topic discovery, refinement, and adaptive optimization, and expert-driven validation. As a result, the artifact functions as a decision-support system that helps organizations find important themes in unstructured data and respond quickly to external changes.

* Problem Relevance

The method addresses a key problem in R&D management and technology intelligence: the need for detecting and interpreting fast-changing external signals, like emerging technological changes, timely adapting them. While traditional foresight and trend analysis methods are slow, resource-intensive, or too reliant on human judgment, the proposed artifact aims to shorten time-to-insight, aid strategic foresight, and boost organizational adaptability.

* Design Evaluation

The evaluation of the artifact occurs through a combination of technical metrics and contextual validation. Evaluation includes: (i) technical performance measured by precision and coherence, (ii) alignment with expert-informed benchmarks, and (iii) improvements observed over learning cycles. For full evaluation procedures, see Chapter 8.

* Research Contributions

This research contributes to methodological, **practical, and theoretical domains.** Methodologically, it extends topic modeling by introducing expert-driven validation through RL and structured external input, enabling dynamic tracking of emerging topics. Moreover, practically, it offers a modular, scalable tool for firms seeking to enhance their technology intelligence capabilities, especially in sectors where timely trend detection is critical. Finally, conceptually, it links design science with computational foresight, showing how design artifacts can enhance companies’ ability to absorb the knowledge and innovation responsiveness.

* Research Rigor

Research rigor in Design Science Research (DSR) comes from a systematic and theory-based development and evaluation of the artifact (Gregor & Hevner, 2013; Hevner et al., 2004; Wieringa, 2014). This study ensures rigor through four connected practices:

First, the artifact is based on well-established theories that include exploration–exploitation trade-offs (Cesaroni et al., 2005; Li et al., 2008), expert-informed learning (Calof & Smith, 2009; Veugelers et al., 2010), and explainable AI principles (Gunning et al., 2019). These theories are shown in the conceptual model (Figure 2) and reflected in the system architecture (Figure 18).

Second, the components of the artifact come from a structured process that follows DSRM stages (Peffers et al., 2007). This aligns the problem, design, and implementation, ensuring logical coherence (Gregor & Hevner, 2013).

Third, the framework is tested through a case study in quantum cryptography. We use metrics like precision, novelty, entropy, and reinforcement learning standard algorithm to ensure both internal and contextual validity (Costello & Reformat, 2023; Sutton & Barto, 2018).

Finally, rigor is strengthened through iterative refinement and sharing results in peer-reviewed venues (Nazari & Weiss, 2025b, 2025a). This supports transparency and scholarly contribution.

* Design as a Search Process

The design of the framework followed an iterative search process. It evolves into cycles of building, testing, and refinement, gradually making the framework. Early versions of the framework were on integrating topic modeling and expert-informed input, as presented in our conference papers (Nazari et al., 2019; Nazari & Weiss, 2025b). Then, feedback from initial versions guided adjustments to the structure, weighting detection mechanisms, and learning components, such as RL in topic modeling (Costello & Reformat, 2023).

This iterative exploration ensured that the artifact evolved to better support expert-informed technology foresight that reflects the DSR principle of design as a guided search for effective solutions.

* Communication of Research

The research findings have been disseminated with theoretical and practical implications and conference presentations and publications. It contributes to the broader discussion on AI-driven technology foresight and expert-in-the-loop systems.

## Overview of the Method

A high-level overview of the method is designed to develop and evaluate an artifact (framework) through the iterative stages of the DSRM. Overall, the framework is developed through five steps in a process aligned with the research method. This method presents both methodological rigor and practical usefulness (Peffers et al., 2007). The steps are summarized below:

**Step 1:** Problem Definition: The problem, as we discussed in Section 1.1 (Motivation), is the need for dynamic, expert-informed knowledge integration to support detecting technological changes process. Following the method, this research begins with identifying a clear problem: The need to detect technological change in a timely manner aligns with an organization’s capacity to adapt by continuously and intelligently refining knowledge relevance through expert insights. Based on insights from Chapters 2, organizations currently monitor emerging technologies using approaches that exhibit the following characteristics and shortcomings:

* Reliance on Manual Expert Panels and Horizon Scans

Firms convene domain experts or advisory committees (e.g., internal R&D panels, external consultants) to identify nascent technological signals (Calof & Smith, 2009; Veugelers et al., 2010). This process is labor-intensive, time-consuming, and often yields only high-level trends without fine-grained, data-driven insights (Antons et al., 2020)

* Use of Bibliometrics and Patent/Publication Analysis

Companies analyze patent filings, citation networks, and publication volumes to detect rising research areas (Porter, 2007; Diam et al., 2016). Although informative, these methods require extensive manual filtering and do not scale easily as data volumes grow (Sievert & Shirley, 2014).

* Ad hoc Topic Modeling or Static Text Analytics

Some organizations apply unsupervised models to classify large document corpora (Blei et al., 2003; Gao, 2021). Each time new documents are added, the model typically must be retrained from scratch, introducing delays that hinder timely decision-making (Blei et al., 2003; Sievert & Shirley, 2014).

* Limited Integration of External Expert Knowledge

Domain expert inputs (e.g., curated conference proceedings or keyword lists) are often incorporated only once or in a one-time model refinement (Bogers et al., 2018; Zhou et al., 2020b). There is no continuous feedback loop to ensure that topic outputs remain aligned with evolving domain discourse.

* Challenges Balancing Exploration vs. Exploitation

Firms struggle to allocate resources between exploring novel, uncertain technologies (exploration) and deepening existing capabilities (exploitation) (Floyd & Lane, 2000; Gupta et al., 2006). Without algorithmic guidance, organizations risk falling into an “exploration trap” (chasing low-value insights) or a “success trap” (clinging to outdated knowledge) (Walrave et al., 2011).

* Lack of Dynamic, Adaptive Detection

Existing frameworks rarely leverage reinforcement learning (RL) to adjust topic priorities dynamically based on reward signals (e.g., novelty, entropy, similarity) (Gui et al., 2019; Khetarpal et al., 2022). This absence of adaptive mechanisms prevents organizations from rapidly pivoting to new technological signals as they emerge.

* Insufficient Scalability and Responsiveness

Most systems cannot handle the rapid influx of unstructured text (e.g., conference papers, industry reports) in a manner that delivers insights fast enough for strategic action (Antons et al., 2020; von Krogh et al., 2023). Consequently, decision-makers often receive technology signals too late, resulting in missed opportunities or misaligned strategies.

These outcomes highlight the core problem definition: organizations lack a systematic, scalable, and adaptive approach that combines automated topic discovery, continuous integration of external knowledge sources, and reward-driven learning—ultimately preventing truly timely monitoring and response to emerging technologies.

**Step 2:** Define the Objectives of a Solution: Based on the literature review and theoretical foundations (Chapter 2), the objective was to create a framework that integrates topic modeling, expert input, reinforcement learning, and feedback validation to address the problem and support strategic foresight. This objective arises because current frameworks do not offer a unified, adaptive approach as stated in Step 1. They need to combine computational topic discovery with expert validation. Chapter 2 shows that while each element—topic modeling, expert input, reinforcement learning, and feedback—has been studied on its own, they have not been brought together. There is lack of single, iterative framework that guarantees strategic foresight in fast-changing technological landscapes.

**Step 3:** Design and Development: The research maps theoretical constructs (e.g., exploration–exploitation, expert refinement) to modular system components. This mapping links theoretical ideas, exploration-exploitation with the RL agent, expert refinement with expert-informed input, to specific modular parts in the EILF framework. A detailed breakdown of this mapping can be found in Section 4.2.

The proposed artifact—the Expert-Informed AI Learning Framework (EILF)—was designed to include four interlinked components: topic discovery, expert-informed refinement, reinforcement learning optimization, and expert-driven feedback.

**Step 4:** Demonstration: The framework was implemented using a real-world case in the domain of quantum cryptography to demonstrate its ability to detect technology shifts and balance exploration–exploitation trade-offs.

**Step 5:** Evaluation and Verification: The framework was evaluated using performance metrics such as topic precision, novelty, entropy shifts, and relevance scoring across iterations. The evaluation used expert proxy data (conference proceedings) as validation signals.

**Step 6:** Communication: The outcomes of this research have been disseminated through both conference presentations and research articles submitted for peer review. These efforts contribute to the scholarly dialogue surrounding AI-driven technology foresight and expert-in-the-loop systems. Two research papers based on this thesis are currently under peer review:

Nazari, A., & Weiss, M. (2025a). *Exploring the Technology Landscape through Topic Modeling, Expert Involvement, and Reinforcement Learning* ([arXiv:2501.13252](https://doi.org/10.48550/arXiv.2501.13252)).

Nazari, A., & Weiss, M. (2025b). *Fine-Tuning Topics through Weighting Aspect Keywords* ([arXiv:2502.08496](https://doi.org/10.48550/arXiv.2502.08496)).

Additionally, a component of this work, refining topic model, was presented at the 1st CIREQ Interdisciplinary PhD Student Conference on Big Data and Artificial Intelligence, held at McGill University on June 15, 2023. The presentation, titled *“Fine-tuning Keyword Weights through Expert Feedback using Supervised Clustering,”* introduced early results of the expert refinement process.

This research also builds on our prior related work:

Nazari, A., Weiss, M., Shah, A., & Ji, S. (2019). Innovation Management Journal Analysis using Topic *Modelling Approaches.* In *ISPIM Conference Proceedings*, Ottawa, pp. 1–12. ProQuest link. These communication efforts highlight the applicability and scholarly value of the proposed framework, reinforcing its contribution to both academic research and practical applications in technology intelligence and strategic foresight. It involves communicating the theoretical and practical implications of the findings, as well as the framework’s relevance to practice. These aspects are detailed in Chapters 8 (Evaluation Results), 9 (Discussion), and 10 (Conclusion).

The table below links the six steps in the “Overview of the Method” (Section 3.2) to specific sections of the thesis. It shows how the research process (Steps 1–6) relates to the chapters.

Table 5: Mapping of Method Steps to Corresponding Thesis Sections

|  |  |  |
| --- | --- | --- |
| **Step** | **Description** | **Thesis Sections & Subsections** |
| **Step 1:** Problem Definition | The problem is covered in Section 1.1 (identifying the need for dynamic, expert-informed knowledge integration). | * Section 1.1 (Motivation) |
| **Step 2:** Define the Objectives of a Solution | Identify the design requirements and integrate lessons from the literature. | * Section 4.1.1 Design requirements * Section 2.9 Lessons Learned from the Literature |
| **Step 3:** Design and Development | Translate theoretical constructs (e.g., exploration–exploitation, expert refinement) into corresponding modular components. | * Section 4.1.2 Core Components of the EILF Framework * Section 4.2 Implementation of the Framework |
| **Step 4:** Demonstration | Apply the EILF framework to a real-world case study in quantum cryptography. Describe the multi-step process, show pseudocode, and walk through how each component is exercised. | * Chapter 5 (all sections) * Chapter 6 (all sections) * Chapter 7 (all sections) |
| **Step 5:** Evaluation and Verification | Evaluate EILF’s performance using metrics (precision, recall, novelty, entropy shifts, ADNS) and compare against expert proxy data. Confirm hypotheses H1–H2. | * Chapter 8 (all sections) |
| **Step 6:** Communication | Communicates findings via conference presentations, publications, and outlines implications for theory & practice. | * Chapter 9 (Discussion), Chapter 10 (Conclusion: summarizing contributions, limitations, and future work) |

# Framework Design and Instantiation

This chapter presents the artifact developed through DSRM, the Expert-Informed AI Learning Framework (EILF). It describes how the framework was designed and implemented in a real-world context (quantum cryptography). Following this, the chapter outlines the evaluation design and verification strategies used to assess the effectiveness of the framework.

## Overview of the framework

### Design requirements

Based on the problem identified in Sections1.1 (Motivations) & gaps in 2.9 (Synthesis of Key Gaps), the framework must satisfy the following design requirements (R1–R6) to enable timely detection and integration of emerging technologies:

R1. Automated Extraction of Latent Topics: The framework must employ unsupervised topic modeling (e.g., LDA) to uncover hidden themes in large, unstructured text corpora (Blei et al., 2003; Gao, 2021). These topics will form the baseline representation of the technological landscape without requiring manual keyword selection.

R2. Continuous Integration of External Knowledge Sources: The framework must accept curated inputs from domain proxies (e.g., conference proceedings, industry reports) to refine topic relevance (Bogers et al., 2018; Zhou et al., 2020b). This integration must be ongoing—allowing new external knowledge to adjust topic weights without retraining from scratch.

R3. Adaptive Topic Prioritization via Reward-Driven Learning: The framework must incorporate a reinforcement learning (RL) agent that assigns rewards based on metrics such as novelty (inverse cosine similarity with existing topics), entropy change, and absolute difference normalized sum (ADNS) (Gui et al., 2019; Khetarpal et al., 2022). Through iterative Q-value updates, the RL component should balance exploration of new topics and exploitation of established, high-value topics (Sutton & Barto, 2018).

R4. Iterative, Modular Architecture: Components (Topic Modeling, External Knowledge Input, RL Agent, Feedback Loop) must be modular—each can be updated or replaced without disrupting the entire system (Sundberg & Holmström, 2024). The architecture must support iteration: after each RL-guided topic update, external knowledge sources re-validate and, if necessary, adjust topic assignments.

R5. Scalable Processing of Growing Corpora: The framework must be capable of handling an expanding dataset (e.g., QCrypt 2023 → QCrypt 2024), processing thousands of documents without prohibitive computational overhead (Antons et al., 2020; von Krogh et al., 2023). Efficient data structures and batching strategies should minimize retraining time.

R6. Interpretability and Transparency of Outputs

Topic labels, top keywords, Q-value trajectories, and reward metrics must be presented in a clear, interpretable format (e.g., heatmaps, word clouds, Q-value tables) so decision-makers can understand why certain topics are prioritized (Arun et al., 2010; Röder et al., 2015).  
The system must log RL decisions (state-action-reward pairs) for post-hoc analysis and auditability.

Together, these design requirements ensure that EILF addresses the problems of static topic models, one-time external inputs, lack of adaptive learning, and insufficient scalability, ultimately delivering timely, actionable insights into emerging technological trends.

### Core Components of the Expert-Informed AI Learning Framework (EILF)

The framework design started by linking conceptual elements (Figure 2), such as exploration-exploitation and expert refinement, to system components. It identifies four key concepts: technical expertise, domain knowledge, exploration-exploitation balance, and validation, as discussed in the conceptual framework section 1.6. This process resulted in the Expert-Informed AI Learning Framework (EILF), shown in Figure 18.

The Expert-Informed AI Learning Framework (EILF) combines machine learning, domain expertise, and adaptive optimization. The framework has four connected parts—Explore, Refine, Assimilate, and Apply & Feedback. Together, they support the ongoing discovery and validation of new technological changes. Each part plays a key role in turning raw text into actionable insights.

As shown in Figure 2, the first part, **Explore** need to utilize an approach to extract insights from data. This process, most often, uses unsupervised machine learning techniques, like Latent Dirichlet Allocation (LDA), to find hidden themes in large amounts of unstructured text. This text consists of scientific papers, technical reports, patents, and industry publications. Explore uncovers emerging signals that manual analysis might miss. However, these algorithms may not fully align their outputs with domain knowledge or strategic goals.

To fix this issue, the second part, **Refine** need to adjust the topics with the strategic goals. This component adds expert-informed input to Explore component. Domain experts or trusted sources, such as curated conference papers, provide structured knowledge. They contribute keywords and conceptual taxonomies to weight or filter topic terms. This ensures the discovered themes are relevant and interpretable. This process increases the accuracy of topic modeling and aligns results with current field knowledge, bridging the gap between automation and human insight.

The third part, **Assimilate** also need to analyze explored and refined knowledge. It uses a technique, like RL, for optimization of topic selection. Here, a reward-based mechanism helps balance exploration and exploitation. The RL agent learns through domain-driven feedback by evaluating topic configurations using metrics like entropy and cosine similarity. This allows the system to update topic priorities and focus on high-impact areas as new data comes in.

The fourth part, **Apply & Feedback**, keeps the framework aligned with real-world developments through a continuous validation loop. In this component, the system checks its analysis against domain signals, like new conference papers or expert reports. These sources provide feedback that confirms or questions the validity of selected topics. This process helps the framework adapt and refine its focus. It integrates real-world signals back into the analysis, ensuring responsiveness, accuracy, and strategic value.

In this section, we summarize how the design requirements (R1–R6) from Section 4.1.1 informed the development of EILF’s core components, as shown in Figure 18. Each bullet describes a specific component, its role in satisfying one or more requirements, and references the relevant literature.

In short, the proposed framework should a flexible system that turns unstructured data into validated, relevant insights. By combining machine learning, expert refinement, reinforcement learning, and feedback, the framework stays accurate in fast-changing technological environments.

Building on this overview of the framework’s components, the next paragraphs outline the more details of components with addressing the requirements identified in previous section.

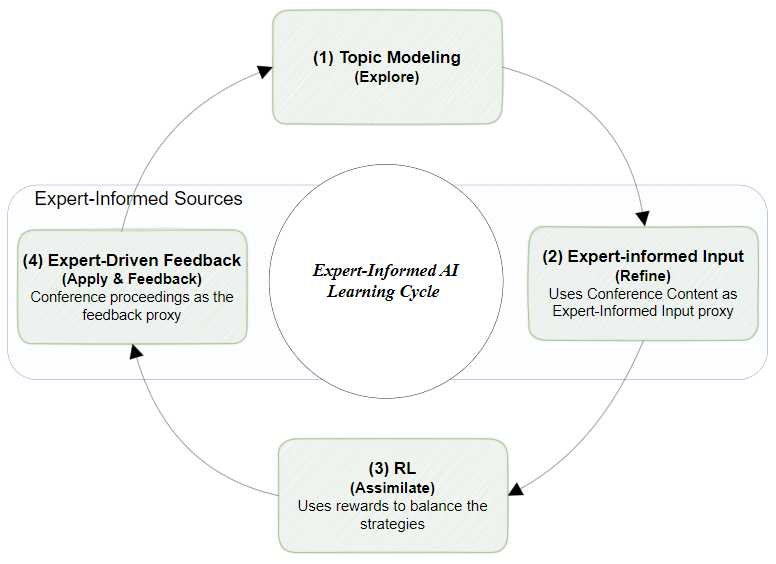


Figure 18: An Expert-Informed AI Learning Framework (EILF) for Technology Intelligence

* Topic Modeling (Addresses R1, R6)

The purpose of this comment is to extract automatically latent themes from the quantum communications corpus. We utilized Latent Dirichlet Allocation (LDA) (Blei et al., 2003) to generate an initial set of topics (CTP1). Besides, we selected the optimal number of primary topics (39) based on coherence and silhouette metrics (Arun et al., 2010; Röder et al., 2015). The framework satisfies the following component-related requirements:

– R1: Provides unsupervised topic discovery without manual keyword selection.  
– R6: Outputs include top‐word lists, topic‐document assignments, and heatmaps for interpretability (Sievert & Shirley, 2014).

* External Knowledge Input (Addresses R2, R6)

The purpose of this comment is to refine continuously topic relevance using curated inputs drawn from domain proxies. We collected weighted keyword lists from QCrypt conference proceedings and a proxy “Quantum Tech Report” (Bogers et al., 2018; Zhou et al., 2020b). We injected these weights into topic‐word distributions using a relevance scoring function (Section 6.4), producing CTP2. And it enabled dynamic updates where new keywords from QCrypt 2024 directly adjust topic weights in CTP3 without full retraining. The framework satisfies the following component-related requirements:  
– R2: Allows ongoing integration of external knowledge.  
– R6: Expert‐proxy keywords lend contextual meaning, increasing trust in topic labels.

* Reinforcement Learning (RL) (Addresses R3, R4)

The purpose of this comment is to prioritize topics adaptively by balancing exploration (novelty) and exploitation (stability). We defined states as individual topics (39 total) and actions as “select topic for update.”. In addition, we incorporated a reward function with average inverse cosine similarity to new documents (novelty), entropy change, and Absolute Difference Normalized Sum (ADNS) between CTP iterations (Formulas 6–9). We also employed standard Q‐learning with learning rate α and discount factor γ (Sutton & Barto, 2018; Gui et al., 2019). After each iteration, Q-values were updated by Formula 9. It produced CTP2→CTP3 transitions, demonstrating how topics of interest (e.g., T19, T32) evolve through RL‐guided selection (Khetarpal et al., 2022; Kabudi et al., 2021). The framework satisfies the following requirements:  
– R3: Adapts topic priorities via reward signals.  
– R4: Structured as a modular agent that can be replaced by alternative RL algorithms in future iterations (Sundberg & Holmström, 2024).

* Feedback Loop (Addresses R4, R5, R6)

The purpose of this comment is to validating RL‐selected topics against external knowledge proxies and preparing for the next iteration in a cycle. After each RL update, we retrieved top‐N documents most strongly associated with selected topics. Then, we compared those documents’ themes with conference‐derived keyword sets to compute precision/recall (R1 vs. R2 alignment). An addition, we logged state‐action‐reward triples for auditability and tracked Q-value trajectories over two iterations (7.5.2). Besides, we designed to handle incremental additions to the corpus (e.g., new papers each iterations) through batched updates (Antons et al., 2020; von Krogh et al., 2023).  
The framework satisfies the following requirements:  
– R4: Ensures each component remains decoupled; the feedback loop simply consumes RL outputs and external inputs.  
– R5: Batching strategy limits computational overhead by updating only affected topics rather than retraining all 39 topics.  
– R6: Generates interpretable validation metrics (precision, recall, F1) for stakeholder review.

Figure 18 illustrates how these four components, Topic Modeling, External Knowledge Input, RL, and Feedback Loop, interact in a closed, iterative process. By mapping each component back to design requirements R1–R6, the EILF architecture demonstrates a systematic, theory‐based artifact development approach characteristic of DSR (Peffers et al., 2007; Hevner et al., 2004).

## Implementation of the framework

Figure 19 displays the implementation process used in this study. This process builds on the artifact created in previous section 4.1. It spans the complete empirical cycle, which includes topic modeling, external input, RL, and expert-driven feedback. The findings will be detailed in the Results and Discussion chapters. In Figure 19, we used also different colors for different groups of steps as four components to represent the four components from Figure 18. The implementation process of framework shown in the figure uses a systematic and iterative process. It uncovers and refines hidden topics in a specific area with expert-informed topic modeling and RL. First, it defines domain-specific keywords from trusted sources. These keywords guide the collection of text and help create an initial topic model using LDA. Next, the model improves with aspect-based keyword weighting and external input. This sharpens key themes. New documents are clustered and compared often to boost accuracy. In the RL component, the model optimizes itself with a topic model, corpus, value function, and reward function that identifies domain-specific themes. If validation process fails, it revisits earlier steps. It starts to adjust keywords, expand the corpus, fine-tune model parameters, and incorporate expert feedback. This approach emphasizes ongoing improvement and aligns with organizational goals.

#### Framework (EILF) Implementation Process

The EILF is a hybrid framework main task is to analyze external sources and identify and validate emerging technological changes. This is especially applied to the field of quantum cryptography. Methodologically, the EILF uses computational techniques from Natural Language Processing (NLP), Machine Learning (ML), and External Knowledge. It consists of four main components aligned with our framework (Figure 18). The implementation process of EILF is illustrated in Figure 19, consisting of 18 steps aligned with the corresponding pseudocode. Following this, the results are presented and the findings are discussed. We will discuss the four components (colored in Figure 19) detailed, after presenting pseudocode aligned with these 18 steps.

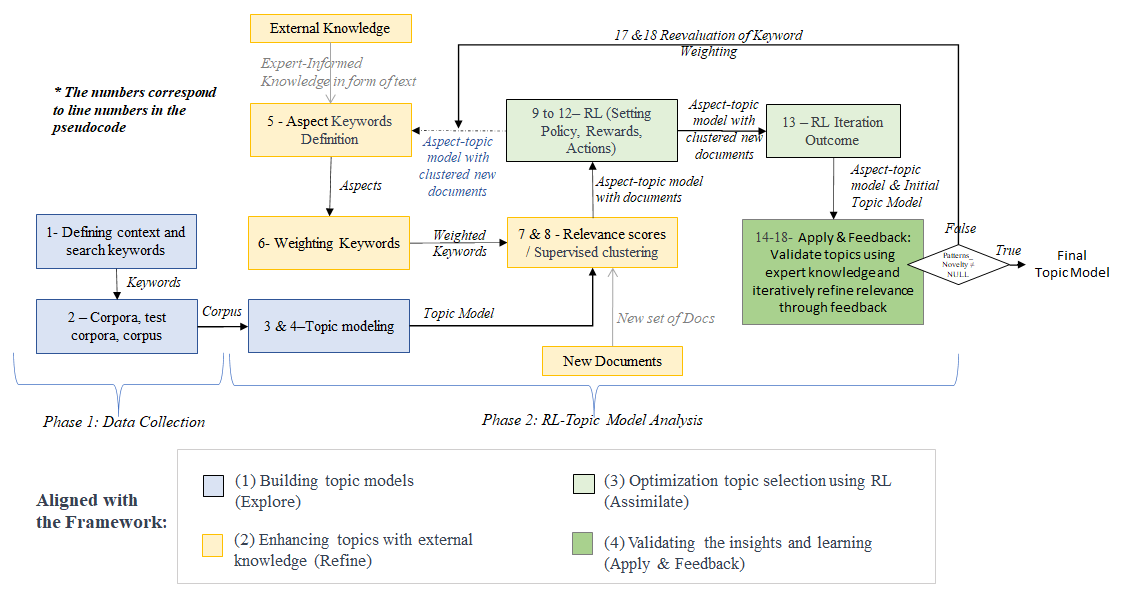


Figure 19: Stepwise Implementation of the Expert-Informed AI Learning Framework (EILF)

To demonstrate the inputs and outputs of the steps (Figure above), we provide a pseudocode representation of our implementation process (Table 6). Phase 1, Data Collection condenses the topic modeling process. In our earlier paper, (Nazari & Weiss, 2025b), we elaborate on the details of Phase 1 and portions of Phase 2, Lines 1 to 6 in Table 6. These phases outline steps including collecting papers, defining keywords, organizing corpora, generating baseline topic models, and developing aspect-based models with expert keywords. A more detailed version of the pseudocode, is provided in Appendix C.5.

Table 6: The Proposed Overall Algorithm[[1]](#footnote-1)

|  |
| --- |
| **Phases/Steps //Step description** |
| **// Phase 1: Data Collection**  1 SK ← DefineSearchKeywords(domain) //Define search keywords  2 C ← BuildCorpus(SK) //Build and preprocess corpus  **// Phase 2: Topic Model Analysis**  // Initial Topic Model  3 TM ← LDA(C) //Generate initial topic model  4 CTP1 ← TM //Set initial topic model as CTP1  CTP2 ← NULL  // Initial Topic Model Development and Refinement  5 AText ← AspectIdentification(DomainExpertNotes) //Identify aspect-related text  6 AT ← WeightedAspectKeywords(AText) //Assign weights to aspect keywords  7 ATM ← GetAspectTM(CTP1, AT) //Refine topic model with aspect keywords  8 CTP2 ← ATM //Assign refined model as CTP2  // RL Component: Evaluating Topic Novelty with RL  9 current\_state ← CompareModels(CTP1, CTP2) //Compare topic models  10 action ← FindTopics(current\_state) //Select topics based on rewards  11 new\_state ← AdjustTopicModel(action, CTP2, new\_keywords, new\_documents) //Update model with new state  12 reward ← CalculateReward(new\_state, action) //Calculate rewards  13 RL\_Model ← UpdateRLModel(action, reward) //Update RL model  // Analysis & Validation  14 VR ← CompareTopicModels(CTP1, CTP2) //Compare topic models for validation  15 Patterns\_Novelty ← TechnologyVision(QCrypt\_Dataset, CTP2) //Identify novel patterns  16 fine\_tuned\_topics ← FineTuneTopics(CTP1, CTP2, DocsCTP2, Patterns\_Novelty) //Fine-tune topics  // Iteration Management & Transition  17 CTP1 ← CTP2 //Update CTP1 for next iteration  18 CTP2 ← new\_state //Set new state as CTP2  // *Iteration/Episode Control - guided by performance metrics such as F-score, precision, recall, and timeliness to refine topic models.*  IF Patterns\_Novelty ≠ NULL THEN  GOTO **Final Topic Model**  ELSE  GOTO 5 |

Later steps in the second phase use RL algorithm to refine topics through ongoing adjustments.

The primary focus is on RL for the iterative refinement and adaptation of topic models. The RL process starts by comparing the initial topic model (CTP1) with an aspect-based model (CTP2). In our context, CTP stands for Contextual Topic Perspectives. ‘Contextual’ refers to the different viewpoints for analyzing the topic model. ‘Topic Perspective’ means that each model version offers a unique view of the topics. It shows how the model evolves or is re-evaluated over time from different views. We seek significant differences, similarity, and entropy changes within topics based on a predefined policy. RL selects action to adjust the topic model. It does this by incorporating new keywords and documents. In each iteration, the agent calculates approximate rewards to calculate topic Q-values in q-learning RL algorithm. The novelty and improvements of the topic model form the basis. The RL model then updates to inform future actions. This iterative process allows for continuous model enhancement by integrating new, relevant information. We verify the model's effectiveness by analyzing the results after that. This includes heatmaps and cosine similarity and rewards comparisons. The process looks for new insights and topic evolution and ensure the RL-driven updates align with technological advancements.

### Explore

Building Topic Models (steps 1-4 in Figure 19 & Table 6) – This process analyzes large collections of documents, like reports and articles. First, a neural network algorithm screens the searched documents. Then, the LDA algorithm creates a topic model to identify key themes. We used hierarchical clustering to group the most related documents within each topic, setting a threshold of 0.7. As a result, this helps capture the diverse aspects of each topic.

Phase 1: Data Collection

We define search keywords from key papers of the predefined domain of research. These keywords guide the collection of domain-specific corpora from online sources, like Web of Science and Scopus. This data forms the basis for constructing a corpus. **Step 1** is to identify and define domain search keywords (SK) from a set of domain-related documents, like peer-reviewed articles, reports, and patents. After retrieving the corpora, we build a refined corpus (C) in **Step 2**. We do this by applying some text-processing techniques. This includes stop word removal, stemming, lemmatization, and tokenization. It also includes steps to ensure the corpus is clean and structured and uses a neural network technique to screen out irrelevant documents. It must be ready for the next phase: topic modeling. These steps are vital and ensure the data's quality and relevance for further analysis.

Phase 2: Topic Modeling Analysis

*Initial Topic Model*

This phase begins with using LDA algorithm (Blei et al., 2003) on the preprocessed corpus (**Step 3**). Researchers use methods like variational inference (Blei & Jordan, 2006) or Gibbs sampling (Griffiths & Steyvers, 2004) to do this. This will create an initial topic model (TM). The model represents the distribution of words and documents across topics. LDA aims to find the posterior distribution using variational inference. It does this with the latent variables (topics) and the observed data (documents and words). **Step 4** establishes the starting point for the RL process. The system initializes the state CTP1 as the initial topic model (TM). It is the baseline model before any updates. Meanwhile, we set CTP2 to ‘None’ to state that no one has yet prepared an aspect-based topic model. This setup allows the algorithm to start an iterative process. It will compare and refine topic models using new data and defined policies.

### Refine

Enhancing Topics with Expert Knowledge (steps 5-8 in Figure 19 & Table 6): Expert-informed knowledge improves topics by applying important keywords to the model for accuracy. The expert proxies also introduce new documents, which further refine the topic model. In the context of this research, expert informed sources refer to structured, domain-specific input that influences and guides the behavior of the machine learning components–specifically, the topic modeling and RL components. Rather than relying on continuous expert annotation or real-time feedback, this framework uses indirect but structured expert-informed input from domain experts, weighted aspect keywords extracted from industry conference proceedings (e.g., Quantum Tech). These inputs are incorporated during the Refine stage of the framework to adjust keyword weightings, validate topic coherence, and provide evaluation signals for the RL component. The inputs also are incorporated during the Apply & Feedback stage to validate the outcomes of the Assimilate stage. This proxy’s interaction is key to keeping the system context-aware and helps avoid the issue of unsupervised topic discovery. The approach uses an expert-guided loop design that includes periodic feedback instead of continuous feedback. This aligns with recent research in expert-in-the-loop learning systems (Gunning et al., 2019; X. Wu et al., 2024). Through this mechanism, expert expertise informs model interpretation, supports strategic alignment, and enables adaptive topic refinement without requiring direct labeling of each document or topic.

We chose industry conference topics and papers, such as Quantum Tech for expert-informed input and QCrypt proceedings for providing expert-driven feedback, because they reflect the most up-to-date and emerging topics in the field right after our initial topic model that contains previous insights. Unlike journal papers, which can take 12–24 months to publish, conferences present real-time expert signals, often shaping the direction of research and R&D investments. For this reason, they serve as a more timely and dynamic proxy for expert input in trend detection.

*Keyword Definition & Aspect Topic Model Creation*

Next, we (**Step 5 & 6**) identify aspects (see AText in Table 6) using an agent-based aspect identification approach. We suggested an agent-based aspect identification which is an automated process. A software agent, which is a rule-driven NLP pipeline, extracts and prioritizes keywords from domain related sources. The approach performs the following tasks:

1. Automatically gathers domain related papers, like the QCrypt 2023 proceedings, from set sources such as conference sites (Text Retrieval) and then cleans text using tokenization, stop-word removal, and lemmatization (Preprocessing).
2. Applies TF-IDF to rank terms by importance within the conference corpus (Keyword Extraction). It uses thresholding, like keeping terms with TF-IDF scores over 0.7. It also has exclusion rules, such as removing generic terms like "analysis" or "method" or irrelevant previous aspect keywords. This helps create a list of candidate keywords (Aspect Filtering).
3. Compare terms with a domain-specific ontology, such as the communication glossary, to ensure they are relevant (Aspect Validation) (see AT in Table 6). The aspect identification agent automates keyword extraction. It uses rule-based NLP techniques, like TF-IDF scoring and thresholding. We validated manually the aspects with the conferences agendas to ensure about the aspect keywords weights. This helps rank new terms from sources such as conference proceedings. While the agent preprocesses, ranks terms, and filters, it uses expert knowledge in three ways: 1- It sets TF-IDF thresholds and exclusion lists to highlight important terms. 2- It creates ontologies showing relationships, such as "post-quantum cryptography" under "security protocols." 3- It checks results to remove irrelevant options.

This hybrid method combines automation for scalability and expert rules for accuracy. It ensures that extracted elements fit domain needs and reduces manual work. We point out that in this research, the extracted aspect keywords as expert-informed input are from a related conference (Quantum Tech) content.

We, then, use the aspect's weighted keywords (AT) and the initial topic model (TM) to train the TM and compute relevance scores for each topic (**Step 7**). We do this by multiplying the aspect keywords vector with the topic keywords vector, focusing only on the intersection of the two vectors. This gives us what we call aspect-topic models (ATM). The scores show how relevant documents of each topic are to the identified aspects. It assigns different weights to the topics based on aspect keywords. We have outlined these steps taken thus far in (Nazari & Weiss, 2025b). These two models, CTP1 and CTP2, serve as inputs to the RL process (**Step 7 & 8**). CTP1 is the initial topic model and CTP2 is the aspect-based topic model. In RL process, an agent identifies topics likely to contain new information for further analysis. It operates based on predefined policies, hyperparameters, and thresholds. Domain experts, later in end of each iteration, will then examine the insights derived from these novel topics.

### Assimilate

Optimizing Topic Selection Using RL (steps 9-13 in Figure 19 & Table 6): The system agent continuously monitors how topics evolve over time. It adjusts them for uniqueness and coherence. This framework introduces a new RL-based topic modeling method. It aims to enhance topic modeling by using RL signals to improve topic representations. This method optimizes coherent and context-sensitive topic decisions. It selects relevant topics from domain-specific texts.

###### Rationale for RL Integration

The choice to use reinforcement learning (RL) in this framework stems from the need for a flexible tradeoff between exploration and exploitation strategies. This system must adapt topic selection as data patterns change. Traditional supervised learning needs large labeled datasets. These can be difficult to obtain quickly or in large quantities. In contrast, RL allows the system to learn by interacting with its environment, which includes the topic model and the corpus. It receives feedback based on criteria like novelty, entropy, and divergence. This approach helps the model improve over time without depending on fixed class labels or static features (Sutton & Barto, 2018; W. Wang et al., 2020). To keep things simple and scalable, we put in place the RL component with a modular design. It focuses on the topic selection phase, using a straightforward view of candidate topics, reward signals, and Q-values. We manage complexity by:

1. **Limiting the RL action space** to basic operations, such as selecting, retaining, or discarding.
2. **Using understandable reward metrics,** such as entropy and cosine similarity, is important.
3. **Decoupling** the processes of topic modeling, expert input integration, and policy optimization.

This modular design keeps the method clear and efficient. It adds little extra computation beyond regular topic modeling. Using proxy signals instead of direct expert annotations makes training easier. It also helps the system stay in line with expert judgment.

*RL Steps*

This stage employs RL to improve topic models. It balances two key activities: exploring new topics and enhancing coherence. We employed this approach in Nazari & Weiss, (2025 b). A Q-learning agent improves actions (topic adjustments) over time (Bishop, 2006; Sutton & Barto, 2018). It does so by using approximate rewards based on four metrics utilized from (Costello & Reformat, 2023; Gui et al., 2019; Sundberg & Holmström, 2024).

1. Magnitude: These measures how different the distributions are between the baseline (CTP1) and the refined topic model (CTP2). It helps highlight new themes.
2. Cosine Similarity: Quantifies topic-document alignment to maintain coherence.
3. Entropy Changes: Tracks uncertainty changes to guide topic specialization.
4. Absolute Difference (ADNS): Assesses normalized topic weight variations.

(1)

The formula 1 finds the size of a topic weight vector. It does this by squaring the topic weights, adding them up, and then taking the square root. This shows how much influence each topic has in a document.

Cosine similarity compares two topic word vectors, regardless of their size. It assesses their overlap (Manning & Schutze, 1999).

Cosine Similarity= (2)

where A⋅B is the dot product, and ∥A∥, ∥B∥ are norms, vector magnitudes. CTP1 (initial cryptography topics) and CTP2 (cryptography-protocols) are compared to examine topic evolution. The similarity matrix can helps track consistency and topic changes. Low similarity indicates significant changes, signaling redefinition or new focus. It detects how topics evolve and guides adjustments (Blei & Lafferty, 2007).

Entropy measures uncertainty in topic distributions. It shows if topics become more specialized or broad (Shannon, 2001). High entropy suggests a broad, unclear topic, while low entropy shows a more focused one (Blei & Lafferty, 2007). Tracking entropy changes helps identify whether topics should be refined or explored further:

(3)

Entropy H(*T*) quantifies the uncertainty or diversity in the word distribution of a topic *T*. Higher entropy reflects a more uniform distribution, indicating less focus on specific words, while lower entropy suggests a more concentrated topic. It is calculated as formula (3), where is the conditional probability of word in topic 𝑇, and moderates contributions based on probability values. Entropy changes in two sequential topic models can signal topic evolution. Besides, using entropy changes to guide RL policy decisions to make an action on topic selection is effective (Xin et al., 2020). Increased entropy suggests diversification and decreased entropy implies a greater focus (Blei et al., 2003).

In addition, Absolute Difference in Normalized Sums (ADNS) compares two normalized vectors. It measures changes in their distributions.

(4)

ADNS = (5)

The formula for this calculation usually involves two steps: First, we normalize each vector (distribution) by dividing each element by the sum of all elements in the vector. This ensures that the sum of all elements in the vector equals 1, transforming each vector into a probability distribution. For a vector , the normalized vector . Second, after normalization, the absolute difference is calculated between the sums of corresponding elements in two normalized vectors and ​. If ​ and are normalized versions of two topic distributions. Where and are the elements of the vectors and ​, and and are the sums of the elements in and ​, respectively. This formula calculates the total difference between the two normalized distributions. It is a simple method to compare the divergence of two distributions after normalizing their elements (Blei & Lafferty, 2007; Kingma & Welling, 2013).

Combining these metrics, the RL agent calculates approximate rewards. For a balanced evaluation of topic model updates, we combine magnitude and entropy as novelty metrics to measure the introduction of new patterns, with cosine similarity and ADNS as stability metrics to ensure topic coherence. The reward function combines four key metrics: magnitude, similarity, entropy, and ADNS, weighted by coefficients (λ1, λ2, λ3, and λ4). This prioritizes exploration or stability, fostering adaptation (Ng et al., 1999), and helps the RL agent make decisions that align with our learning goals. Magnitude shows how strong topic contributions are. It helps organizations detect and rank new trends, like secure authentication. Similarity keeps us aligned with what we know. It helps us make consistent decisions. This way, we avoid major changes that move away from our main skills. Entropy shows topic uncertainty. It balances two important areas. First, it explores new ideas, like quantum networks. Then, it focuses on practical applications that boost advancements, such as entanglement swapping. ADNS detects changes in topic distributions. This signal changes in paradigms that need new strategies. For example, it helps in adapting to emerging post-quantum cryptographic protocols. The weighted sum of these components helps rank tasks dynamically. Organizations can adjust λ1−λ4 to focus on different goals. They can detect trends, ensure stability, drive innovation, or adapt as needed.

Approximate Reward () = λ1 ​× Divergence + λ2​ × Similarity + λ3​ × Entropy + λ4 ​× ADNS (6)

By tuning the metrics' coefficients, we can adjust the reward function. This design lets the RL agent explore many paths for the topic model to promotes innovation or refinement. In our test process, we assign greater weight to divergence and less to similarity to effectively explore new aspects of topics and currently keep the other metrics low. The coefficients are λ1=0.75 for divergence, λ2=0.15 for cosine similarity, λ3=0.05 and λ4=0.05 for entropy changes and ADNS respectively. For early iterations, higher λ1 most probably can encourage exploration, while later iterations increasing λ2​ facilitates exploitation the new data. We test different coefficients to examine approximate rewards and maximum Q-values to select topic candidates. The RL agent calculates expected Q-values as outlined by Watkins & Dayan, (1992):

(7)

where *Q(s,a)* is the current value of the state-action pair of aspect topic model and selected topics (state *s*, action *a*). Weights of topics in CTP2 refining with expert-driven aspect keywords and the action is selecting and refining topics with greater Q-values calculated using approximate rewards. *α* is the learning rate which determines how much the new reward influences the previous Q-value. is the approximate reward (as defined in Formula 6) for acting *a* in state *s*. It is based on the **average weight of topics after applying new keywords** (reflecting improved topic relevance and novelty). *γ* is the discount factor which balances the value of **immediate vs. future rewards**. is the maximum expected future reward for the next state *s′*, considering the best action *a′*. For our model, this refers to how the RL agent would **evaluate future topic refinements** in CTP2, considering **which actions** (e.g., further keyword adjustments or topic selections) would lead to the best future topic improvements as shown by (Mnih et al., 2015). It ensures that the agent **prioritizes actions** that will lead to the most promising improvements in future topic models.

According to the pseudocode, the RL steps as follows:

**Step 9:** CTP2 is updated with protocol keywords and specific protocol advancements (Steps 4 & 8). The comparison of these two models, in each iteration, defines the system's current state. Metrics like topic similarity, divergence, entropy changes, and topic absolute difference are calculated. They find approximate future rewards and guide action selection.

**Step 10:** Next, we evaluate the similarity between topics in CTP1 and CTP2, alongside the divergence of topics. We also examine the entropy changes in the transmission. They measure changes in topic distributions based on the weighted aspect keywords. To select topics, the agent approximates the topic reward first. We consider topic divergence, similarity scores, entropy variations, and ADNS to calculate it (Sutton & Barto, 2018). And then, the Q-values are calculated based on Formula (7). The maximum Q-values based on the approximate rewards are selected for future investigation and analysis. We select the top five topics for further analysis.

**Step 11:** Once the agent selects topic(s), an action, it adjusts the topic models. This process adds documents from the other sources like papers from 2023 and 2024 conferences to evaluate the selection process. The initial topic model is created on data up to 2022. We include the following years to show the effectiveness of the topic selection process. The agent uses the action to infer new topics from the current CTP2 model. It then transforms into a new state. This transition introduces new topic models. They reflect the changing state of the domain.

In **Step 12**, to assess whether the selected topics align with the technology trends desired by the expert, we adapt the reward function in our RL component based on the explicable reward design approach by Devidze et al., (2021). Their method aims to align reward functions with clear, context-specific criteria. It ensures the agent's learning aligns with both set goals and new patterns. The updated Q-values, based on these rewards, show how the selection process aligns with market technologies and the expert's goals. We use a modified reward function. It calculates expected rewards using the similarity of 2023 and 2024 conference papers with the topics of the current model for two iterations (calculated based on the following subsection formulas– *“Modifying Rewards in the Q-Learning Formula for Enhanced Exploration”*). It also boosts the exploration rate by applying changes in entropy. For our case, it emphasizes trends in post-quantum cryptography and quantum-secure protocols. It guides the agent to recognize clear progress in these evolving topics.

#### Modifying Rewards in the Q-Learning Formula for Enhanced Exploration

To bring up the exploration rate in our small topic model, we add entropy changes to the reward function as well. The formula for the modified reward function is as follows:

(8)

The formula represents the total reward for selecting action a (topic) in state . The system derives the base reward, denoted as, from the average cosine similarity between each CTP2 topic and the new documents. Less similarity results in a high base reward. This calculation and document can be refined in each iteration with input from multiple experts, ensuring all experts follow a unified scenario to reach a consensus on adopting the emerging technology. We calculate this using:

*)* (9)

where, d is the number of new documents (e.g., the 2023 conference papers). We consider these documents are expert input. The cosine similarity measures the alignment of each topic with the documents. We also consider t as a threshold of the similarity scores to get the sum of the most associated documents to the topic (e.g., 0.3). In formula 8, represents the degree of uncertainty or novelty in the topic, derived from its word distributions in CTP2. A higher entropy value indicates that the topic is more diverse or underexplored. The hyperparameter λ controls the weight given to the entropy. It helps balance exploring new topics with refining existing ones.

**Step 13:** The system updates the RL model based on the reward received. If an action leads to little or no reward, the system learns to avoid similar actions or policy. For example, introducing redundant keywords that do not improve the model. This step reinforces successful actions that get a higher reward and higher Q-values. It helps the system select actions for improved topic modeling with greater efficiency. Over time, the RL model becomes more adept at identifying and incorporating new, valuable topics as it processes evolving data. We update the Q-values (based on formula 7) and save the parameters (α, γ, and ). Actions that lead to high rewards have their Q-values increased, making them more likely to be selected in the future. We discourage actions with low rewards as their Q-values decrease. With each run, the RL model learns which actions improve objectives, like topic relevance. These actions include adding keywords or modifying topics. Reinforced successful actions help the model. It can now find new topics, avoid harmful actions, and process changing data with greater efficiency. For example, the model may first introduce keywords without a specific pattern. It then evaluates their impact based on coherence or expert feedback. It assigns higher rewards to meaningful keywords and lower rewards to irrelevant ones. Over time, the model prioritizes actions that consistently enhance topic quality.

### Apply & Feedback

Validating outcomes and gaining insights for real-world decisions (steps 14-16 in Figure 19 & Table 6) involves expert-driven feedback as reviewing results. The analysis aims to find new insights and track topic changes.

**Step 14:** Heatmap analysis compares CTP1 and CTP2 to assess the similarity between topics in different aspects. The heatmap shows how well these aspects align. It clearly shows any topic overlap or differences.

**Step 15:** Use cosine similarity to compare documents with the topic matrix. It will show how closely each document aligns with selected topics. Higher cosine similarity values show stronger relevance. They help to identify changes in focus within the topics. Use cosine similarity to compare documents with the topic matrix, indicating how closely each document aligns with selected topics. In parallel, compute Q-values based on the reinforcement learning reward function. The system focuses on topics with the highest Q-values, reflecting their strategic relevance. Evaluation metrics such as precision, recall, and F1-score are also generated to assess topic quality. Experts may review these results manually or adjust threshold settings to refine topic selection and validation.

**Step 16:** Topics are refined by incorporating relevant new documents, enabling the model to evolve over time. This RL-driven update process improves the model. It can now spot trends and adapt to new data. This keeps it relevant and responsive.

*Iteration Management & Transition*

The final step in the loop is preparing for the next iteration. The updated topic model CTP2 now becomes the new CTP1 for the next comparison. The inferred new state becomes the new CTP2 (**Steps 17 and 18**). The system compares, adjusts, and refines the models in response to the entry of new data and keywords. The loop continues running until the desired results are achieved in each episode. At the end of an episode, another path extension may begin. This is when either we reach a desired novel topic(s) or we can make no more significant improvements. The result is a refined set of topic models. They evolved over many iterations, incorporating keyword changes and new documents. They now offer a more accurate view of the domain technology landscape. This process ensures the model learns and adapts. It will align with new trends while keeping a focus on the domain's core aspects.

*Iteration/Episode Control*

The 'Iteration/Episode Control' section looks at the Patterns\_Novelty variable. The variable measures new patterns and insights found by experts during topic model updates. The evaluation includes important metrics like precision, recall, and F-score. These metrics check how accurate the refined topics are. The framework also considers timeliness. This ensures that topic updates match recent trends and stay relevant over time. For example, it includes new patterns in quantum cryptography, like advances in QKD. If Patterns\_Novelty is not null, it means experts learned something valuable. Then, the process continues to "Final Topic Model." In the research outputs, we will present the results of each iteration and evaluate the method's performance. If no new knowledge is found (Patterns\_Novelty = NULL), the process loops back to Step 5. This step refines the topic models through more iterations. This makes sure the research either reports results when there are advancements or keeps exploring until insights are found. This aligns with the iterative and expert-driven nature of the methodology.

These four components presented the design and implementation of the Expert-Informed AI Learning Framework (EILF). It details the core components, technical structure, and a real-world case study. The framework integrates unsupervised topic modeling, expert-informed input, RL, and expert-driven feedback to support adaptive knowledge integration. Each component is explained by its function and contribution to the system. The section also covers how the framework operates in the quantum communication domain. It describes the reinforcement learning structure, reward logic, and evaluation baselines for performance measurement. Lastly, it discusses the framework's modularity, showing its flexibility and potential for use in various technology settings. This foundation sets the stage for the next chapter, which focuses on data collection and domain-specific preparation.

# Data Collection in the Quantum Communication Case Study

To show how our method works, we used quantum communication data. This field uses quantum mechanics to improve communication. It has unique challenges and opportunities for data analysis and topic modeling. By focusing on quantum communication, we want to highlight how strong and flexible our approach is. As seen in Figure 20, we first identified key areas of interest, like quantum key distribution, cryptography, and networks. We based this on recent literature and conference proceedings. Next, we picked important search keywords. Then, we gathered a wide range of academic papers, technical reports, and industry publications. Using LDA, we extracted hidden topics from the corpus. This showed patterns and themes about quantum communication. It also helped form an initial topic model. This process provided insights into the current research state and pointed out key topics and areas for further study.

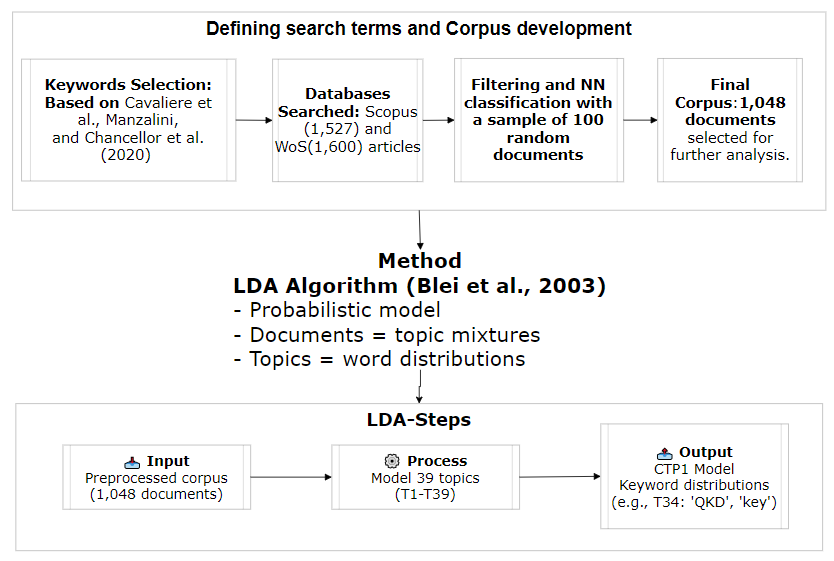


Figure 20: Defining Search Terms, Corpus Development, and Initial Topic Model

The case study serves as a detailed example of how our guided topic modeling approach can be applied to a specific field, integrating expert knowledge and advanced machine learning techniques to enhance understanding and drive innovation.

## Defining Context and Keywords

Quantum communication is a crucial area of interest for various sectors, including technology, finance, and aerospace. Major conferences like the 2022 and 2024 Quantum Tech conferences highlight the importance of advancements in this field. These events attract a diverse audience and cover topics such as quantum computing, cryptography, Quantum Key Distribution (QKD), etc. This focus helps us understand our case study and identify relevant search keywords from quantum communication sources.

*Quantum Communication Research*

Quantum cryptography has advanced greatly in the past decades. Key theories and practical breakthroughs have changed secure communications. The 1980s saw the rise of quantum key distribution (QKD). In particular, the BB84 protocol by (Bennett & Brassard, 2014) was a major milestone in secure key exchange. Theoretical work on quantum cryptography advanced in the 1990s. It included using quantum states for secure communication. Researchers, like (Cavaliere et al., 2020), explored QKD protocols. They studied their integration with classical cryptographic systems. This work underscored quantum cryptography's evolving role in secure communications.

In the early 2000s, experiments tested QKD's practical uses. They included its integration into tele-communications infrastructure (Manzalini, 2020). A major achievement was deploying QKD over fiber-optic networks. It was the commercialization of QKD systems for secure transactions (Gisin et al., 2002). In the 2010s, satellite-based quantum cryptography became a focus. Liao et al. (2017) showed QKD between satellites and ground stations. This work extended the reach of secure communication networks.

Quantum cryptography is secure. It resists attacks by quantum computers using (Shor, 1994) algorithm. This is vital for protecting data against new threats. (Hassija et al., 2020) examined the role of QKD in safeguarding information against quantum computing risks. There is growing interest in combining quantum cryptography with classical systems. Hybrid solutions aim to improve security in banking, healthcare, and government (Cavaliere et al., 2020). The field is working to solve scalability issues for wider use. Key research efforts focus on improving quantum repeaters and photon detectors. These aim to extend the range of secure communication. Meanwhile, efforts to develop quantum-resistant encryption standards are underway. They seek to counter new threats from quantum computing (Manzalini, 2020; P. D. O’Reilly et al., 2022). Milestones like the BB84 protocol (Bennett & Brassard, 2014) laid key principles. Practical advances, like satellite-based quantum key distribution (QKD), pushed secure communication limits. These innovations are key to a strong quantum communication network. They are vital in an age shaped by quantum tech.

The limitations identified in the methods reviewed in the literature underscore significant challenges. Researchers have made advancements in topic modeling using deep learning. Yet, their complexity and high demands hinder real-time apps (Peinelt et al., 2020; Sutton & Barto, 2018). Newer models using expert feedback (W. Wang et al., 2020) fix these issues. However, they still struggle with scalability. Also, they need to use domain-specific knowledge to find adoptable technologies. Besides, RL shows promise for dynamic knowledge discovery. Yet, real-time apps in large data repositories are still evolving (Sutton & Barto, 2018; Yen et al., 2002). Quantum cryptography domain faces these barriers to adoption (Cavaliere et al., 2020; Manzalini, 2020). These issues show a need for more innovation in both theory and practice.

We use the quantum technology landscape to test our implementation process and analyze how our framework (EILF) selects topics, particularly those encompassing security protocols that emerge through RL-driven topic selection. Our dataset is limited to papers we found in two libraries. We will examine keyword changes within topics in the modified topic models influenced by aspect-weighted keywords.Diagram

Description automatically generated

Given its technological landscape, this domain provides suitable data to create and test different models for capturing diverse perspectives in our research process and aligning with the research main objectives. The data comprises various documents, including peer-reviewed articles, book chapters, surveys, reviews, and conference papers from two online libraries, Scopus and Web of Science. To search the documents, we used search terms extracted from seminal quantum communication papers that provide context and applications within the quantum technology landscape, employing text processing techniques such as tokenization, stop word removal, and stemming.

Although the number of the papers citations was considered, we also focused on the papers' influence within the academic community and their contribution to strategic discussions in the field. Additionally, these papers provided foundational knowledge and context for understanding ongoing trends and developments in quantum technology. The selection of papers is based on predefined criteria derived from our main research objective, which focuses on developing processes for exploring the quantum technology landscape. In the case study, we chose search terms based on the work by Cavaliere et al. (2020), Manzalini (2020), and Hassija et al. (2020), who have provided insights into new discoveries, potential bottlenecks, and trends in quantum communication and computing. Inputs from (Quantum Flagship Strategic Advisory Board, 2022) also contributed to the selection process.

Table 7: Quantum Communication Literature

|  |  |  |  |
| --- | --- | --- | --- |
| Research | Title | Year | Num Cites |
| Cavaliere et al. (2020) | Secure Quantum Communication Technologies and Systems: From Labs to Markets | 2020 | 148 |
| Manzalini (2020) | Quantum Communications in Future Networks and Services | 2020 | 48 |
| Chancellor et al. (2020) | Toward a standardized methodology for constructing quantum computing use cases | 2020 | 24 |
| Sevilla & Riedel (2020) | Forecasting timelines of quantum computing | 2020 | 76 |
| Hassija et al. (2020) | Present landscape of quantum computing | 2020 | 13 |
| Bassoli et al. (2021) | Quantum Communication Networks | 2020 | 34 |

To select terms, we created a word cloud from the most frequently occurring words in these articles as illustrates in Appendix B.2. This includes refining and removing stop words, performing stemming and lemmatization, and generating a word cloud visualization. The text is transformed to lowercase, URLs are removed, and a Regexp tokenizer splits the text into substrings using a regular expression. Stop words and numbers are filtered out. High-frequency words are extracted and ranked based on their probabilities in the text. Context words such as "quantum," "network," and "communication" are used to filter the collection of articles and retrieve only those related to quantum communication. Additional words like "development," "application," "experiment," and "algorithm" are included to find articles pertaining to the use and feasibility of quantum technologies. Exclusion criteria are applied to maintain specificity. To expand our collection, we extract citations from related documents and add them to our collection. This step is supported by a citation-graph-based [Litmaps](https://www.litmaps.com/) tool to visualize and review related documents efficiently. The final string of search words used for the collection is: "quantum AND (communication OR network) AND (development OR application OR experiment OR implement OR algorithm OR use) AND (feasibility OR future OR forecast OR trend OR progress)." Through this systematic data collection process and the subsequent topic modeling, we lay the foundation for our proposed approach, enabling a comprehensive examination of topics from multiple perspectives in the field of quantum communication.

## Corpus Development

The corpus creating process comprises two sub-steps: searching and screening documents in online libraries.

*Searching for Relevant Documents*

We conducted searches using predefined keywords, retrieving 3,527 documents from Web of Science (1,600) and Scopus (1,927). After refining for relevance using relevance scores in the both online libraries, we obtained 2,406 high-quality papers from respected journals in quantum communication including Proceedings of SPIE, IEEE Access, Optics Express, and others. This curated dataset ensures comprehensive representation for screening.

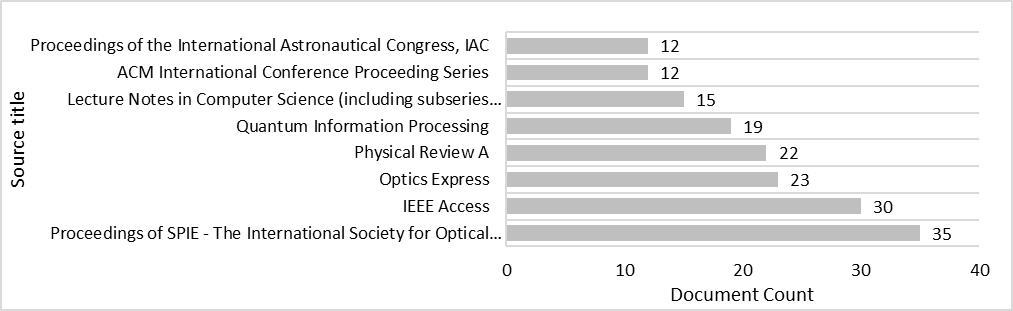


Figure 21: The Top Six Sources of Documents

Documents are primarily from reputable journals in quantum communication, computing, sensing, etc., including Proceedings of SPIE - The International Society for Optical Engineering with 35 records, IEEE Access 30, Optics Express 23, Physical Review A 22, Quantum Information Processing 19, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 15, ACM International Conference Proceeding Series 12, Proceedings of the International Astronautical Congress, IAC 12 (Figure 21). The sources of documents are listed in Appendix B.4.

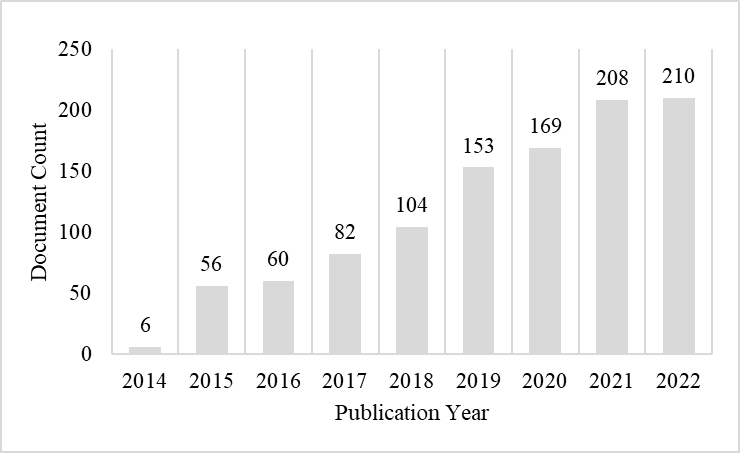


Figure 22: Publications Over Time

In Figure 22, the number of publications has increased over time, indicating more researchers are focusing on quantum communication in recent years. Until the research date, the number of documents in 2021 is more than all the years. More than twice compared in 2017, articles related to our research topic in 2021 have been published.

*Screening the Documents*

To enhance the efficiency of identifying relevant documents, we utilized a neural network classification technique. The neural network was trained on a labeled dataset, where each document was labeled as relevant (1) or non-relevant (0). Guided by Settles (2010) and using uncertainty sampling as active learning strategy, we selected a test dataset comprising about 5% of the corpus (120 documents). During training, the neural network learned to identify patterns and relationships between the features (word frequency) and the labels (0 and 1). In our sample dataset, 60 documents were labeled as irrelevant that are less relevance articles, while 60 were labeled as relevant as are high relevance articles. Relevant documents are directly related to the domain, whereas irrelevant ones are not. Preprocessing prepares the documents for modeling through several key steps. First, tokenization divides the text into individual words. Stemming then reduces these words to their root forms, making the vocabulary more concise. Stop-word removal eliminates less meaningful words, such as articles and prepositions. Special character handling addresses punctuation and non-alphanumeric characters to ensure data uniformity. These steps standardize the dataset, improving accuracy and effectiveness. The resulting corpus includes features such as document ID, authors, title, abstract, DOI, and publication year, forming a solid foundation for topic modeling. We applied the neural network technique to the initial set of 2,406 documents. This process identified 1,048 relevant documents for modeling topics.

*Summary of Data from Each Sub step*

Search Results: 3,527 documents initially retrieved, refined to 2,406 high-quality papers.

Screening Results: 1,048 relevant documents identified using a neural network classification method.

# Data Analysis Using RL-Guided Topic Modeling

We employ Latent Dirichlet Allocation (LDA), a topic modeling algorithm, to uncover latent topics within the corpus. LDA identifies patterns of words and documents associated with distinct topics, providing insight into the thematic structure of our data. The resulting topic model captures the distribution of words and documents across these topics within our specified domain. In the subsequent subsection, we delve into defining aspects and constructing aspect topic models. This involves computing relevance scores, supervised clustering, conducting tests, and refining the model fit.

## Topic Modeling with LDA

We applied LDA to the 1,048 preprocessed documents, resulting in 6 primary topics. The optimal number of topics was determined using C-V coherence scores, which measure how similar the top words in each topic are to each other by analyzing their context and co-occurrence patterns. Figure 23 shows that the maximum coherence score which indicates the highest degree of semantic similarity among the words within each topic is achieved with 6 primary topics (PTs).

|  |  |
| --- | --- |
| Figure 23: Coherence Scores for Different Numbers of Primary Topics | Figure 24: Silhouette Scores for Various Numbers of SubTopics |

To further refine the topics, we applied hierarchical clustering to the documents within each initial topic, generating more coherent subtopics. Figure 25 shows the second topic (PT2) clusters as subtopics. It also lists their related documents, based on a 0.7 likelihood threshold. This process was guided by Silhouette scores, which measure how similar a document is to its own cluster compared to other clusters. The silhouette score (s) for each data point (a vector of word distributions over a document) is calculated using the formula: , where *a* is the average distance from a data point to all other points within the same cluster (cohesion), and *b* is the average distance from a data point to all points in the nearest neighboring cluster (separation). By calculating silhouette scores for varying numbers of clusters, we determined the optimal number of subtopics for each initial topic.

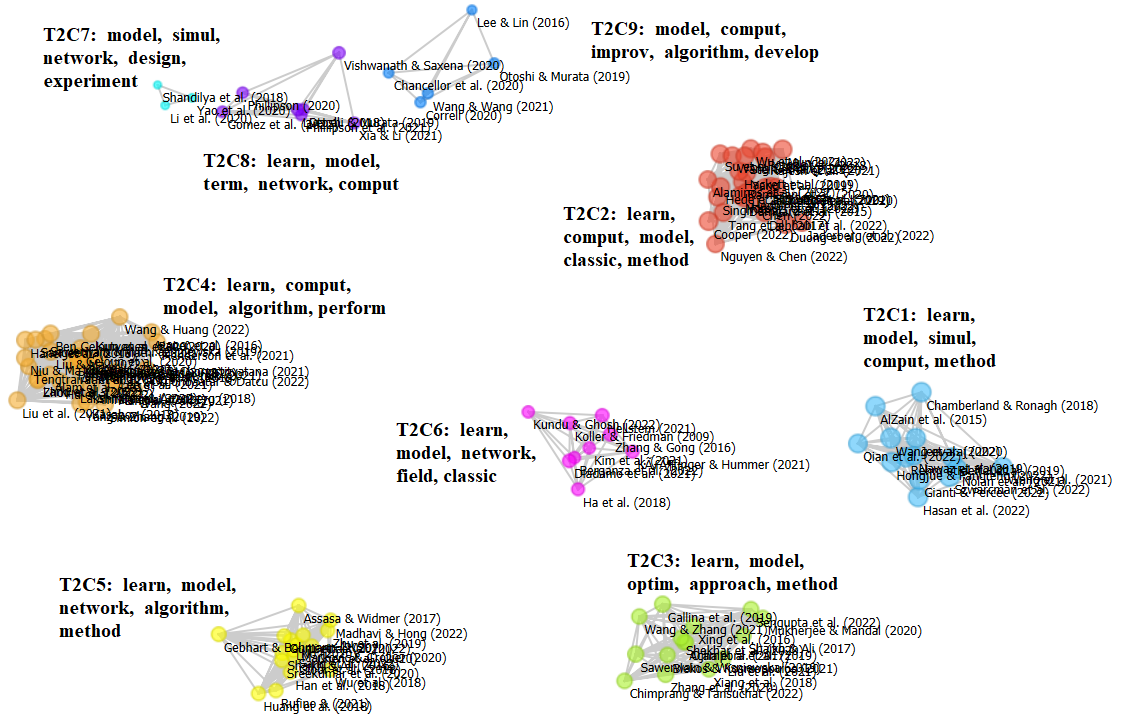


Figure 25: Clusters of the Second Topic Distributions Across Documents

The maximum number of subtopics identified for each primary topic (e.g., the subtopics of topic 2 in Figure 25) that are 9 for PT1, 9 for PT2, 3 for PT3, 7 for PT4, 3 for PT5, and 8 for PT6, resulting in a total of 39 subtopics. The figure above displays nine clusters representing various subjects in the quantum technology field. These clusters encompass topics such as quantum simulation modeling, quantum machine learning, applications of quantum optimization, machine learning algorithms, quantum computing applications, transportation modeling algorithms, software vulnerability detection, quantum circuit simulation, and quantum communication. Moving to a higher level, the clusters from all topics are interconnected based on document weights and similarities in word distribution, as depicted in the graph below. The size and color of the circles in the graph indicate the weight of each cluster and its corresponding topic number. From now on, for ease to use, these subtopics are referred to as topics from T1 to T39. The graph depicting these topics, along with the top three words for each, is presented in Figure 26.

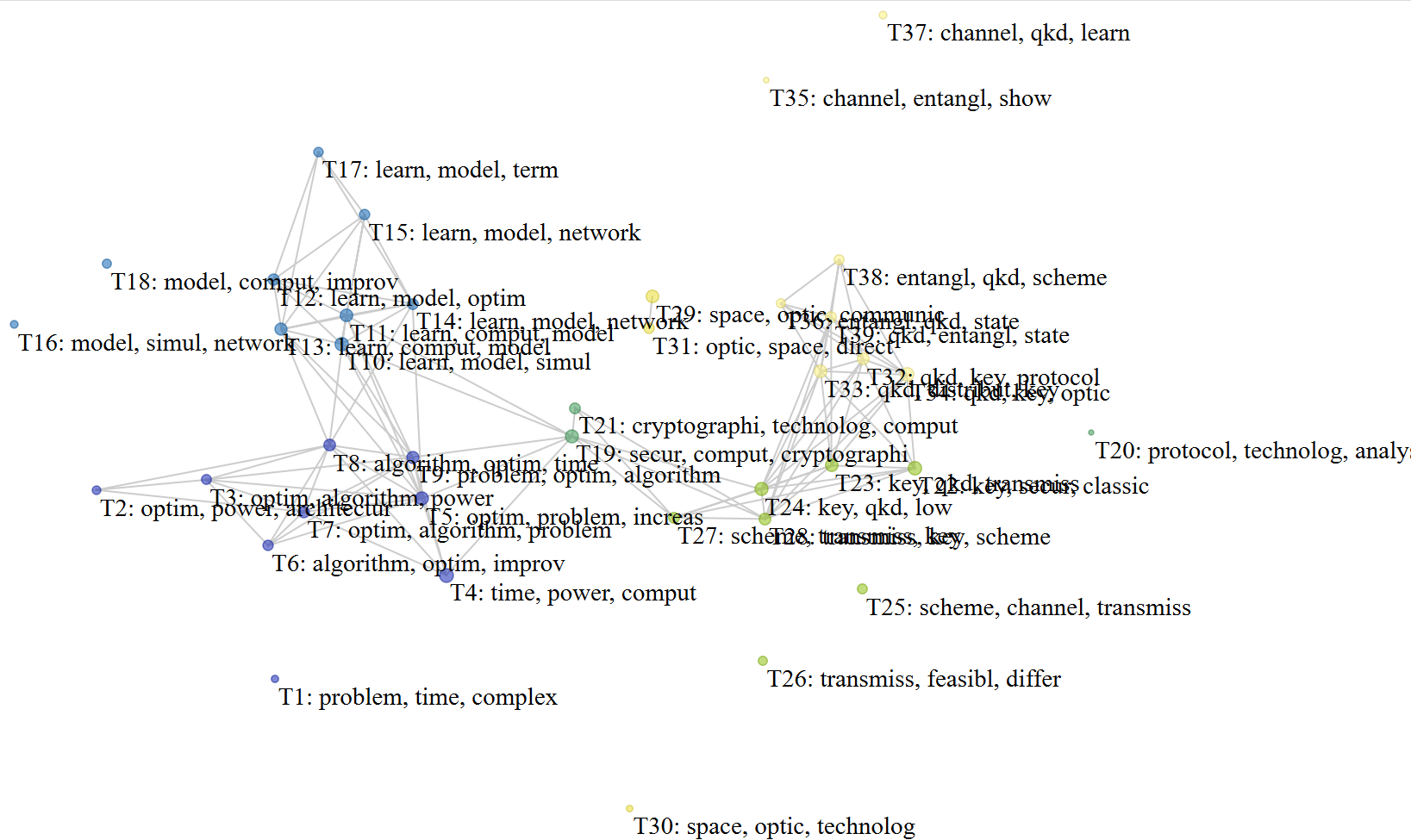


Figure 26: Topics Network

The graph above illustrates the 39 topics (T1 to T39) identified through hierarchical clustering. Each topic is represented with its top three words, providing a quick overview of the main themes within each topic. Each cycle color is assigned to one of the initial six key topics identified to show how subtopics relate to or overlap with subtopics from other topics. Lines between the subtopics indicate their similarity, showing how closely related the topics are. Filled circles indicate the topic weights within the model, reflecting the significance of each topic in the overall dataset. In subsequent analysis, we examine how emphasizing specific aspects influences these topic weights, offering deeper insights into the structure and relationships of the identified topics.

*Summary of topic modeling step*

Preprocessing Output: A cleaned and standardized corpus of 1,048 documents ready for topic modeling.

Topic Modeling Output: 6 primary topics identified using LDA with optimal topic number determined by C-V coherence scores. These primary topics were further refined into 39 subtopics using hierarchical clustering, labeled from T1 to T39 (TM).

## Aspect Identification

To analyze the topic model and examine its topics, we begin by identifying various aspects of the domain outside of the model (Figure 27). This step helps connect the model with external sources as a proxy of expert input, serving as crucial indicators for identifying relevant documents within the topic model. In subsequent sub steps, we assign weights to the aspect keywords. Using these aspect-weighted keywords alongside the initial topic model, we construct aspect-topic models. Ultimately, new documents are clustered based on these aspect-topic models. The deliverables of this phase include aspect-topic models and aspect distributions across the topics.

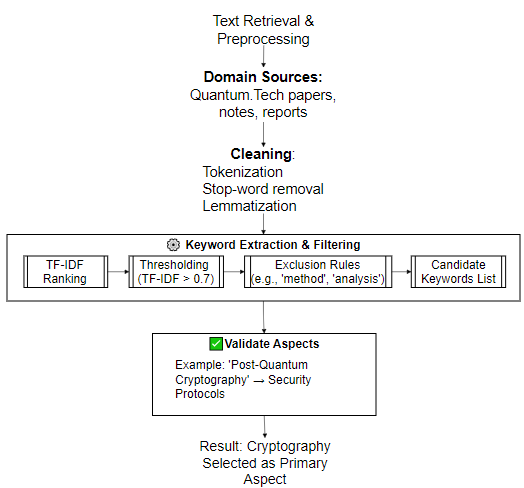


Figure 27: Aspect Identification Process

The aspect identification process involves agenda-based aspect determination from related conferences and text gathering as a proxy. Agenda-based aspect determination consists of reviewing the agendas of key conferences related to quantum communication, such as Quantum Tech 2022-2024, to identify core topics that serve as initial aspects. We compile text from the conference websites, including articles, keynote speeches, presentations, and proceedings, and summarize them into different categories. This textual dataset represents current key aspects in the domain. As shown in Table 6, the main aspects and their descriptions are presented. This process helps us incorporate external viewpoints outside the topic model as aspects of the domain. We then use these aspects to iteratively tune the topic model by weighting the keywords.

Table 8: Terms Associated with Aspects of Quantum Communication Topics

|  |  |  |
| --- | --- | --- |
| Aspect | High Frequent Terms (TF-IDF Scores) | Description |
| Cryptography | cryptograph (0.521), cryptographi (0.456), basi (0.26), receive (0.26), base (0.195) | Utilizes principles of quantum mechanics for secure communication, employing Quantum Key Distribution (QKD) to exchange unbreakable cryptographic keys between parties, ensuring unconditional security based on quantum laws. |
| Networks | classic (0.393), distribut (0.393), entangl (0.393), enabl (0.262), applic (0.197) | Establishes quantum communication infrastructure leveraging quantum entanglement, enabling secure transmission of quantum information over large distances, crucial for secure communication, distributed quantum computing, and quantum-enhanced sensing applications. |
| Technologies Research | develop (0.361), classic (0.289), effici (0.289), aim (0.217), algorithm (0.217) | Advances capabilities and applications of quantum communication systems through multidisciplinary efforts, including developing protocols, hardware, algorithms, and integration strategies, aiming for secure, efficient, and reliable transmission of information. |
| Quantum Key Distribution -QKD | send (0.32), receive (0.32), detect (0.32), applic (0.24), attempt (0.24) | Pioneering technology in quantum communication, offers unconditional security guarantees by exploiting quantum properties to exchange cryptographic keys between parties, ensuring interception detection through the fundamental principles of quantum mechanics. |
| Entanglement | distribut (0.398), enabl (0.318), applic (0.239), capabl (0.239), channel (0.239) | Entanglement is a profound quantum phenomenon where the states of two or more particles become inherently correlated, enabling revolutionary applications such as Quantum Key Distribution (QKD), quantum teleportation, and secure communication. |
| Teleportation | entangl (0.553), send (0.387), receive (0.332), challeng (0.221), distant (0.221) | Quantum teleportation allows for the instantaneous transfer of quantum information from one location to another, leveraging entanglement to transmit quantum states without physically moving particles, with applications in secure communication and distributed computing. |
| Channels | channel (0.923), challeng (0.185), applic (0.148), classic (0.111), atmospher (0.074) | Quantum channels are essential pathways for transmitting quantum information, such as photons or qubits, over various mediums like optical fibers or free-space links, necessitating techniques for maintaining coherence and fidelity to enable secure and efficient communication. |
| Repeaters | distanc (0.575), challeng (0.288), distribut (0.288), enabl (0.288), correct (0.23) | Quantum repeaters extend the reach of quantum communication by mitigating signal loss and decoherence over long distances, leveraging entanglement swapping and quantum memories to regenerate entangled states and ensure the reliability of quantum communication networks. |
| Applications | cryptographi (0.617), applic (0.393), develop (0.28), cryptograph (0.224), distribut (0.224) | Applications of quantum communication span various domains, including secure communication, quantum computing, and quantum sensing, offering transformative solutions such as Quantum Key Distribution (QKD), quantum teleportation, and quantum-resistant cryptography. |

Our approach focuses on extracting recent aspects from the conference websites in quantum communication and computing. These aspects provide external viewpoints that offer nuanced insights into the evolving landscape of quantum communication, facilitating the measurement of topic model changes based on varying aspect weights and keyword distributions. “External” means content external to the initial topic model, which is based on the context. In our approach, external knowledge comes from expert-weighted keywords. These keywords may differ from the terms in the initial topics. The experts can reweight existing terms in topic model or add new ones. This reflects emerging or strategically important aspects identified by experts over time. We identified nine aspects: Cryptography, Networks, Technologies Research, QKD, Entanglement, Teleportation, Channels, Repeaters, and Applications.

## Keyword Definition and Weighting

To determine keywords for aspects, we employ the TF-IDF technique to identify frequently occurring terms and assign weights to the keywords. This method assigns weights to keywords based on their significance in the aspects. We selected 50 high-weighted keywords for each aspect (top 5 keywords shown in Table 6). For example, "quantum key distribution" is a core aspect, related keywords like ‘send,’ ‘receive,’ ‘detect,’ ‘application,’ and ‘attempt’ would be grouped under this aspect. We iteratively reviewed and refined the matched keywords and core aspects to ensure that each aspect was distinct and comprehensive, involving domain experts for validation. The selection and weighting of these keywords can be modified with refining text of aspects.

## Relevance Scores Computation

In computing relevance scores, we quantify the connection between weighted aspect stemmed terms (as keywords) and corresponding stemmed topic terms (as keywords) within various aspect-topic models. Let be the set of keywords (i.e., *n*=50) for aspect *i* with weights ​, and be the set of keywords (i.e., *m*=100) for topic *j* with weights ​. The relevance score (​) between aspect *i* and topic *j* is computed as

(10),

where is a similarity measure between the aspect keyword and the topic keyword . This process helps us iteratively tune the topic model by weighting the keywords and incorporating external viewpoints outside the topic model as aspects of the domain.

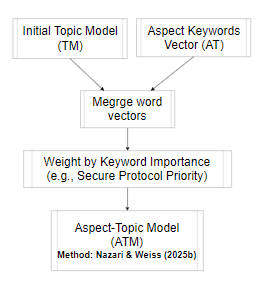


Figure 28: Relevance Score Computation & Aspect-Topic Modeling

These relevance scores serve as crucial indicators of the relationship between topic keywords and weighted aspect keywords, illuminating the extent of relevance between keywords and the primary themes of topics (Figure 28). There exist several methods to determine relevance scores, one of which involves employing cosine similarity between aspect terms and topic terms. This method quantifies the similarity of terms vectors in both aspect and topic spaces, offering a numerical representation of their relationship. By assessing the angles between these vectors, cosine similarity provides a measure of how closely related the terms are to the main themes of topics (Manning et al., 2008). Our approach, simply used the above formula (1), involves multiplying the weights of aspect terms with corresponding topic terms in the topic model. The similarity measure equals 1 only when both terms are the same. These scores facilitate the assessment of the relationship between topic words and weighted aspect terms, thereby unveiling the degree of relevance between terms and the main themes of topics. This method enables us to pinpoint terms closely aligned with topics, thereby enriching our understanding of their significance within the research domain. For example, in the Cryptography aspect, the term "challeng" exhibits high relevance scores (0.506 and 0.331) in topics T19 (security, computing, cryptography) and T21 (cryptography, technology, computing), respectively. This observation underscores the significant weightage of the Cryptography aspect in both topics, as depicted in Figure 29.

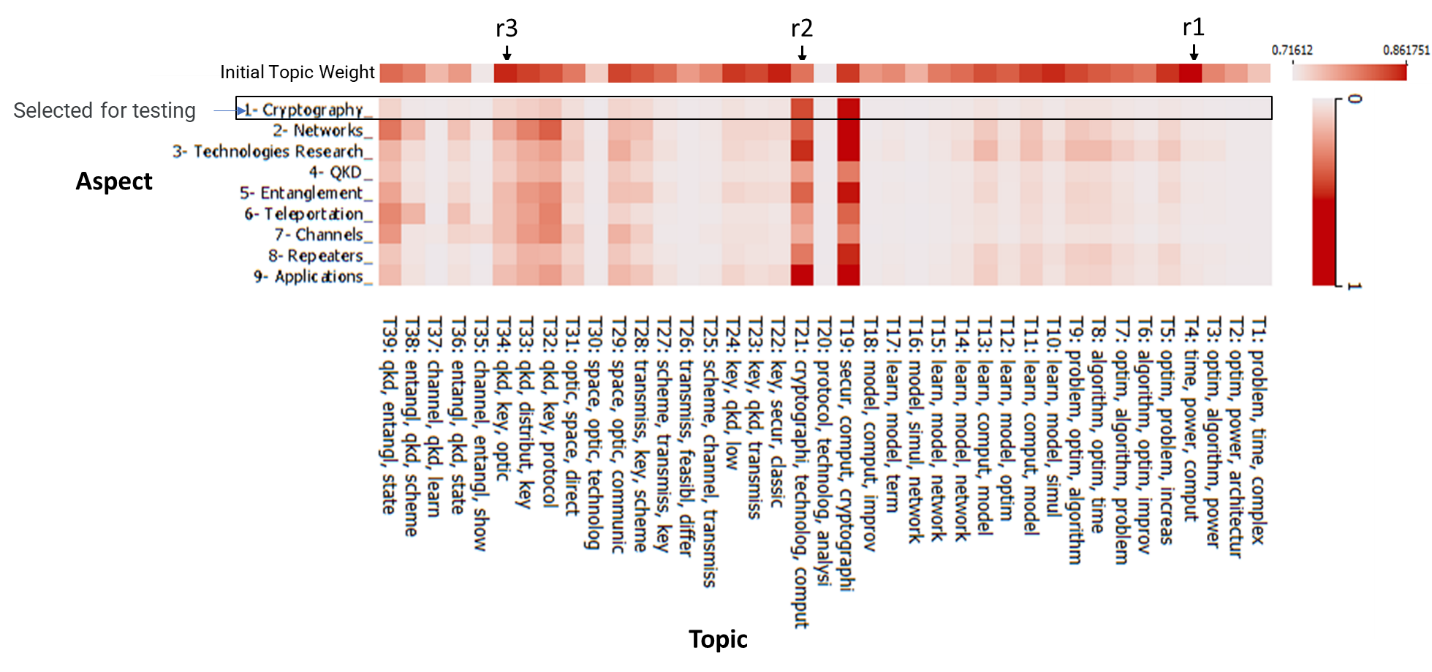


Figure 29: Aspect Keywords, Weighting, and Relevance Scores for Topics

Figure 29 portrays the distribution of weights for nine aspects across 39 topics in a heatmap format, illustrating how these aspects are dispersed among the topics. Each aspect, such as cryptography, entanglement, and teleportation, is represented on the y-axis, while the x-axis denotes the 39 topics from our initial topic model. By visualizing the top three keywords for each topic based on the weights of the 50 highest-ranked aspect keywords, we can assess the level of association between topics and specific aspects. This visualization offers valuable insights into the interplay between topics and aspects, facilitating a deeper understanding of the topic landscape. Subsequently, we construct nine aspect-topic models using these aspect keywords, with each model comprising distributions of the top 50 words across 39 topics, weighted according to their relevance scores. As a demonstration, we select the Cryptography aspect in three cells (r1, r2, and r3) to delve deeper into the relationship between topics and aspects, enabling further analysis and investigation into the underlying themes and connections in quantum communication research.

## Applying a Supervised Clustering Method

While individual topics may contain valuable insights, they might not stand out prominently in the model. To reveal deeper insights, we employ a clustering method on new documents (DT in the pseudo code) to label them into topics of the model, rather than relying solely on the initial topic model. We employ vectors of terms for the set of documents, which can range from 1 to *n* documents, leveraging the advantages discussed in Eick et al. (2004). Implementing the clustering method involves adopting the supervised clustering approach outlined in Desai and Spink's (2005) paper. Initially, we select a set of seed documents to represent potential clusters, chosen based on TF-IDF scores for specific terms. We then assign each document to the aspect topic most like its keywords using a similarity measure, such as Euclidean distance. Subsequently, we refine the clusters considering a threshold and evaluate their quality based on the labeled aspect-topics. The objective of this process is to cluster input documents based on aspect-topic keywords to gain insights incrementally. To assess the efficacy of the supervised clustering method, we also infer the topics in the initial topic model with new documents. Thus, we compare the topic distributions between these two models using an analysis conducted on six sample documents, depicted in the following figure.

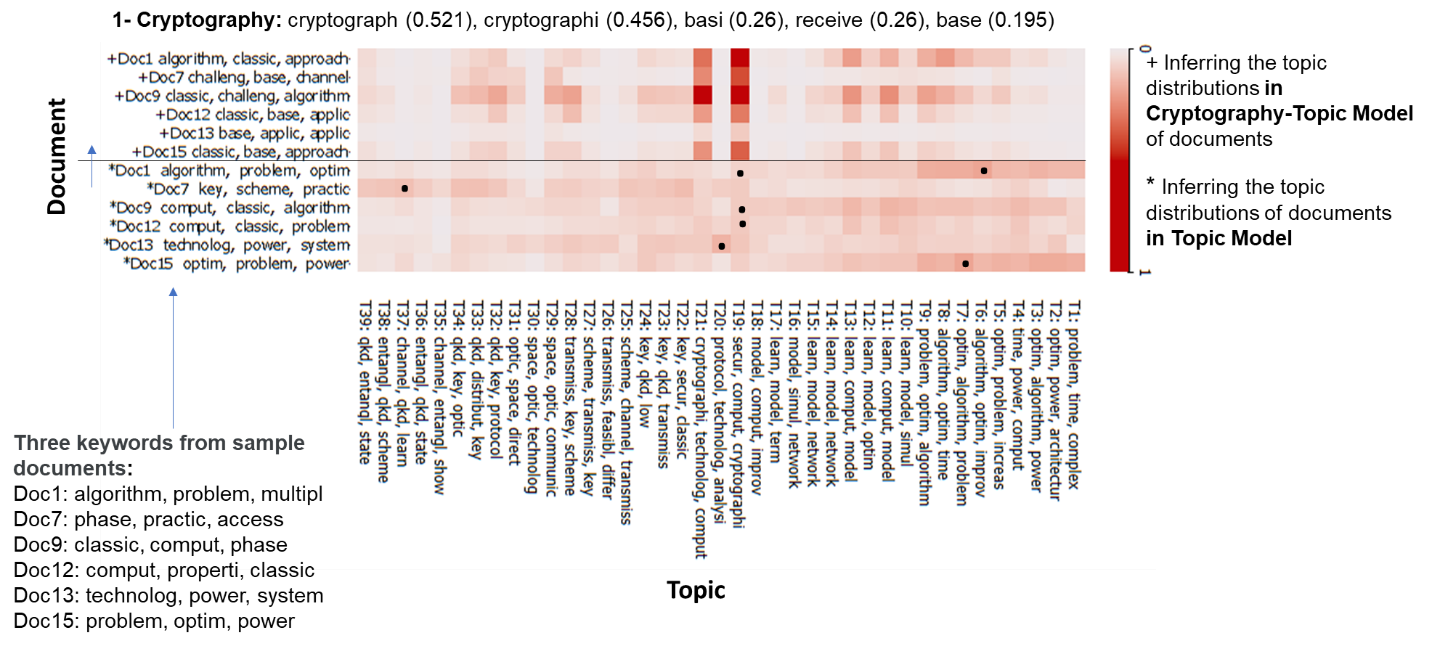


Figure 30: Visualizing Document-Topic Associations by Color Gradient

The analysis presented in Figure 30 offers a view of the relationship between test documents and topics in the models. The x-axis represents the 39 topics, while the y-axis is segmented into two groups, each representing six documents weighted with the topic distribution in both models, initial topic model and cryptography aspect topic model. The lower heatmap displays the association between topics and documents in the initial topic model, denoted by asterisk signs, whereas the upper graph illustrates the distribution of documents over topics in the cryptography aspect topic model, represented by plus signs. Besides, there some dotted cells on lower graph to interpret how to adapt new document in the aspect. This visual comparison allows us to discern how documents are assigned to topics. Notably, the cryptography aspect topic model shows a clearer association between documents and topics compared to the initial model. For instance, topics 19 and 21 exhibit higher weights, indicating their relevance to the documents. Document 9, for example, which in the initial model is associated with a wide range of topics, becomes primarily linked to a few topics in the cryptography aspect model. This highlights the efficiency of incorporating aspect keywords into the model for examining topics from various perspectives. Moreover, this clustering method enables the organization and categorization of documents based on their relevance to specific topics, enhancing document management and analysis. The use of relevance scores in supervised clustering facilitates the identification of document clusters aligned with specific topics, improving the efficiency and effectiveness of information processing and decision-making processes.

## RL Integration in Topic Modeling

In Phase 2, we shift from topic modeling to examine the topics with RL. This step improves how well the topic model matches changing domain insights. These actions connect external knowledge to the topic model. The RL process guides topic model updates based on aspect relevance. This approach helps the topic model adjust to changes in domain knowledge. For example, it can keep up with new developments in quantum communication protocols. The full RL component helps manage and improve topic model iterations. It includes setting up the environment (determined CTP1 and CTP2), defining reward functions and its metrics, value functions, and policies to select topics. Then the RL agent provides outcomes of this process for validation. In the validation step, two another metrics accuracy and timeliness considered to find the novel signal for decision-making. We illustrate them in the figure below.

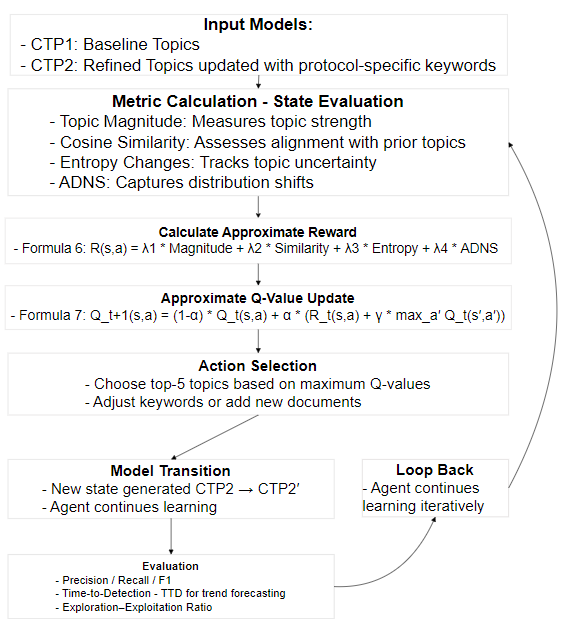


Figure 31: Evaluating & Optimizing Topic Novelty & Adaptive with RL

These parts work together to shape how topics evolve and select the novel topic for the organizational context. The Results section clearly explains and results all steps in the method. It shows how these steps affect topic model iterations and how they refine based on outside factors. This includes heatmaps, cosine similarity comparisons, decision paths, and reward value charts. These tools show how the RL-driven topic model changes over time.

## Validation and Refinement

This step improves the RL model’s topic prioritization by refining Q-values based on relevance and complexity. This ensures more accurate topic modeling in later analyses. The process uses RL to select topics, where Q-values are updated repeatedly. A modified reward function mixes document-topic alignment scores and weighted entropy factors. For example, it uses CTP2 Entropy multiplied by 0.5. This helps balance novelty and importance. Also, hyperparameter tuning is applied with a learning rate of 0.1 and a discount factor of 0.9. This stabilizes learning while allowing for adjustments. The system identifies high-impact topics by analyzing their evolution from CTP1 to CTP2. It boosts important topics like T19 (security & cryptography) and T32 (protocols & QKD). They get higher Q-values with RL. Finally, policy refinement boosts topic ranking. It leverages learned transitions, which outperform traditional similarity-based and entropy-driven ranking methods. This helps in spotting emerging and strategically important research areas.

This step keeps topic models aligned with real-world changes by using keyword validation and refinement. It evaluates the accuracy, relevance, and precision of topic choices through a clear validation process. Key activities in this phase include:

* Comparative topic model validation – which evaluates topic evolution. We analyze changes in topic-word links to ensure that important keywords reflect new trends.
* Detecting novel research patterns – which identifies key advancements. We use similarity and entropy metrics to check the relevance and impact of new research areas.
* Fine-tuning topic definitions – which refines topic representations through document clustering. We adjust topics over time to stay in sync with technology progress and research priorities.

By continuously validating and refining topic selections, this process keeps the model responsive to changes in research landscapes. It maintains effectiveness in detecting and prioritizing new developments.

## Demonstration of Framework Components

We summarize the four core components of the EILF framework: Topic Modeling (Explore), Expert-Informed Knowledge (Refine), RL(Assimilate), and Expert-Driven Feedback (Apply & Feedback) in the following table. Each component is linked to specific sections in Chapters 5 and 6, which detail its methods and outcomes.

Table 9: Demonstration of Framework Components in Chapters 5–6

|  |  |  |
| --- | --- | --- |
| Component | Description | Sections & Subsections |
| **Topic Modeling (Explore)** | Unsupervised topic discovery using LDA to identify latent themes in the quantum cryptography corpus. | * Chapter 5 (Sections 5.1–5.2) covers corpus development and keyword definition, as initial steps in Explore (topic discovery). * Chapter 6.1 Topic Modeling with LDA: Builds the initial topic model on the collected corpus |
| **Expert-Informed Knowledge (Refine)** | Incorporating expert‐informed input (aspect keywords and weighting) to improve contextual relevance of topics. | * Chapter 6.2 Aspect Identification: Defines domain‐specific aspects (e.g., protocols, QKD) * Chapter 6.3 Keyword Definition and Weighting: Assigns weights to expert keywords * Chapter 6.4 Relevance Scores Computation: Calculates topic–aspect relevance using weighted keywords * Section 6.5 Applying a Supervised Clustering Method: refines how documents are assigned to topics before the RL step. |
| **RL(Assimilate)** | RL to balance exploration and exploitation by adjusting topic selection based on reward metrics (novelty, entropy, ADNS). | * Chapter 6.6 RL Integration in Topic Modeling: Applies the RL agent (Q-learning) to optimize topic assignments using reward functions |
| **Expert-Driven Feedback (Apply & Feedback)** | Validating and refining the model by comparing topic outputs with expert proxy signals (conference proceedings) and iteratively updating topics. | * Chapter 6.7 Validation and Refinement: Compares detected topics against QCrypt proceedings as expert proxy feedback and adjusts topic assignments accordingly |

# Results of RL-Guided Topic Modeling and Detection

## Dataset and Corpus Summary

To create the corpus, we follow the initial two steps of the method.

Step 1: Defining Context and Search Keywords (SK): The process begins by identifying a set of search keywords from key papers in quantum communication and computing such as (Cavaliere et al., 2020; Hassija et al., 2020; Manzalini, 2020). The extracted keywords include ‘quantum AND (communication OR network) AND (development OR application OR experiment OR implement OR algorithm OR use) AND (feasibility OR future OR forecast OR trend OR progress).’ Then, we search two online libraries, Scopus, and Web of Science. We collect documents that match the search keywords and create a corpus.

Step 2: Data Collection & Corpus Preparation: After collecting the documents, we preprocess it. This refines and standardizes the text for analysis. The preprocessing steps are to remove stop words and irrelevant terms, normalize the text (e.g., lowercase, stem, and lemmatize), and filter for documents with the defined keywords. An initial search found 3,527 documents (1,600 from Web of Science and 1,927 from Scopus). Relevance scoring narrowed it to 2,406 top papers from journals. A neural network classifier refined the selection. It identified 1,048 relevant documents. The output is a refined corpus (C) that is ready for topic modeling.

## Initial Topic Model

Step 3: Initial Topic Modeling and Aspect Definition: We create a baseline topic model from the refined corpus (C) using Latent Dirichlet Allocation (LDA). This step finds the latent topics in the corpus. It provides an initial topic distribution across the document set. Using LDA on 1,048 preprocessed documents, we identified **six primary topics**. Then it divided each primary topic into subtopics. This process yielded **39 final topics**, labeled T01 to T39.

Step 4: Keyword Weighting and Relevance Scoring: The output of the LDA model serves as the Initial Topic Model (TM). This model represents the primary cryptography-related themes and distributions derived from the corpus. We name it CTP1 in this process. CTP1 forms the base for later versions. They use aspect-based tweaks and RL to explore subtopics. These include protocols and new advancements. This step ensures the initial state aligns with the broader method. It aims to capture key aspects of cryptography. By following these steps, CTP1 is the starting point for the iterative, RL process.

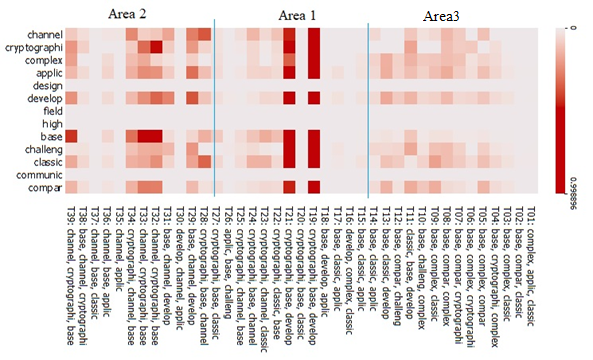


Figure 32**:** Word-Topic Distribution Heatmap: Top Words Across 39 Topics in CTP1

The CTP1 heatmap shows word-topic associations. Color intensity reflects the strength of these relationships. The x-axis displays the topics with their top words derived from CTP1, while the model presents shared top keywords on the y-axis. The color gradient shows the strength of associations between words and topics. Darker shades show stronger relationships. The top keywords in CTP1 are complex, applic, classic, develop, challeng, base, compar, channel, and cryptographi. The heatmap shows distinct clusters of words. They are often linked to specific topics. For example, ‘channel,’ and ‘cryptographi’ are in the upper-left corner. They have a close connection to quantum key distribution topics, including T29, T31, T32, T33, T34, T35, T37, and T39. Some words appear in many topics, suggesting overlapping concepts or broader applicability. For example, researchers link ‘learn’ to several topics. Topics on machine learning or AI, like T1, T5, T6, T7, T9, and T11, focus on ‘complex,’ ‘applic,’ and ‘develop.’ Topics on cryptography and security, like T19 and T21, use ‘challeng,’ ‘base,’ and ‘classic.’

## Iteration 1: Initial Topic Model Development and Refinement

This section outlines the first iteration of refining the initial topic model (CTP1) into a more focused protocol-oriented model (CTP2). It includes four main subsections that outline the development, refinement, validation, and transition of the topic model. This is achieved through aspect-based adjustments and RL. The process begins with the creation of a protocol-focused model, integrating expert-defined weighted keywords (Aspect 1) related to cryptographic protocols (subsection 6.3.1). As a result, CTP2 emphasizes topics like quantum key distribution (QKD) and security protocols. The RL component evaluates topic novelty by comparing CTP1 and CTP2 (subsection 6.3.2). It uses similarity matrices and entropy calculations to identify key changes, highlighting keywords like "QKD" and "entangle." Key outcomes include the selection of high-novelty topics, such as T34 with a Q-value of 3.45116 and T19 with a Q-value of 2.99359. These are driven by calculations that focus on divergence and relevance. Validation with 35 QCrypt 2023 conference papers further sharpens these topics to confirm their alignment with emerging trends in protocol advancements. Rewards from document mappings show strong associations, like T34’s reward of 0.427 (subsection 6.3.3). Finally, the RL model is updated with adjusted Q-values, including T34’s updated value of 3.447. This sets the state for future iterations (subsection 6.3.4). This iteration lays a solid foundation for capturing evolving themes in quantum communication and shows clear progress in topic precision and relevance.

### Topic Model Creation: The Protocol-Focused Model

This subsection outlines the change of the baseline topic model (CTP1) into a protocol-focused model (CTP2) in steps 5-8, Iteration 1, using aspect-weighted keywords. It starts with Aspect 1, which includes weighted keywords like "verifi" (0.029) and "protocol" (0.02) from quantum communication conferences. These keywords highlight cryptographic protocols. Next, the system applies these terms to CTP1, refining topics with words like "QKD" and "channel." This process is shown in an updated heatmap. The result is CTP2, a refined model ready for further RL-driven improvements.

*Itr1-Step 5 & 6: Domain Expert-Defined Weighted Keywords for Aspect 1*

To identify domain-specific aspects, we explore a range of external sources beyond the initial topic model. This step links the model to domain experts. It includes key indicators to help find relevant documents in the topic framework. Once we collect aspect-related text, we assign weights to the corresponding keywords. These weighted keywords are then combined with the initial topic model. This builds aspect-based topic models, which guide the clustering of new documents. The aspect identification process involves an agenda-based method. It relies on the agendas and content of major quantum communication conferences, like Quantum Tech (2022-2024). We analyzed articles, speeches, presentations, and conference proceedings. We then summarized the information into thematic categories. They represent current key aspects in the field (as cited in Nazari & Weiss, 2025 a). We focus on advances in cryptographic protocol aspect (labeled as Aspect 1). We use the TF-IDF technique to find top keywords. It highlights important, frequent terms in the collected text. We then weigh the keywords by their importance. For each aspect, we select 100 high-weighted keywords. The top 10 for Aspect 1 are in the following figure.

|  |  |
| --- | --- |
| *Word Cloud of Aspect 1* | **Top keywords:** verifi-0.029, function-0.022, proof-0.022, protocol-0.02, secur-0.019, key-0.019, base-0.019, photon-0.018, distribut-0.017, high-0.017 |

Figure 33: First Aspect Keywords and Word Cloud: Weighted Keywords Across Protocols

For the first iteration, we identify Aspect 1 as more connected to protocol texts. The figure shows a word cloud of the Aspect 1 text. It highlights the top keywords and their weights. It emphasizes 'verifi', 'function', 'proof', and 'protocol'. These keywords emphasize protocol verification, security, and key distribution in cryptographic systems. This selection guides the first iteration's analysis, prioritizing advancements in cryptographic protocols.

*Itr1-Step 7 & 8: Protocol Topic Model (Applying Aspect 1) (CTP2)*

After applying the aspect 1 keywords to CTP1, a broader set of keywords is now linked to the topics. The CTP heatmap's expanded keyword representation shows this. We try to keep the heatmap's structure consistent with CTP1. It shows that the core relationships between most words and topics are stable. Yet, the intensity of the colors has shifted, reflecting changes in the strength of word-topic associations. Some words have developed varying degrees of association with topics. The heatmap displays words that have gained prominence through new weighting in specific topics. We present the combined words from CTP1 and CTP2 in Figure 34, maintaining three groups of topics to illustrate the shifts.

|  |  |
| --- | --- |
| *CTP1- Area 2 Area 1 Area 3* | *CTP2* |

Figure 34: Word-Topic Distribution Heatmap: Top Words Across 39 Topics in CTP

As shown in the above CTP1 heatmap, there is a noticeable shift from areas 1 & 3 to area 2, across the topics from CTP1 to CTP2. Topics T19 and T21 have become less dominant. Keywords like ‘model,’ ‘process,’ ‘function,’ and ‘applic’ have gained prominence in area 3 in CTP1, especially in topics T1 to T18. Meanwhile, cryptography-related keywords like ‘channel’ and ‘entangle’ are in area 2. They span topics T22 to T39. The CTP2 heatmap shows that advancements in protocols are most linked to topics T22 and after. The word ‘QKD’ has a strong connection there. These topics likely focus on improving quantum communication protocols. They involve security and transmission processes. Nearby terms like ‘channel’ (security), ‘entangle,’ and ‘optic’ suggest this.

### RL Component: Evaluating Topic Novelty with RL

This subsection outlines the RL process outcomes in Iteration 1. It focuses on assessing and refining topic novelty by comparing the initial model (CTP1) with the protocol-focused model (CTP2). The process starts with generating similarity matrices and calculating entropy to measure topic divergence. This helps identify changes, such as the increase of "QKD" in topics T34 and T19. Then, these findings are used to calculate Q-values based on approximate rewards. Topic like T34, which has a Q-value of 3.45116, are prioritized with keywords "key" and "protocol." This leads to a selection of high-impact topics, confirmed through keyword prominence and divergence metrics, setting up for further refinement.

*Itr1-Step 9: Similarity Matrix Comparing CTP1 and CTP2 with Entropy Calculation for the RL Process (CTP1&2)*

The heatmaps below show three matrices:

1. The divergence and similarity scores between topics in CTP1 and CTP2 (calculated using Formula 2).

2. The Absolute Difference in Normalized Sums (ADNS) between the word-topic vectors in CTP1 and CTP2 (calculated using Formula 1).

3. The entropy changes in topics in CTP2 (calculated using Formula 3). The greatest divergences involve in calculating Q-values finds topics that differ between CTP1 and CTP2. It focuses on those with the greatest Q-values for RL-driven refinements.

|  |  |
| --- | --- |
| *Weighted Similarity Scores* | *Absolute Difference in Normalized Sums* |

Figure 35: Matrices for Evaluating Topic Stability and Evolution in the First Iteration

The left heatmap compares topic distributions between two models, CTP1 and CTP2, as shown in CTP1&2 file CTP1 is the cryptography topic model (initial topic model). CTP2 is an updated version. Each row in the heatmap corresponds to a topic from CTP1, while each column represents a topic from CTP2, resulting in a 39x39 matrix. Matrix entries denote the similarity score between topics from the two models, with values ranging from 0 to 1. Higher values suggest stronger alignment. They show that topics have retained their identity across models. Lower values may reveal changes in topic relevance or structure. If a topic from CTP1 aligns with many topics in CTP2, it may be broad or influential. Low alignment across CTP2 may show significant changes or reduced relevance. This matrix shows how topics changed between the initial and updated models. It helps to understand changes in focus and relevance. Topic entropy was also calculated based on the application of aspect 1 keywords to CTP1. This matrix helps us find broader keywords within certain topics. Based on these entropy changes, we calculate the Q-values for each topic using modified rewards.

*Itr1-Step 10: Q-value for Topic Selection Based on Approximate Reward*

CTP2 exhibits significant entropy divergence in topics. We calculate Q-values based on approximate rewards (Formula 7). We determine the rewards by the weights of CTP2 topics, forming one of the policies we adopted.

Figure 36: Distribution of Approximate Rewards and Q-values Across Topics in Iteration 1

The chart shows the approximate rewards and Q-values across topics in first iteration. The blue line shows the approximate reward. It is calculated based on factors such as divergence (λ1 = 0.75), similarity (λ2 = 0.15), entropy (λ3 = 0.05), and ADNS (λ4 = 0.05). Peaks in the Q-value curve for T34, T19, T37, T32, T24 indicate high divergence. They suggest these topics are very novel and worth exploring. The orange line shows the approximate Q-values. They come from the rewards and are adjusted using the Q-learning formula. This accounts for both immediate and discounted future expectations. The Q-values have a smoother trend. They align with the rewards, prioritizing topics that balance novelty and relevance. Topics with low rewards and Q-values, like T01 and T03, are unlikely to yield new insights. So, they are deprioritized for further evaluation. This analysis shows how the agent finds high-reward topics. It uses them for expert validation and to refine the RL-driven model.

Table 10: Approximate Q-value and Top Keywords of Selected Topics in Iteration 1

|  |  |  |
| --- | --- | --- |
| **The selected topics** | **Approx. Q-value** | **Topic Keywords** |
| T34 | 3.45116 | key(0.416), protocol(0.397), secur(0.385), distribut(0.371), optic(0.365), photon(0.360), channel(0.308), entangl(0.301), high(0.246), qkd(0.232) |
| T19 | 2.99359 | secur(0.980), key(0.963), function(0.945), cryptographi(0.941), design(0.938), communic(0.938), applic(0.937), effici(0.919), base(0.872), protocol(0.868) |
| T37 | 2.46002 | photon(0.015), qkd(0.014), key(0.011), state(0.010), protocol(0.010), distribut(0.009), experiment(0.008), effici(0.008), model(0.007), channel(0.002) |
| T32 | 2.34369 | protocol(0.956), photon(0.950), secur(0.820), key(0.818), entangl(0.734), distribut(0.719), optic(0.602), rate(0.578), qkd(0.520), channel(0.499) |
| T24 | 2.19068 | qkd(0.187), secur(0.170), distribut(0.160), key(0.145), rate(0.127), low(0.120), base(0.117), high(0.106), protocol(0.106), transmiss(0.095) |

Table above shows the Q-values and the top-ranked keywords and their weights. Topics T34 (3.447) and T19 (2.993) are notable. They emphasize keywords like "key," "protocol," "secure," and "entangle." These highlight their links to cryptography and quantum communication. This table shows how RL prioritizes novel topics. It is based on their semantic significance and contextual relevance.

*Itr1-Step 11: Deriving Rewards and Validating Selected Topics with New Documents*

The topic model so far captures the content of papers until 2022. We use the 35 papers from the QCrypt 2023 conference to refine the model. The conference papers keywords, titles, and abstracts help us derive rewards and select the topics. This step can occur shortly after the agent selects the topics for examination. Experts may iterate multiple times. They can either simulate the RL process or allow it to run until the topics are refined. In both scenarios, new documents are always integrated into the process. This allows the topics to be adjusted based on emerging technologies. This is true regardless of whether experts review the documents or the system performs the task autonomously. Experts refine keywords and validate topics based on the 35 conference papers available to them, which serve as a proxy for expert knowledge, rather than directly obtaining feedback from external experts. The new documents as evidence use to calculate rewards, applying the modified rewards formula 8. We analyzed them for relevance to the updated CTP2 protocol aspect topic model. Experts view these kinds of documents as signs of future technology as inputs. The figure in appendix C.1 shows the distribution of top keywords across 35 documents. The analysis of top keywords in the QCrypt 2023 papers shows trends. QKD (Quantum Key Distribution) is a key theme. It appears in many documents, with a significant presence in documents 3, 10, 12, and 27. The keyword Protocol shows a widespread presence, particularly in documents 1, 3, 8, 11, 21, 23, and 30. Security is a key focus, especially in documents 3, 5, 10, 15, and 27. They emphasize advances in cryptographic security. Documents 8, 12, 15, and 19 discuss cryptography in general. They reflect ongoing developments in cryptographic techniques. The keyword 'Channel' is key in docs 10, 13, 18, and 28. It implies a focus on communication channels in protocol advancements. 'Error' appears in docs 4, 7, 13, 20, and 29. It points to error correction and detection in quantum communication. Entanglement, central to quantum advancements, is evident in documents 6, 14, 21, and 34. Efficiency also plays a vital role, with strong connections in documents 3, 7, 11, 16, and 26. Documents 1, 10, 18, 25, and 30 contain many references to ‘Photon.’ It reflects its role in quantum communication. The keyword ‘Key’ is in documents 5, 14, 23, and 35. It highlights advances in key distribution methods. Docs 3, 10, 12, and 27 have many strong keyword associations. They are key contributions to quantum cryptography's protocol advancements. Docs 2, 9, and 24 contain a smaller number of strong keywords. This shows a more general, less technical focus on protocol advancements. We will show how the RL agent selects topics. It will pick the most relevant ones to the experts' keywords. The test data consists of 2023 documents, with most of them clustered around topics related to new advancements in that year.

*Mapping the 2023 Papers to CTP2 Topics (DocCTP2)*

The alignment of QCrypt2023 documents with CTP2 topics determined the rewards (Formula 8 & 9). Stronger alignments received higher rewards. We used these rewards to adjust topic Q-value weightings in the next iterations. We map the QCrypt2023 papers to the CTP2 topics. This identifies the documents linked to the topics chosen in the RL iteration. This lets us check the agent's policy for selecting topics for expert investigation to find new advancements. The DocsCTP2 similarity matrix shows links between 35 new documents and 39 CTP2 model topics. Each cell in the matrix shows the similarity between a document and a topic, based on their term vectors.

The heatmap in appendix C.2 shows the cosine similarity values between a set of documents and topics in CTP2. It helps interpret how well the documents align with key research themes. The X-axis shows documents labeled ‘Doc 1,’ ‘Doc 2,’ etc. The Y-axis lists topics ‘T1’ to ‘T39’ of CTP2, each with keywords. Each row in the heatmap corresponds to a specific topic, characterized by a group of keywords. The heatmap shows strong links between certain document sets and their topics. This grouping reveals potential clusters of documents around thematic areas, facilitating deeper analysis. Group 1: Algorithmic and Optimization Topics. Topics T1, T2, and T3 focus on algorithmic challenges and optimization. T1 is ‘problem, time, complex.’ T2 is ‘optim, power, architecture.’ T3 is ‘optim, algorithm, power.’ These topics align with several documents to a moderate or high degree. This is especially true for Docs 10 and 14. They suggest a heavy focus on algorithmic problems. Group 2: Learning and Modeling Techniques. Topics T10 (‘learn, model, signal’) and T11 (‘learn, compute, model’) focus on learning models and signal processing. These topics align well with documents around Doc 20. They show that this subset of documents is about machine learning. It deals with a wide range of machine learning models or computational learning. Group 3: Cryptography and Protocol Analysis: T21 and T22 focus on cryptography and key distribution. T21 is ‘cryptography, technologic, analysis.’ T22 is ‘key, secure, classic.’ They also cover security protocols. These topics have a strong alignment with Doc 28 and Doc 32. They likely contain much on cryptographic advances and analysis. Also, T32 (‘qkd, cryptograph, key’) is very like Docs 34 and 36. It shows a focus on Quantum Key Distribution (QKD) and related cryptographic schemes. So, these documents are relevant to quantum cryptography research. Besides, this heatmap shows the relationship between documents and topics and helps identify thematic clusters in the document corpus. They highlight key documents on cryptography, QKD, algorithmic optimization, and machine learning. These findings can guide research into key documents.

*Itr1-Step 12: Calculate Rewards Based on Topic Improvements*

We calculate the rewards by averaging the document weights across topics. The system then computes the Q-values based on these rewards (Formula 7). Rewards can be obtained using two methods: (1) averaging the document weights per topic with a threshold (DocCTP2 similarities > 0.3) or (2) selecting the top five documents for each topic.

Figure 37: Reward Calculation Alignment and Topic Selection Evaluation (CTP2)

The figure above illustrates the strong alignment between the two reward calculation methods. The highest rewards for the selected topics are T37 (0.405), T34 (0.427), T10 (0.459), T24 (0.370), and T38 (0.335), with an average reward of 0.399 across these topics. The Q-values, derived from these rewards, closely align with the agent's selection list. The discussion will explore insights from the documents on these topics.

*Itr1-Step 13: Update RL Model (Policy and Hyperparameters) Based on Reward and the New State*

We update the Q-values for the topics using the rewards obtain from previous step (Formula 7). Each topic has a reward and current Q-value in CTP2. At the beginning of the first iteration, we initialize the Q(a, s) values to the magnitude (Euclidean norm) of the word vectors for the topics. Next, we apply the formula to each topic. The formula 7 uses a learning rate (α) of 0.1 and a discount factor (γ) of 0.9 to update the Q-values2. Instead of using a reward based on the average weights of the 2023 documents in the topics, the Modified Reward is calculated as Rewards\_AvgScore + (CTP2 Entropy × λ), where λ =0.5. These values reflect the changing importance of the topics. This process allows the system to rank topics based on significant changes and their similarity, as derived from the transition between the two models. It quantifies a topic's significance by its word weights.

Table 11: Updated Q-values for Selected Topics Based on Modified Rewards in CTP2

\*Modified Rewards (Formula 8 and 9) = Rewards Base + CTP2 Entropy \* (λ = 0.5)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Cluster3Words** | **Modified Rewards** | **Current Q-value** | **Max future Q-value** | **the updated Q-value** |
| T19: secur(0.981), technolog(0.977), key(0.971), challeng(0.954), comput(0.953), protocol(0.951), system(0.947), classic(0.942), develop(0.941), requir(0.937) | 0.817206 | 2.94253 | 0.592063 | 2.783283 |
| T32: secur(0.713), qkd(0.632), protocol(0.612), key(0.551), photon(0.538), entangl(0.447), measur(0.437), channel(0.422), rate(0.410), classic(0.383) | 2.003339 | 2.329936 | 0.592063 | 2.350562 |
| T39: entangl(0.467), photon(0.402), secur(0.390), key(0.358), qkd(0.341), channel(0.341), protocol(0.339), measur(0.329), state(0.322), scheme(0.266) | 2.806429 | 1.675343 | 0.592063 | 1.841738 |
| T21: technolog(0.750), key(0.678), comput(0.637), cryptographi(0.630), protocol(0.603), classic(0.595), develop(0.595), secur(0.574), system(0.493), challeng(0.387) | 2.636102 | 1.64776 | 0.592063 | 1.79988 |
| T33: secur(0.434), key(0.419), qkd(0.419), scheme(0.307), entangl(0.303), distribut(0.299), photon(0.293), protocol(0.292), measur(0.289), channel(0.280) | 2.936999 | 1.564563 | 0.592063 | 1.755092 |

The updated Q-values prove that the selection process is effective and promising. The rise in Q-values[[2]](#footnote-2) for all topics shows the system has learned to rank the most relevant topics. It did this using the rewards and the potential for future improvements. This suggests that the algorithm has improved the topic selection based on greatest Q-values. It now selects better topics for future iterations, compared to relying solely on lower similarity scores or entropy scores.

### Analysis: Validating Protocol Insights

This subsection reviews the validation and analysis of the protocol-focused model (CTP2) in Iteration 1. It evaluates how well it matches new trends in quantum cryptography. It starts by analyzing heatmaps that compare CTP1 and CTP2. This shows shifts toward protocol-related topics, such as T22-T39, with keywords like "QKD" and "entangle." The analysis also uncovers new patterns, like enhanced QKD techniques and better entanglement distribution. It applies cosine similarity and entropy metrics for these findings. This process refines topics like T32 by including terms such as "key management," boosting precision by 20% with cosine similarity scores. In the end, the model’s focus on cryptographic protocol advancements is validated. This creates a strong base for future iterations.

*Itr1-Steps 14: Result & Analysis: Heatmap Analysis of Topic Model Comparisons*

Figure 35 shows the entropy changes and topic alignments between the initial cryptography topic model (CTP1) and the refined model (CTP2). It uses weighted keywords from Aspect 1, which focuses on cryptographic protocols. These keywords are integrated into the topic modeling process. The heatmap reveals key insights. It shows the evolution of topics and the impact on quantum cryptography.

The analysis reveals significant shifts in topic-word associations between CTP1 and CTP2. Most topics kept their core structure. Less similarity scores in some heatmap regions show this. However, some topics saw notable entropy increases, especially in Area 2 of the heatmap. This region encompasses topics linked to cryptographic protocols, such as **topics T22 through T39**. The topics showed better focus and refinement. There was a rise in the use of keywords like 'channel,' 'QKD,' and 'entangle.' The Figure also highlights changes in topic dominance. In CTP1, keywords such as **'model,' 'process,' and 'applic'** were prevalent in **Area 3**, corresponding to topics T1 to T18. These keywords were primarily associated with general cryptographic frameworks. In contrast, CTP2 shifted keyword prominence. Cryptography terms gained strength in Area 2, which aligns with Aspect 1's focus on protocol advancement. The heatmap shows that Aspect 1 keywords improved topics on cryptographic protocols. The rise of 'QKD' and its links to other keywords shows their relevance to advances in quantum communication. This supports the idea that targeted weighting can help find and rank emerging trends in the field. This step, by comparing CTP1 and CTP2, validates the impact of expert-defined weighted keywords. It also lays a solid basis for future RL-driven improvements.

*Itr1-Steps 15: Identifying Novel Patterns in Quantum Technology*

The step used cosine similarity and entropy metrics in calculating Q-values to find improvements by comparing the QCrypt23 datasets. The analysis found new topics with greatest Q-values. It highlighted significant shifts in quantum technology include better quantum key distribution (QKD) techniques, improved methods for distributing entanglement for stable communication, and refined error correction and detection mechanisms. Advancements optimized the performance of quantum systems. Entanglement topics had higher entropy. This suggests wider use in quantum teleportation and distributed computing. Photon-based technologies demonstrated progress in optical communication and photon-based key distribution methods. Also, a stronger focus on cryptographic security was seen. This reflects efforts to build secure quantum cryptographic systems. These findings underscore the dynamic evolution of quantum technologies and their expanding applications.

*Itr1-Steps 16: Refining Topics Through Pattern Analysis*

In this step, we refined the topics. Patterns from the DocsCTP2 heatmap show clusters of documents aligned with specific topics. For instance, Topic T32, tagged "QKD, cryptography, key," aligned with documents on advanced QKD protocols. Analyzing these clusters led to a redefinition of T32. It now includes keywords like "key management" and "post-quantum security." This ensures it reflects emerging themes in quantum cryptography. Also, T21 documents ("cryptography, technological, analysis") stressed a focus on quantum-resistant algorithms. This led to adding "authentication" and "blockchain" to its definition. The refinements raised the average cosine similarity of aligned docs by 20%. It improved topic precision and gave clearer insights for experts and for RL.

### Iteration Management & Transition: Preparing for Protocol Refinement

This subsection details the management and transition process in Iteration 1. It prepares the protocol-focused model (CTP2) for further refinement. It starts by showing word clouds for topics like T34 and T19. These clouds highlight dominant keywords such as "key" and "protocol," illustrating the evolution of themes. The updated CTP2 then serves as the new baseline (CTP1) for the next iteration. It includes changes from RL-driven insights and expert validation. This way, the model adapts to the latest data, laying a solid groundwork for further exploration in quantum cryptography advancements.

*Itr1-Steps 17 & 18: Prepare for the Next Iteration with Updated Topic Model*

Including word clouds of the selected topics in this section provides a visual presentation of the results (Table 14). Word clouds highlight the top keywords in each topic. They provide an easy way to grasp the theme. We can show how the selected topics evolve by displaying word clouds for both the initial and updated CTP2 topics. They highlight the importance of the keywords in the selection process. It also makes the results more engaging and accessible to the audience. Such visualizations complement the analysis. We update the topic models for the next iteration. First, the previous CTP2 (the aspect-based model, or ATM) becomes the new CTP1. Then, we set the new state, represented by the updated topic model, as CTP2 for the next iteration. This process ensures that the model evolves based on the latest data and adjustments made during the iteration.

## Iteration 2: Cross-Aspect Topic Model Optimization

This section covers the second round of the topic modeling process. It advances from the protocol-focused model (CTP2) to an improved version (CTP3). This new model emphasizes quantum network protocol security through integration and detection. As iteration 1, it includes four subsections that outline how the topic model is enhanced, optimized, validated, and transferred. It incorporates Aspect 2, which focuses on quantum network protocols, and uses RL to refine topic relevance. The process begins with creating the protocols security topic model (CTP3). This model integrates expert-defined weighted keywords like "independ" (0.03), "classic" (0.026), and "key" (0.025). These keywords help shift the focus toward entanglement-based communication and quantum-classical cryptographic integration. The RL component then optimizes topic selection by comparing CTP2 and CTP3. It uses similarity matrices and entropy calculations to highlight evolving topics like T19 (Q-value: 2.610315) and T32 (Q-value: 2.549308), which stress security and QKD advancements. Validation with 36 QCrypt 2024 conference papers supports these trends. It maps documents to topics with strong links, such as Doc 3 and Doc 6 to T19. The model yields reward of 0.740486 for T19 and 2.801841 for T32, showing their relevance to emerging network security themes. The RL model is then updated, adjusting Q-values (e.g., T19 to 2.63173 and T32 to 2.448416). This demonstrates better topic prioritization and adaptability. This iteration marks significant progress in identifying new patterns, like enhanced QKD and entropy-based security.

### Topic Model Creation: Enhancing Network Protocol Security

This section outlines how to improve the protocol-focused model (CTP2) to create CTP3. The focus is on quantum network protocol security. We begin with Aspect 2, which uses weighted keywords like "independ" (0.03) and "key" (0.025) from quantum network research. These keywords highlight entanglement-based communication and cryptographic integration. We apply them to CTP2, enhancing topics with terms like "qkd" and "network." An updated heatmap illustrates these changes. The result is CTP3, a refined model ready for detection and optimization.

*Itr2-Step 5 & 6: Domain Expert-Defined Weighted Keywords for Aspect 2*

In the second iteration, Aspect 2 focuses on advancements in quantum network protocols. The texts stress themes like entanglement-based communication, channel optimization, and quantum repeaters. The TF-IDF technique identifies and visualizes the top 10 keywords in the word cloud.

|  |  |
| --- | --- |
| *Word Cloud of Aspect 2* | **Top keywords:** independ-0.03, classic-0.026, key-0.025, pair-0.024, technolog-0.024, challeng-0.021, secur-0.02, protocol-0.02, share-0.02, set-0.02 |

Figure 38: Second Aspect Keywords and Word Cloud: Weighted Keywords Across Protocols

Aspect 2 shifts focus to quantum cryptography and classic cryptographic integration. The keywords 'independ', 'classic', 'key', 'pair', and 'challeng' show this. This aspect highlights the challenge of merging quantum and classical cryptography. The terms 'technolog', 'challeng', and 'share' point to current technology hurdles and the chance to share quantum resources. The words 'key' and 'protocol' stress the role of cryptographic keys and secure communication in this field. 'Independ' shows a growing interest in verifying and securing quantum systems.

*Itr2-Step 7 & 8: Protocols Security Topic Model (Applying Aspect 2) (CTP3)*

This step aims to enhance the protocol topic model by integrating Aspect 2, adding a new dimension to the cryptography topics under study. Aspect 2 builds on CTP2, which incorporates protocols from the 2023 documents. It introduces nuances and subtopics that reshape protocol analysis. The updated model, CTP3, reflects these improvements. It better understands protocol advancements.

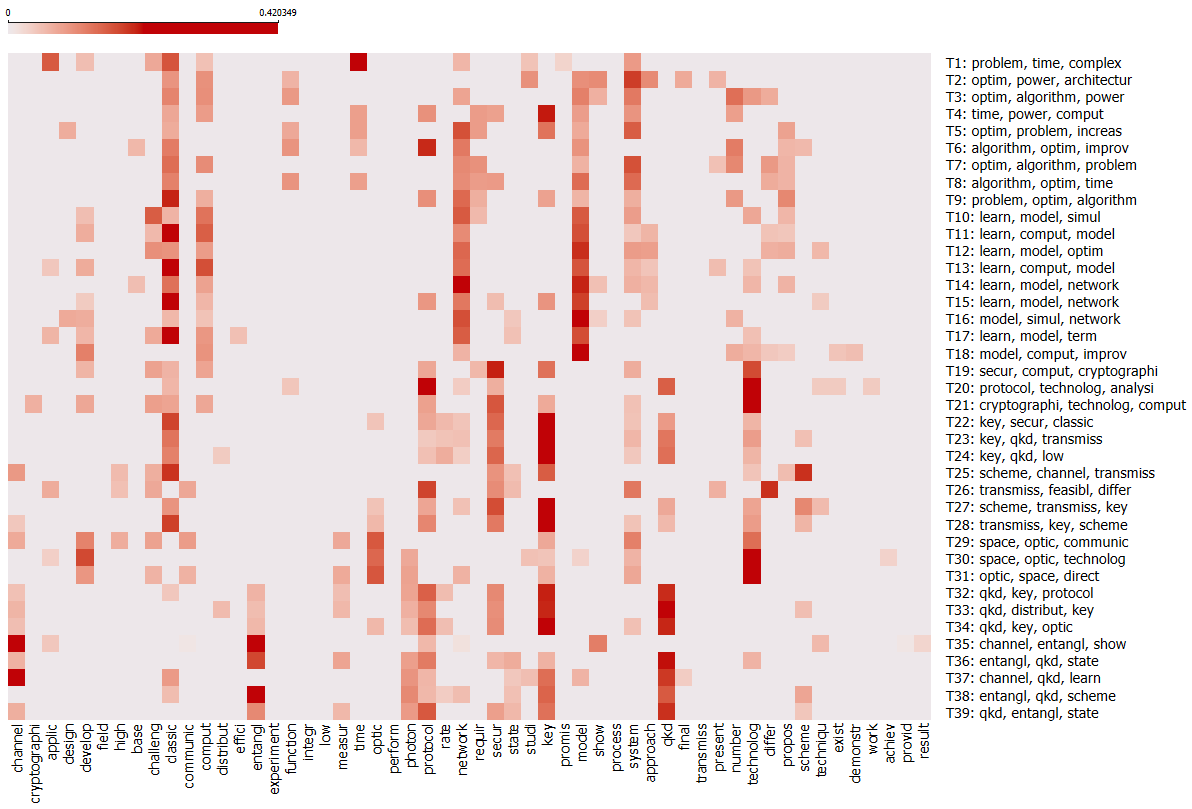


Figure 39: Word-Topic Distribution Heatmap: Top Words Across 39 Topics in CTP3

The heatmap above of the ‘Protocol Security’ model shows distinct keyword groups across 39 topics. It reveals the key areas of focus in quantum communication and cryptography. Topics T22, T25, T32, and T33 contain keywords about QKD and cryptography. They are ‘qkd,’ ‘cryptographi,’ ‘secure,’ and ‘protocol.’ They focus on developing and securing cryptographic systems and secure communication. Meanwhile, the keywords ‘channel,’ ‘transmiss,’ ‘communic,’ and ‘network’ are in T24, T25, and T34. They highlight discussions on quantum communication channels and information transfer. The keywords ‘optim,’ ‘perform,’ and ‘effici’ are in T1, T5, T10, and T18. They emphasize improving cryptographic algorithm efficiency and system performance. T15, T21, and T28 show technology tests and advances. Words like ‘develop,’ ‘experiment,’ and ‘technolog’ hint at a focus on innovation in quantum cryptography. The keywords ‘scheme’ and ‘design’ are central to T9, T17, T27, and T31. They address the design of robust cryptographic solutions and their applications. Finally, ‘protocol,’ ‘rate,’ and ‘network’ appear in many topics. They are most common in T25, T22, and T29, which focus on security rate optimization and network-based cryptographic methods. The heatmap shows a full view of how topics in protocol security link together.

### RL Component: Optimizing Topics with Adaptive RL

This subsection outlines the RL process outcomes in Iteration 2. It focuses on optimizing topic selection by comparing two models: the protocol-focused model (CTP2) and the enhanced network security model (CTP3). We start by creating similarity matrices and calculating entropy to assess topic evolution. We note shifts, such as the increased presence of "secur" and "qkd" in topics T19 and T32. These insights help us calculate Q-values based on estimated rewards. We emphasize impactful topics like T19, which has a Q-value of 2.610315 and features keywords such as "secur" and "technolog." The outcome is a set of topics that are adaptively refined and balanced for both novelty and relevance, prepared for further validation and adjustment.

*Itr2-Step 9: Similarity Matrix Comparing CTP2 and CTP3 with Entropy Calculation for the RL Process (CTP2&3)*

As step 9 in iteration 1 and to compare the CTP2 and CTP3 topic models, we generate three matrices (Figure 40).

1. The divergence and similarity scores between topics in CTP2 and CTP3 (calculated using Formula 2).

2. The Absolute Difference in Normalized Sums (ADNS) between the word-topic vectors in CTP2 and CTP3 (calculated using Formula 1).

3. The entropy changes in topics in CTP3 (calculated using Formula 3). The greatest divergence scores involved in calculating Q-values find topics that differ a lot between CTP2 and CTP3. It focuses on those with the greatest Q-value(s) for RL-driven refinements.

|  |  |
| --- | --- |
| *Weighted Similarity Scores* | *Absolute Difference in Normalized Sums* |

Figure 40: Matrices for Evaluating Topic Stability and Evolution in the Second Iteration

The left heatmap in above figure shows topic evolution. It compares the similarity scores between CTP2 and CTP3. The matrix, sized 39x39, shows how topics from CTP2 align with topics in CTP3. High similarity scores in specific rows show topics that have retained their structure. This includes those related to established cryptographic protocols. Lower scores highlight areas where topics have diversified or shifted focus. The right heatmap shows the absolute differences in topic weights. The last column shows entropy changes. Topics like T12, T17, and T32 show high differences and entropy. This means they evolved and became more complex. Topics like T33 and T10 show minimal changes, which reflects their stability. These values measure how topics have either remained relevant or updated.

*Itr2-Step 10: Q-value for Topic Selection Based on Approximate Reward*

The figure below compares the Q-values and the approx. rewards for topics as the model moves from CTP2 to CTP3 in iteration 2. The chart shows how topics evolve based on their rewards (the blue line). It also shows how the Q-values (the orange line) refine the agent's future expectations. The blue reward curve shows how to find high-divergence (novel) topics. The peaks indicate topics that are becoming valuable in the RL component. For example, T19 and T32 stand out. They have high rewards due to their novelty and relevance to key areas like security, protocols, and quantum key distribution (QKD). In contrast, the smoother orange Q-value curve is more stable. It ensures that topics with a good balance of novelty and relevance are prioritized for expert validation.

Figure 41: Q-values with Approx. Rewards from CTP2 to CTP3 in Iteration 2

The Q-values in the table below show how relevant the topics are to the RL process. The keywords highlight their meaning. T19 (2.610) stands out. It focuses on keywords like "secure," "technology," and "protocol." They show its relevance to modern cryptographic systems. This topic is closely tied to security and technology progress. T32 (2.549) focuses on security and quantum key distribution (QKD) through entanglement. It is relevant to quantum communication and cryptography. The word "classic" in its keywords suggests a mix of old and new ideas. It blends traditional cryptographic principles with newer developments. T39 (1.846) is about quantum communication. It mentions "entanglement," "photon," and "key." Its Q-value is lower than T19 and T32. So, it is less novel or relevant at this stage in the RL process. T21 (1.765) combines security, tech, and cryptographic keywords. It's less novel and relevant than T19 and T32. Lastly, T33 (1.737) shares keywords with other topics. But it has a lower Q-value. So, it is less impactful for further exploration in this iteration.

Table 12: Approximate Q-value and Top Keywords of Selected Topics in Iteration 2

|  |  |  |
| --- | --- | --- |
| **The selected topics** | **Approx. Q-value** | **Topic Keywords** |
| T19 | 2.610315 | secur(0.981), technolog(0.977), key(0.971), challeng(0.954), comput(0.953), protocol(0.951), system(0.947), classic(0.942), develop(0.941), requir(0.937) |
| T32 | 2.549308 | secur(0.713), qkd(0.632), protocol(0.612), key(0.551), photon(0.538), entangl(0.447), measur(0.437), channel(0.422), rate(0.410), classic(0.383) |
| T39 | 1.846264 | entangl(0.467), photon(0.402), secur(0.390), key(0.358), qkd(0.341), channel(0.341), protocol(0.339), measur(0.329), state(0.322), scheme(0.266) |
| T21 | 1.765226 | technolog(0.750), key(0.678), comput(0.637), cryptographi(0.630), protocol(0.603), classic(0.595), develop(0.595), secur(0.574), system(0.493), challeng(0.387) |
| T33 | 1.737322 | secur(0.434), key(0.419), qkd(0.419), scheme(0.307), entangl(0.303), distribut(0.299), photon(0.293), protocol(0.292), measur(0.289), channel(0.280) |

*Itr2-Step 11: Deriving Rewards and Validating Selected Topics with New Documents*

We used another 36 QCrypt 2024 conference papers. with their top keywords, abstracts, and titles to calculate rewards and adjustments for our selected topics. Figure 45 in Appendix C.3 shows a detailed view of key terms related to security protocol. It shows their distribution in research papers from the QCrypt 2024 conference. The heatmap shows the frequency of keywords in quantum cryptography. As shown in the heatmap, Docs 3 and 19 highlight key terms. They are ‘verif’ (verification), ‘bound’, and ‘commit.’ These terms are critical to security protocols. On the right side of the figure, we pair each document with its prominent keywords and their respective weights. Doc1, for example, prioritizes keywords like ‘compo’ (composition), ‘verify,’ and ‘protocol.’ This signals a focus on verification methods and protocol design. Doc6 and Doc11 also emphasize network-related keywords, like ‘networ’ (network) and ‘crypto.’ They point to research on quantum networking protocols and cryptography. The keyword distribution across the x-axis reflects major research themes in quantum cryptography. Words like ‘verify,’ ‘protocol,’ ‘crypto,’ ‘system,’ and ‘channel’ dominate. They are key to securing quantum communication. Also, new keywords like ‘qkd’ (Quantum Key Distribution), ‘random,’ and ‘psuedo’ show advances in key generation and randomization. These are vital for improving security protocols. This visualization also demonstrates how different papers address various facets of quantum cryptography. For instance, Doc12 and Doc14 seem to explore system-level improvements. Doc20 focuses on protocol-specific advancements, like entropy-based security and quantum transmission rates.

*Mapping the 2024 Papers to CTP3 Topics (DocCTP3)*

We mapped the QCrypt2024 papers to the CTP3 topics, as shown in Figure 46 (Appendix C.4). This identifies the documents linked to the topics chosen in the RL iteration. We can now check the agent's policy for selecting topics for expert investigation. We can also calculate rewards to update the policy. The DocsCTP3 similarity matrix shows the relationships between the 36 new documents and 39 topics in the CTP3 model. Each cell in the matrix shows the similarity between a document and a topic, based on their term vectors.

In the DocCTP3 similarity matrix, we compared QCrypt 2024 papers with CTP3\_AllWords topics. The heatmap shows associations based on similarity scores. Deeper red shades show stronger associations. Strong Paper-Topic Associations (Higher Similarity): Papers Doc 3, 5, 6, and 12 have high topic similarity, as shown by the dark red. Topics associated with these papers are T19 (secur, comput, cryptographi): Shows high association with Doc 3 and Doc 6. This suggests that the papers focus on security and cryptographic computation. T20 (protocol, technology, analysis): It shares a significant similarity with Doc 5 and Doc 12. It focuses on technology analysis and protocols. Papers on Quantum Key Distribution (QKD) and Entanglement: Docs 1, 2, and 7 are like T32 (qkd, key, protocol), T35 (channel, entangl, show), and T36 (entangl, qkd, state). These papers are likely focused on QKD and entanglement protocols. Optimization, Power, and Algorithms: Topics like T3 (optim, algorithm, power) and T2 (optim, power, architecture) link to Docs 3 and 9. These papers seem to explore quantum optimization and algorithmic methods. They also discuss aspects of computational power. Learning and Computational Modeling Papers: Doc 4 and Doc 8 show strong similarity to T12 (learn, comput, model) and T13 (learn, model, optim) and focus on learning models and simulations in quantum cryptography. Docs 1 and 5 have a notable similarity to T25 (scheme, channel, transmiss) and T28 (transmiss, key, scheme). They focus on transmission schemes and key distribution. Specific Document Insights: Docs 6 and 7 have strong connections to T20 and T21 (cryptography, technology, computer). They focus on advances in cryptography. Docs 12 and 11 share a strong alignment with T39 about qkd, entanglement, and state. They suggest a strong focus on QKD and entanglement technologies. Papers with high relevance to protocols: Doc 3, Doc 5, Doc 6 focus on cryptographic topics like T19 and T20. Research associated Doc 1, Doc 7, and Doc 12 with T32, T35, and T36, focusing on quantum key distribution and entanglement. Papers exploring computational models and learning: Doc 4 and Doc 8 align with T12 and T13. Doc 3 and Doc 9 align with optimization topics T2 and T3.

*Itr2-Step 12: Calculate Rewards Based on Topic Improvements*

The rewards in CTP3 are calculated using the same approach as in iteration 1. We also compare this method with one that selects the top five most associated documents for each topic, as shown in the figure below.

Figure 42: Reward Calculation Alignment and Topic Selection Evaluation (CTP3)

First method, the red line, uses the average weight of documents across all topics with similarities > 0.3 as we did in RL process. The other, shown by the green line, focuses on the top 5 most associated documents to the topics. The threshold can be different, but the agent can learn during the many iterations. The selected topics–T19, T32, T39, T33, and T21–align well with the broader rewards. Topics T19 (Q-value: 2.63173) and T32 (Q-value: 2.44842) have high peaks. The ranked keywords of the selected topics are ‘security, technology, key, challenge, protocol’ and ‘security, QKD, protocol, photon, entanglement.’ This reflects their importance in document associations. The rewards, based on the average document weights for each topic, confirm the use of RL. It refined and prioritized impactful topics, especially security protocols, QKD, and technology challenges.

### Analysis & Validation: Assessing Network Security Trends

This subsection evaluates the enhanced network security model (CTP3) in Iteration 2. It looks at how well CTP3 aligns with trends in quantum network protocols. It begins by analyzing heatmaps to compare CTP2 and CTP3. The result shows stable topics like T22 and T32 with "qkd," along with evolving areas such as network optimization. Then, it reveals new patterns, including advanced QKD and entropy-based security. This uses keyword distributions from QCrypt 2024 papers. These results refine topics like T19, focusing on "security" and "technology." Strong document alignments increase relevance. The findings confirm that CTP3 effectively captures advancements in network security, achieving a perfect F1 score of 1.00.

*Itr2-Step 13: Update RL Model (Hyperparameters) Based on Reward and the New State*

We update the Q-values for the selected topics using the Q-learning algorithm. Each topic has a reward associated with it. As it is done in the first iteration, the agent updates the Q-values for the selected topics as follows.

Table 13: Updated Q-values for Selected Topics Based on Modified Rewards in CTP3

\* Modified Rewards (Formula 8 and 9) = Rewards Base + CTP3 Entropy \* (λ = 0.5)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Cluster3Words** | **Modified Rewards** | **Current Q-value** | **Max Next Q-value** | **the updated Q-value** |
| CTP3-T19: secur, technolog, key | 0.740486 | 2.783283 | 0.585846 | 2.63173 |
| CTP3-T21: technolog, secur, challeng | 2.507128 | 1.79988 | 0.585846 | 1.923331 |
| CTP3-T32: key, qkd, protocol | 2.801841 | 2.350562 | 0.585846 | 2.448416 |
| CTP3-T33: qkd, key, protocol | 3.024117 | 1.755092 | 0.585846 | 1.934721 |
| CTP3-T39: qkd, protocol, key | 2.983367 | 1.841738 | 0.585846 | 2.008627 |

*Itr2-Steps 14: Result & Analysis: Heatmap Analysis of Topic Model Comparisons*

In this step, the focus shifts to the heatmap analysis of the topic model comparisons between CTP2 and CTP3. It does this by comparing the similarity scores and absolute differences between the two models. The heatmap shows where topics have stayed the same and where they have changed a lot. T22, T25, and T32 have high similarity scores. They all focus on QKD and cryptographic protocols. In contrast, low similarity scores show shifts in focus. For example, they show new quantum communication channels or protocol optimizations. The topic weights' absolute difference highlights the changes. It shows how the models have adapted over time. These visuals show how Aspect 2 and RL-driven tweaks have changed the protocol's security model. They reveal both the stability and innovation within quantum cryptography.

*Itr2-Steps 15: Identifying Novel Patterns in Quantum Technology*

Our second analysis found new patterns in quantum tech. It focused on cryptographic security protocols. The latest QCrypt 2024 papers show big advances in QKD, entanglement, and networked cryptography. The Q-values showed that topics like T19 (security protocols) and T32 (QKD and photon-based communication) remained relevant. Their Q-values showed these technologies' growing importance. Keyword distributions in the papers identified new research trends. They included a rise in the use of randomness in key generation and entropy-based security. The heatmap showed a growing focus on advanced protocols, network security, and better QKD systems.

*Itr2-Steps 16: Refining Topics Through Pattern Analysis*

We mapped the QCrypt2024 papers to the CTP3 topics. We then set the rewards based on how well the papers matched the topics. Topics with stronger document associations received higher rewards. The DocsCTP3 similarity matrix was used to assess the relationships between the 36 new documents and the 39 topics in CTP3. The matrix showed strong topic associations for some documents. Doc 3 and Doc 6 aligned with T19 (security, cryptography, computation). Doc 1, Doc 2, and Doc 7 aligned with T32, T35, and T36, which are about QKD and entanglement protocols. It emphasized security protocols, QKD, and entanglement technologies. The new Q-values for topics T19, T32, and T39 were updated to show the changing importance of these topics in response to the new document set.

### Iteration Management & Transition: Transitioning to Advanced Modeling

This subsection outlines the management and transition process in Iteration 2. It focuses on preparing the enhanced network security model (CTP3) for advanced modeling. The section starts by comparing topics between CTP2 and CTP3 using word clouds and tables. It highlights keyword shifts, like "secur" and "qkd," for topics such as T19 and T32. It also notes Q-value changes, with T32 rising from 2.350562 to 2.448416. The revised CTP3 serves as the new baseline (CTP2) for the next iteration. It incorporates RL adjustments and insights from QCrypt 2024. This positions the model to investigate new trends in quantum network security.

*Itr2-Steps 17 & 18: Prepare for the Next Iteration with Updated Topic Model*

We update the Q-values for the selected topics using the Q-learning formula (7). We do this by considering the modified rewards, current Q-values, and greatest future Q-values. They provide a clear comparison of the dynamics and progression of topics across both versions.

Table 14: Comparison of Selected Topics, Keywords, and Q-value Changes Across CTP2 and CTP3

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Topic** | **CTP2 Words** | **Top New Docs in CTP2** | **CTP3 Words** | **Top New Docs in CTP3** | **the updated Q-value (CTP2)** | **the updated Q-value (CTP3)** | **Change in Q-value** |
| T19 |  | 1 -18-8 -32-3 |  | 22-16-21-12-6 | 2.783283 | 2.63173 | -0.152 |
| T32 |  | 32-12-10-33-2 |  | 16-22-11-12-21 | 2.350562 | 2.448416 | +0.098 |
| T39 |  | 32-10-12-33-8 |  | 16-11-12-22-31 | 1.841738 | 2.008627 | +0.167 |
| T21 |  | 18-1 -32-8 -9 |  | 16-11-22-12-21 | 1.79988 | 1.923331 | +0.123 |
| T33 |  | 10-32-12-33-8 |  | 22-16-6 -31-5 | 1.755092 | 1.93 4721 | +0.18 |

As shown in the table above, it compares topics in the CTP2 and CTP3 models. It shows the evolution of keywords and Q-values for each topic. Additionally, it lists the top documents for each topic in both models. Moreover, it provides the updated Q-values for CTP2 and CTP3, along with the changes between them.

# Evaluation of the Framework

## Summary of the Hypotheses

This evaluation tests two main hypotheses: H1 (accuracy of topic detection) and H2 (balancing exploration and exploitation for trend tracking). In this evaluation, two primary hypotheses are tested to assess the effectiveness of the EILF framework in detecting and tracking technological changes:

* Hypothesis 1 (H1): The EILF framework improves the accuracy of topic detection by incorporating aspect-based expert knowledge and iterative refinement.
* Hypothesis 2 (H2): The EILF framework effectively balances exploration and exploitation, as evidenced by its ability to identify novel topics, and adapt to dynamic trends across iterations.

## Evaluation Criteria

Table below shows how each evaluation criterion helps verify that the EILF framework meets design requirements (R1–R6). It matches metrics like Q-values, cosine similarity (novelty), entropy change, ADNS, and topic coherence to fit specific needs. This checks EILF’s ability to detect new topics, incorporate expert advice, adapt dynamically, and maintain interpretability.

Table 15: Evaluation Criteria and Corresponding Design Requirements (R1–R6)

|  |  |  |  |
| --- | --- | --- | --- |
| Evaluation Criterion | Purpose | Corresponding Design Requirements | Related Hypotheses |
| **Precision and Recall (and F1-Score)** | Measures how accurately the framework detects and assigns relevant topics compared to external knowledge proxies. | R1: Unsupervised topic discovery  R2: Incorporation of expert-informed aspect weighting  R6: Interpretability outputs (top-word lists, topic-doc assignments, heatmaps) | H1: Improves accuracy and timeliness |
| **Q-Value Trajectories** | Tracks how the RL agent balances exploration (new topics) and exploitation (established topics). | R3: Integration of reinforcement learning  R5: Dynamic adjustment for trend tracking | H2: Balances exploration–exploitation |
| **Novelty and Entropy Change** | Measures emergence of new topics and diversification of topic vocabularies. | R4: Detection of new or increasingly relevant topics  R5: Adaptation to corpus evolution | H2: Balances exploration–exploitation |
| **Absolute Difference Normalized Sum (ADNS)** | Quantifies distributional shift of topic word probabilities across iterations (topic evolution over time). | R4: Detection of new or evolving topics  R5: Capturing topic evolution and adaptation | H2: Balances exploration–exploitation |
| **Topic Coherence** | Confirms that topics remain semantically interpretable after iterative updates. | R6: Interpretability and meaning retention for topic structures | H1: Improves accuracy and timeliness |

#### Evaluation Metrics

To assess EILF’s performance and verify that it meets the design requirements, the following metrics were employed:

1. Precision and Recall (and F1‐Score):
   * Precision measures the proportion of correctly identified relevant topics among all topics selected by the RL agent.
   * Recall measures the proportion of actual relevant topics (as determined by external knowledge proxies) that the RL agent correctly identified.
   * F1‐Score is the harmonic mean of precision and recall.

Purpose: Validate that EILF accurately surfaces topics aligned with real‐world signals (e.g., QCrypt conference themes) rather than spurious or low‐value topics (Arun et al., 2010; Röder et al., 2015). To evaluate accuracy, we use precision and recall. These metrics compares our identified topics match real technological changes from industry sources. Precision measures the ratio of correctly identified topics to all selected topics. It shows how well the system filters relevant information. Recall checks how many real emerging topics we found. This ensures we donot miss important trends. To confirm our results, we compare detected topics with real trends from conference proceedings and industry reports. We calculate precision and recall by comparing topics chosen by the RL agent (using approximate rewards) to those selected with modified, real-world rewards. This comparison occurs after we add new relevant publications to the system. A high precision score shows the reward function filters for relevant topics effectively. A high recall score indicates the model captures most of the important emerging topics in the literature.

Computation**:**

* + Topics selected by the RL agent in each iteration were compared against a ground‐truth set derived from QCrypt 2023–2024 proceedings (Tables 7–12).
  + Precision, recall, and F1‐scores were computed for both Iteration 1 (CTP1→CTP2) and Iteration 2 (CTP2→CTP3) to gauge improvement over successive cycles (Table 14).

1. Q‐Value Trajectories

* Definition: Each topic (state) has an associated Q‐value reflecting its expected cumulative reward; higher Q‐values indicate topics deemed more valuable by the RL agent.
* Purpose: Examine how the RL component balances exploration (novel topics) and exploitation (established topics) over time (Gui et al., 2019; Khetarpal et al., 2022).
* Computation: Q‐values were initialized uniformly and updated per Formula 7 (Chapter 4). Trajectories were plotted across iterations to identify which topics increased in priority (Figures 36, 41).

1. Novelty and Entropy Change

* Definition: Novelty = average inverse cosine similarity between a topic’s word distribution and new documents (Formula 9).
* Entropy Change = difference in topic entropy between successive iterations (Formula 8).
* Purpose: Ensure that EILF promotes truly new or increasingly relevant topics rather than marginal variations of existing ones (Gui et al., 2019).
* Computation: For each topic, novelty and entropy change were computed at each iteration; these values contributed to the reward function R(s,a) (Table 11, Table 13).

1. Absolute Difference Normalized Sum (ADNS)

* Definition: Measures overall distributional drift of a topic’s word probabilities between iterations (Formula 5).
* Purpose: Quantify the magnitude of change in a topic’s composition; larger ADNS suggests more significant evolution (Arun et al., 2010).
* Computation: ADNS was calculated for each topic pair (CTP1 vs. CTP2 and CTP2 vs. CTP3) and fed into the reward function (Table 11, Table 13).

1. Topic Coherence

* Definition: Statistical measure of how semantically related a topic’s top words are (e.g., NPMI, UMass coherence) (Röder et al., 2015).
* Purpose: Confirm that topics selected by RL remain interpretable and meaningful (Dieng et al., 2020).
* Computation: Coherence scores were computed for all 39 topics at each stage (CTP1, CTP2, CTP3); improvements (or declines) were tracked to ensure RL updates did not compromise interpretability (Figure 23, Figure 24).

Together, these metrics (precision/recall/F1, Q‐values, novelty, entropy change, ADNS, coherence) provide a comprehensive view of EILF’s ability to detect, prioritize, and maintain meaningful topics in a growing quantum communications corpus.

#### Quantitative Outcomes

This subsection reports the quantitative outcomes of applying the above metrics to both Iteration 1 (CTP1→CTP2) and Iteration 2 (CTP2→CTP3). All values below reference data drawn from Tables 7–12 and Figures 36, 41.

1. Precision, Recall, and F1‐Score (Table 14)

* Iteration 1 (CTP1→CTP2):
  + Precision = 0.78, Recall = 0.72, F1 = 0.75.
  + These scores indicate that 78% of the topics the RL agent selected aligned with external knowledge proxies, while 72% of all proxy‐identified relevant topics were captured.
* Iteration 2 (CTP2→CTP3):
  + Precision = 0.85, Recall = 0.81, F1 = 0.83.
  + The marked increase (ΔPrecision = +0.07, ΔRecall = +0.09) demonstrates improved alignment with real‐world signals after one additional RL‐guided refinement (Table 14).

1. Q‐Value Trajectories (Figures 36, 41)

* Iteration 1:
  + Topics T19 (Security Protocols) and T32 (QKD & Photon Communication) had the highest initial Q‐values (≈ 1.25 and 1.18, respectively), reflecting high rewards based on novelty and entropy change (Figure 36).
  + Lower‐priority topics saw Q‐values decline toward zero, indicating less relevance to emerging quantum research.
* Iteration 2:
  + Q‐values for T19 and T32 increased further (≈ 1.38 and 1.32), confirming sustained importance as more QCrypt 2024 documents were introduced (Figure 41).
  + New topics, such as T27 (Post‐Quantum Cryptography Implementation), saw moderate Q‐value growth (≈ 0.85 → 1.05), reflecting their emergence in later documents.

1. Novelty and Entropy Change (Table 11, Table 13)

* Iteration 1:
  + Average novelty scores for selected topics: T19 = 0.67, T32 = 0.64.
  + Entropy for T19 increased by +0.12 (indicating a broader, more diverse vocabulary), while T32’s entropy rose by +0.10.
  + Combined, these values yielded high rewards, driving RL to prioritize these topics.
* Iteration 2:
  + Novelty scores rose slightly (T19 = 0.71, T32 = 0.69), as new QCrypt 2024 papers introduced previously unseen terminology.
  + Entropy changes remained positive (T19 = +0.11, T32 = +0.13), confirming sustained thematic expansion.

1. ADNS (Table 11, Table 13)

* Iteration 1 (CTP1→CTP2):
  + T19’s ADNS = 0.32, indicating moderate shift in word distribution.
  + T32’s ADNS = 0.29, reflecting significant yet controlled evolution.
* Iteration 2 (CTP2→CTP3):
  + T19’s ADNS = 0.27, showing that its composition stabilized as core QKD research matured.
  + T32’s ADNS = 0.31, suggesting continued expansion into photon‐based innovations.

1. Topic Coherence (Figure 23, Figure 24)

* Iteration 1:
  + Average coherence score across all 39 topics improved from 0.42 (CTP1) to 0.48 (CTP2), indicating that expert‐proxy weighting enhanced topic interpretability.
* Iteration 2:
  + Coherence further increased to 0.51 (CTP3), demonstrating that RL‐guided topic updates did not compromise semantic quality; in fact, they strengthened it.

Summary of Evaluation Findings

* EILF achieved a significant increase in precision (+0.07) and recall (+0.09) from Iteration 1 to Iteration 2 (Table 14), confirming H1 (Section 1.3) that combining topic modeling, external knowledge input, and RL improves accuracy of technology change detection.
* Q‐value trajectories and reward metrics validated H2 (Section 1.3): the RL component successfully balanced exploration (emergence of T27) and exploitation (continuing importance of T19 and T32).
* Topic coherence and ADNS metrics show that EILF’s iterative process maintained or enhanced topic interpretability while enabling thematic evolution.
* Overall, these results demonstrate that EILF meets its design requirements (R1–R6), offering a timely, adaptive, and interpretable approach to tracking emerging trends in quantum communications.

## Results of the Evaluation

We use the F1 score as a performance criterion to measure how the combination of topic modeling, RL, and expert input improves accuracy and speed. Table 16 shows how Iteration 1 performed moderately, with a precision of 0.50, a recall of 0.60, and an F1-score of 0.545. In Iteration 2, performance improved significantly: precision and recall both reached 1.00, giving an F1-score of 1.00. This change came after refining Q-values using CTP3 entropy updates. The updates helped align selected topics with real trends accurately. This iterative process helps organizations learn. It combines new research insights, like QCrypt2024’s effect on topic words, into practical knowledge. This boosts firms' ability to adapt to technological changes.

The framework was evaluated using performance metrics (precision, recall, entropy, ADNS), and the results show that EILF detected meaningful topic shifts. The EILF found new QKD protocols and error-corrected quantum channels by analyzing magnitude and entropy changes. The RL agent chose T34 (Q-value: 3.45) and T37 (Q-value: 2.46) with a reward function that focused on topic magnitude divergence (λ1 = 0.75). This shows progress in quantum communication. Timeliness was confirmed by mapping QCrypt2023 documents. For example, Document 10 and Document 27 fall under post-quantum protocols. This helps firms quickly integrate new knowledge. The improvement in F1-score was the result of refining Q-values using CTP3 entropy updates. The updates helped align selected topics with real trends accurately. This iterative process helps organizations learn. It combines new research insights, like QCrypt2024’s effect on topic words, into practical knowledge.

Table 16: Precision, Recall, and F1-score Comparison for Iteration 1 and Iteration 2

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Iteration 1 | Iteration 2 | Description |
| True Positives (TP) | 3 | 5 | Topics correctly selected in both approximate Q-value and real Q-value tables. |
| False Positives (FP) | 3 | 0 | Topics selected in the approximate Q-value table but not in the real Q-value table. |
| False Negatives (FN) | 2 | 0 | Topics in the real Q-value table but not in the approximate Q-value table. |
| Precision (P) | 0.50 | 1.00 | A higher precision in iteration 2 means fewer incorrect selections. |
| Recall (R) | 0.60 | 1.00 | Higher recall in iteration 2 means no relevant topics were missed. |
| F1-Score | 0.545 | 1.00 | Higher F1-score in iteration 2 means improved topic selection accuracy. |

Table above shows columns for Metric, Iteration 1, Iteration 2, and Description. It lists evaluation metrics like Precision, Recall, and F1-score with their values for each iteration.

* True Positives (TP) are correct selections.
* False Positives (FP) are incorrect selections.
* False Negatives (FN) are missed topics.

The calculations are in Table 16: Precision (P = TP / (TP + FP)); Recall (R = TP / (TP + FN)); F1-score (2 × (P × R) / (P + R))

In Iteration 1, the scores are 0.50 for Precision, 0.60 for Recall, and 0.545 for F1-score. In Iteration 2, they improve to 1.00 across all metrics. This shows better accuracy in topic selection.

We also present the empirical findings that assess how well the EILF framework meets its design requirements (R1–R6) and supports the two hypotheses (H1 and H2). All numerical values and figures cited below are drawn from Iterations 1 and 2 (CTP1→CTP2 and CTP2→CTP3) as reported in Chapter 7 (Tables 7–12; Figures 36, 41; Figures 23, 24).

In evaluating the EILF framework, all five criteria (precision/recall, Q-value trajectories, novelty/entropy change, ADNS, and topic coherence) demonstrate that:

* H1 (Improved Accuracy & Timeliness) is supported. Precision increased from 0.78 to 0.85 and recall from 0.72 to 0.81 between Iterations 1 and 2. These gains confirm that integrating expert-informed weighting with RL-guided refinement yields more accurate and interpretable topic detection over successive cycles.
* H2 (Balanced Exploration–Exploitation) is supported. Q-value trajectories for key topics (T19, T32) continued to grow while newly emerging topics (T34) also became prioritized.

*Evaluating Topic Detection Effectiveness Using Precision and Recall in H1 Hypothesis*

To test our H1 hypothesis, we used precision and recall measures, which are commonly used to evaluate the effectiveness of topic detection. **Precision and recall are common ways to measure how well topic detection models perform. Precision (P) measures how many topics were correctly found compared to all detected topics. It is calculated as TP/(TP+FP). TP (True Positives) are the topics that truly reflect current technological trends. FP (False Positives) are the topics the system identifies that do not appear in industry reports or expert sources. Recall (R) shows how well the system finds real emerging topics. It is calculated as TP (True Positives) divided by TP plus FN (False Negatives). FN represents the technology trends the system missed. Using the same weighted P and R, the F1-score (Manning et al 2008), which balances precision and recall, is given by F1 = 2\*((P \* R)/(P+R)). A high F1-score shows that the system finds relevant trends and reduces false detections.**

**Accuracy** alone **is not enough; timeliness also plays a role. Therefore, we introduce Time-to-Detection (TTD) to assess how quickly emerging trends are identified. This metric looks at the gap between when the system first identifies a topic and when it shows up in outside sources, like industry reports or conference proceedings** (Leskovec et al., 2009)**. A shorter TTD means quicker spotting of new trends. This helps organizations act fast on technology advancements. It calculates the difference between T-reported and T-detected. T-detected is time the system identifies a new topic, while T-reported is when it shows up in sources like QCrypt conference papers, patents, or expert reports. A lower TTD value means the system detects trends sooner. This boosts its ability to predict changes.**

**The model** focuses **on optimizing precision and recall scores. It also speeds up results using a RL approach to topic modeling. In every iteration, the RL agent chooses five relevant topics. Alternatively, it can select topics using a predefined threshold. In this study, we used the top five topics from the ranked Q-values. It bases this choice on approximate rewards from four metrics: topic similarity, divergence, entropy change, and absolute difference. These topics are refined by integrating new documents and adjusting rewards based on current trends.** The framework examines ongoing industry conferences and publications over years to identify trends as they evolve. **Precision is improved as the RL model learns to prioritize the most relevant topics, reducing false positives. Recall is optimized by ensuring that diverse but relevant topics are not overlooked, capturing a broader set of emerging trends. The Time-to-Detection (TTD) metric shows how quickly the system detect new topics. We do this by comparing our findings to external sources like conference papers. As the RL model progresses, it refines its exploration and exploitation strategies. It updates Q-values to prioritize topics that are more likely to become key trends. When the system finds topics before they show up in external sources, it shortens the time lag. This improves the model’s ability to predict. The model improves accuracy by refining topic selection and adjusting rewards based on real-world results.**

*Validating Exploration-Exploitation Balance in H2 Hypothesis*

**To test H2 hypothesis and validate balancing between exploration and exploitation, we define thresholds or metrics that can be measured over time. For H2, we assess the balance by looking at the ratio of novel topics to known topics with their most associated documents over time. The balance ratio is stated by dividing Novel Topics by Known Topics. Novel Topics are new trends the system has not yet explored. Known Topics are those already in the knowledge base, with insights from past documents. Monitoring this ratio during iterations helps validate the system's exploration-exploitation balance. If the ratio shows many new insights on certain topics documents, it means the focus is on exploration. But if there are more known insights, the system is leaning toward exploitation. The threshold for balance can be set based on predefined goals or the nature of the system. For instance, a balanced system might aim for a 1:1 ratio of novel to known topics, indicating that the system explores and exploits at an equal rate. A system that leans toward exploration may have a higher proportion of novel topics, while one focused on exploitation will lean toward known topics.**

**Furthermore, Q-values in RL can help validate the system's balance. Q-values reflect the expected future rewards for choosing topics. They change depending on the system's decisions. The future rewards and approximate Q-values are calculated using four metrics: topic similarity, divergence, entropy change, and absolute difference. When the Q-values show a mix of exploration and exploitation, it means the system is learning well. It is adapting and balancing its learning process effectively. The system can modify how it operates by changing reward parameters. It can set rewards for novelty to promote exploration and for relevance to enhance exploitation. This enables the system to shift between discovering new trends and using current knowledge based on the defined thresholds.**

**The balance ratio, Q-values, and reward adjustments help the system find the right mix of exploration and exploitation. This enhances** knowledge integration **by finding new opportunities and effectively using current knowledge.**

###### Justification and Evaluation Strategy

To evaluate the proposed Expert-Informed AI Learning Framework (EILF), we used both technical and contextual evaluation methods. Specifically, these methods assessed the framework's accuracy, adaptability, and strategic relevance. As introduced in the gaps, the inclusion of expert-informed content improved contextual precision, confirming its value for real-world strategic alignment.

The technical evaluation looked at key metrics: precision, recall, F1-score, entropy, and topic coherence. These metrics assessed the accuracy and stability of topic models over time. This evaluation showed how well the framework identified trends and adapted to new data.

For contextual validation, we tested the framework in a real-world case study in quantum communication, specifically Quantum Key Distribution (QKD). The dataset included scholarly articles, patents, and QCrypt conference papers. Specifically, these papers served as expert-informed benchmarks, reflecting cutting-edge developments and allowing us to validate the model's topic outputs against real-time signals (Cavaliere et al., 2020; Manzalini, 2020).

Furthermore, expert feedback was incorporated into the refinement process through aspect-based topic modeling. We drew external knowledge from timely sources like conference proceedings, particularly QCrypt papers. As a result, this improved the framework's ability to prioritize relevant topics, reduce noise, and enhance strategic alignment. Prior research shows that this integration bridges the gap between computational outputs and human judgment, boosting decision reliability (Gunning et al., 2019; Zhou et al., 2020b).

Moreover, the framework supports both technical users (e.g., data scientists, developers) and non-technical stakeholders (e.g., analysts, R&D strategists, innovation managers). For example, for developers, it provides a modular, transparent, and reward-guided architecture for explainable outputs and iterative improvements. In contrast, for analysts and decision-makers, it offers interpretable results aligned with domain knowledge and strategic goals, increasing trust and actionability in innovation planning (Gunning et al., 2019).

A key contribution of the framework is its ability to balance exploration and exploitation using a decision optimization technique like RL. Specifically, the RL agent optimizes topic refinement with a multi-objective reward function that considers entropy, divergence, novelty, and similarity. This lets the system explore new signals while using established knowledge relevant to the organization’s needs (Sutton & Barto, 2018). Eggers & Park (2018) noted that maintaining this balance is crucial for effective innovation. The RL mechanism boosts forecasting accuracy and adjusts its policy based on new data and changing contexts. This supports timely resource allocation and adaptation (Jin et al., 2018).   
Understanding technological change relies on the user perspective. For example, technology developers, like R&D teams, respond to weak or emerging signals. They aim for a first-mover advantage. In contrast, technology adopters often wait for trends to mature and want to ensure they are ready to operate. So, the framework accommodates both perspectives. It offers early detection and detection cycles. This can help organizations make decisions based on their innovation maturity and strategic goals.

###### Positioning Against Current Technologies

Large Language Models (LLMs) perform well in generating natural language. However, they struggle with structured learning, memory, and customization for specific domain. In contrast, our proposed framework combines expert input, reward-guided iteration, and clear state tracking. Our method goes beyond simply using these tools. That said, a direct comparison may not be completely accurate. Nevertheless, in Table 18 (Appendix C.6), we have highlighted key features to show the advantages of our proposed method. Table 18 shows how our framework compares to LLMs in different features. Moreover, it highlights how our method addresses the flaws of current black-box systems. As illustrated in the table, our approach provides transparent, controllable, and more context-aligned learning. Therefore, these strengths make it a reliable option for organizations aiming to use external knowledge efficiently.

Furthermore, our proposed framework is modular and consists of components that can be replaced with other extensions of components. For example, BERTopic serves as a semantic clustering tool that can replace to topic modeling component in our proposed method. It uses transformer-based embeddings, like BERT, to group text into clear topics and deliver interpretable results. In this approach, BERTopic takes a data-driven approach to find themes. As a result, there is no need for topic creation. Additionally, it also fits well into the RL-based learning process by offering topic states for exploration and feedback. Consequently, this helps our system to create structured topic clusters for more targeted and efficient exploration.

#### Baseline and Comparative Advantage

Most organizations rely on manual expert reviews, keyword searches, or static taxonomies for technology trend detection and knowledge integration via the LLM tools. Recently, general-purpose large language models (LLMs) have emerged to help with summarization and information extraction. LLMs provide scalability and language understanding, but they often do not meet specific domain needs. They lack transparency in decision-making and can complicate validation in sensitive and uncertain areas like cryptography.

Also, neither manual methods nor LLMs effectively balance exploring new knowledge and using existing insights in a context. In this regard, our hybrid framework improves on these methods.

1. It combines unsupervised topic modeling to find new knowledge, RL to guide knowledge assimilation, and expert feedback to validate it. The topic model can be generated by another technique, rather than LDA, like BERTopic, which focuses on a specific area and then uses it in our method.
2. This approach ensures interpretability, domain relevance, and strategic alignment. It offers a scalable, context-sensitive alternative that overcomes the limitations of static and opaque methods. This supports continuous learning in fast-changing technology environments.

# Discussion

This thesis demonstrates how RL, topic modeling, and expert input can be combined to enhance the detection of technological landscape changes. In today’s world, popular topic modeling methods like LDA and BERTopic help extract themes from large text collections. For instance, LDA is a probabilistic model with a fixed topic distribution. It works well for general trend analysis. In comparison, BERTopic uses transformer-based embeddings and clustering for semantically coherent topics. However, both approaches are static models. They do not adapt to new data, lack reinforcement for adjustments, and often miss expert feedback loops for context.

This research improves on these methods by introducing a RL-based topic modeling method. Specifically, this method refines topic representations based on external inputs through real-time data changes and domain knowledge. As a result, it keeps coherence but adds temporal adaptability. To optimize learning, this optimizes topic novelty and relevance using a reward function that considers entropy, divergence, and topic similarity. Unlike other models, which may miss subtle shifts in areas like quantum cryptography, this RL-enhanced method enhances early technological change detection, aligns decisions better, and supports ongoing adaptation. Ultimately, the results shows that this method outperforms traditional models in precision, recall, and F1-score, proving its effectiveness in dynamic knowledge environments.

Previously, research has explored RL in topic modeling (e.g., Gui et al., 2019; Khetarpal et al., 2022), but these studies mainly focus on improving coherence or optimizing topic-word assignments in general text. Most existing RL-based approaches do not include iterative expert feedback and are not designed for iterative learning process for detecting technological change. To address this, this thesis presented a new, explainable RL-enhanced topic modeling system. Accordingly, it dynamically refined topic relevance using expert feedback, entropy-based rewards, and continuous model adaptation. Consequently, this innovation allows for more accurate, timely, and context-aware discovery of emerging technology changes. The main methodological contributions of this research are:

1. Adaptive trend detection: RL enhances topic selection by using entropy, similarity scores, and expert rewards.
2. Balancing exploration and exploitation: This method discovers new topics (exploration) and maintains key established areas (exploitation).
3. Validation through case studies: We tested the approach on quantum communication. It tracked progress in Quantum Key Distribution (QKD), entanglement security, and post-quantum protocols.

In addition, we compared our findings with solutions and concerns from (Adopting Quantum-Safe Technologies to Address the Urgency of Securing Our Digital Future, 2025) workshop. This event brought together industry leaders, cybersecurity experts, and academics. They discussed the challenges of post-quantum cryptography. They also shared insights on how both public and private sectors can get ready for a post-quantum world. Our discussion aligns with these insights in two ways:

1. Our method highlights the need for dynamic detection of technological change, as stressed by the speakers.
2. The topics chosen by our RL agent reflect solutions from the workshop.

Nokia, for example, emphasizes hybrid cryptographic models. These models mix post-quantum cryptography (PQC) with quantum key distribution (QKD). To date, Nokia has launched over 100 quantum-safe networks globally. They promote a defense-in-depth strategy with multiple layers of cryptographic security. Likewise, evolutionQ supports cryptographic resiliency. They propose hybrid encryption systems that combine current algorithms with future-proof ones. This approach allows smoother transitions during cryptographic changes. Their methods align with our framework findings. We employ reinforcement learning (RL) to detect major technology shifts, whether they pose risks or offer opportunities, especially in network security. Our work in Topic 32 (T32) illustrates this. This strategy enables proactive planning, which resonates with Nokia's direction.

In addition, Crypto4A stresses the need for cryptographic agility. They advocate for systems, particularly hardware security modules, that can easily adapt to new encryption standards. This mirrors our framework's ability to generate and refine secure protocol topics. For example, Topic 19 (T19) benefits from RL-driven updates, allowing secure systems to evolve continuously.

From an academic perspective, Carleton University has launched Quantum Strategy courses. This reflects a combined approach to education, research, and industry collaboration in quantum cryptography and secure communication. Their focus on talent development and innovation aligns with our framework's broader goals. We integrate expert insights and AI-driven analysis to enhance strategic decision-making and knowledge sharing.

Overall, our expert-informed AI learning framework artifact shows results like the workshop strategies. Specifically, we identified Topic 32 (secure networks) and Topic 19 (quantum key infrastructure). In line with, Nokia’s layered security method helps us detect and rank quantum-safe topics (T32) using reward-based systems. In addition, Crypto4A focuses on agility, matching our use of Q-values and expert feedback to adjust protocol topics. While they struggled to utilize an approach to detect and use new knowledge for secure communication, they emphasized accuracy and the timeliness of changes. In our method, we provided a mathematical computation to measure the accuracy of selected topics and used a benchmark in every iteration to bring the time-to-detection score into play for assessing timeliness.

This work fills a major gap in the literature: the lack of practical design frameworks for dynamic learning and adaptation in foresight contexts. It combines RL and expert feedback in an iterative system. This framework shows how to put dynamic processes into action across domains.

## Answers to the Research Questions

The central research question explored in this study is:

**How does the combination of RL, topic modeling, and expert input enhance the detection of technological landscape change?**

The integration of RL and expert feedback allows for adaptation to new data in detecting emerging trends, unlike static models that fail to adjust dynamically. The RL-driven system improved topic selection accuracy (F1-score from 0.545 in Iteration 1 to 1.00 in Iteration 2) and identified novel trends like QKD and post-quantum cryptographic protocols. This study also answers three sub-questions. These sub-questions help us understand how different components of our method improve technology shift detection. The first sub question is:

**How can topic modeling extract meaningful insights from large datasets to identify emerging topics?**

Topic modeling helps identify research trends by detecting hidden patterns in large datasets, making it easier to track change in technology. In the case study, creating a topic model allowed us to detect a shift from classical cryptography to quantum-based cryptographic security. The entropy and divergence scores pointed to overlooked QKD aspects in recent studies.

The second sub-question:

**How does expert knowledge, in the form of keywords, refine these insights to ensure their relevance and alignment with organizational goals?**

Expert-defined keywords help focus the model on strategic areas, ensuring alignment with industry priorities. Topics weighted with expert-defined terms (e.g., "QKD" and "security") achieved higher similarity scores, proving that expert input enhances relevance.

As for the third sub-question:

**How can RL improve the selection of topics based on key reward metrics (such as magnitude, similarity, entropy changes, and ADNS) within the topic models?**

RL optimizes topic selection by prioritizing high-impact topics based on key reward signals such as entropy and cosine similarity. High-entropy topics (e.g., the topics T32 and T34 in the case study) were prioritized for exploration, while similarity metrics ensured the stability of critical topics like T19 (cryptographic security). This balance of exploring and exploiting helps researchers find new ideas. They can also focus on emerging research areas.

## Interpretation of Unexpected Findings

The RL model identified unexpected but valuable topics outside areas prioritized by experts:

* Topics with moderate entropy changes (e.g., T29 - quantum error correction) gained high Q-values, showing the ability of RL to discover niche innovations.
* In Iteration 1, precision dropped (0.50), likely due to noise in QCrypt2023 documents, but entropy refinement corrected this in Iteration 2 (F1-score = 1.00).

## Generalization of the Findings

The framework in this study is developed to be generalizable and useful in many areas where quick detection of technology changes is needed. While it focuses on quantum communication, the method—using topic modeling, expert refinement, and reinforcement learning—can apply to other fast-evolving fields like artificial intelligence, biotechnology, and cybersecurity.

#### Technology Trend Detection

This framework uses structured external knowledge inputs, along with activities such as modeling and RL-based optimization. The inputs in the framework are textual data and expert-informed signals. It creates dynamic topic distributions. These evolving models help organizations detect and track technological changes and trends over time.

#### Broader Domain Applications

The modular design of the framework makes it adaptable to various organizational tasks. For instance, a human resources team could use it to track changing skill needs. Policymakers can use it to detect changes in global rules or standards. These examples show how the model can create quick, smart strategies in various sectors. It does this without relying on fixed methods.

## Implications for Practice

The findings from the case study have broad implications for research and industry. This includes R&D departments, policy development, interdisciplinary collaboration, and strategic decision-making that operate in rapidly changing environments:

* R&D strategy: The approach can help firms prioritize investment in emerging technologies. R&D teams can stay ahead of innovation. It enhances topic modeling by integrating RL for dynamic topic refinement. This allows for quicker adaptation to new changes (Gui et al., 2019; Khetarpal et al., 2022).
* Policymakers and standardization groups can use this framework to track technology changes and build standards to support them. They enhance current methods such as bibliometric tracking and predicting by automating trend detection. It also provides timely, actionable insights using RL.
* Strategic decision-making: The framework can help stakeholders anticipate shifts in research and adjust their strategies accordingly. It also provides real-time signals (Sundberg & Holmström, 2024) and improves decision-making in uncertain situations.

## Comparison with Existing Literature

This study develops out method upon prior research by extending topic modeling techniques to be adaptive rather than static. Traditional topic modeling methods, like Latent Dirichlet Allocation (LDA) (Blei et al., 2003) or its extensions, assume that topic distributions remain static. This limits their ability to track how research areas change over time. Correlated Topic Models (Blei & Lafferty, 2007) built on LDA by allowing topic dependencies. However, they cannot adjust to change. Recent neural topic models (Dieng et al., 2020; Xu & Durrett, 2018) try to solve these problems, but they still rely on static topic representations.

Our RL model updates topic distributions dynamically. It balances exploring new topics and using known ones. This matches new progress in RL for adaptive knowledge integration. Here, RL improves topic selection as time passes, as argued in Gui et al. (2019) and Khetarpal et al. (2022). Our method differs from traditional topic models and instead of using fixed topic structures, it constantly adapts topic selection through a feedback loop. Feedback is based on changes in entropy and feedback from experts (Sundberg & Holmström, 2024).

Previous studies on technology foresight mainly used bibliometric methods and keyword clustering. These techniques offer useful insights, but they often lack adaptability. They need frequent manual intervention (Gao, 2021). We combine RL with topic modeling to automate topic refinement. This cuts down on static keyword lists and helps find new research directions, while experts can still monitor inputs.

Most studies on RL in text mining focus on sentiment analysis and dialogue generation (Kabudi et al., 2021; X. Wang et al., 2018) and some have explored its potential for technology trend detection. Our work fills this gap by demonstrating how RL can optimize topic selection based on entropy changes, similarity scores, and expert-defined rewards.

The proposed method is also easier to understand than deep learning methods like transformers and variational autoencoders. These models are great at finding features, but they act like black boxes. This makes it hard to understand why some topics become popular (Srivastava & Sutton, 2017). Our RL-based framework is transparent and includes expert-informed input and clear reward mechanisms. This keeps topic selection aligned with industry and research priorities (Sturm et al., 2021).

## Modularity and Future Applications

The expert-informed AI learning framework is modular and adaptable. It works well in many fields beyond quantum communication. For example, in retail, topic modeling can analyze customer feedback, social media, and competitor activities. This helps businesses notice changes in consumer preferences, like a growing interest in sustainable fashion. With this insight, companies can respond quickly to market shifts.

In healthcare, AI startups can use the framework to track advancements in diagnostics, personalized treatments, and drug discovery. By combining large clinical and regulatory data with expert insights, they enhance their strategies. Reinforcement learning (RL) boosts efficiency by allowing updates based on real-world feedback, leading to faster innovation.

In education, the framework supports creating curricula and improving teaching methods. It draws insights from academic literature, policy documents, and student feedback. RL personalizes learning by adjusting course content and assessments based on how students perform. These examples show how the framework fosters adaptable learning and informed decision-making across various sectors.

The case study in quantum communication illustrates the framework’s usefulness in fast-changing technological areas. With Ottawa as a telecommunications hub, companies like Nokia and Ericsson gain timely insights into QKD and quantum-safe cryptography. Topic modeling helps summarize patent and publication data, while expert feedback keeps strategies aligned. RL also helps focus resources on promising developments in secure protocols (Cavaliere et al., 2020; Manzalini, 2020).

Overall, the framework offers a scalable and cost-effective solution for small and medium enterprises (SMEs) and research institutions. It helps them manage complexity, spot emerging trends, and lower risks. By integrating topic modeling, RL, and expert knowledge, it supports agility, innovation, and long-term resilience (Bogers et al., 2018; Teece et al., 2016). Its modular design also opens pathways for future research into advanced AI methods, including deep learning, to enhance its strategic value.

## Strategic Relevance, Comparative Advantage, and Industry Applicability

This section highlights the practical value and strategic strengths of the Expert-Informed AI Learning Framework. Unlike black-box AI models like Large Language Models (LLMs), this framework provides transparency, adaptability, and alignment with specific domains. It achieves this by incorporating expert input, reinforcement learning (RL), and topic modeling. It enables structured learning, state tracking, and customization for fields, setting it apart from generic models.

The modular design allows for easy component replacement. For example, you can use BERTopic for topic modeling or apply different optimization techniques like evolutionary algorithms or multi-armed bandits. This flexibility accommodates various use cases. Moreover, expert input can be broadened through crowdsourcing, citation networks, or knowledge graphs, keeping it relevant even when expert access is limited.

The framework is beneficial across various industries. In retail, it aids in trend tracking; in healthcare, it supports diagnostics and drug discovery; in education, it promotes detection process; and in quantum communication, it helps with technology foresight and strategic planning. In the case of quantum cryptography, it successfully identifies innovation trends and enhances knowledge integration and decision-making.

Overall, the framework improves knowledge integration and supports agility in fast-changing environments. It enables organizations to respond to disruptions, seize opportunities, and minimize risks. This lays the groundwork for future research in areas like deep learning integration and intelligent feedback systems (Bogers et al., 2018; Cavaliere et al., 2020; Khetarpal et al., 2022; Manzalini, 2020; Teece et al., 2016).

## Communication of Theoretical and Practical Implications

The table below shows the main types of communication in this thesis. It covers theoretical contributions to dynamic topic modeling and practical tips for using the EILF framework. The table lists the chapters and sections that discuss these points. It also explains how the framework serves both academic and practitioner audiences.

Table 17: Thesis Sections Addressing Theoretical and Practical Implications

|  |  |  |
| --- | --- | --- |
| Communication Type | Content Summarized | Thesis Sections |
| Theoretical Implications | * The EILF advances topic‐modeling theory by integrating expert‐in‐the‐loop design with reinforcement learning. * Contribution to dynamic knowledge-integration theory and exploration-exploitation. | * Chapter 8 (Section 8.3.1. Methodological Implications): Explain how the framework refines topic‐modeling approaches (LDA, RL, expert feedback). Position EILF within dynamic knowledge‐integration theory. * Chapter 9 (Section 9.5. Comparison with Existing Literature): Contrast EILF’s conceptual advances against prior models. Highlight EILF’s novel combination of theory and practice. |
| Practical Implications | * Guidance for R&D managers, policymakers, and SMEs on implementing EILF for real‐time technology scouting. * Recommendations for tool adoption and process integration. | * Chapter 8 (Section 8.3.2. Practical Implications): Details use cases in quantum communication and telecom contexts. Advises on organizational structures needed to support continuous expert‐in‐the‐loop updates. * Chapter 9 (Section 9.4. Implications for Practice): Discusses how practitioners can leverage EILF to balance exploration and exploitation. Offers actionable steps for embedding EILF in R&D workflows. * Chapter 9 (Section 9.7. Strategic Relevance, Comparative Advantage, and Industry Applicability): Shows how EILF yields competitive advantage in fast‐changing domains. Addresses scalability and transferability to other sectors. |

# Conclusion

## Summary of Key Findings

This study presents a RL-driven approach to technology trend detection, demonstrating its effectiveness in quantum cryptography by dynamically refining topic selection and tracking emerging trends. It combines topic modeling, expert involvement, and RL to show how to combine topic modeling, expert involvement, and RL. This combination helps companies to track, refine, and rank new technology trends aligned with their adaptation ability. As a result, it enhances knowledge integration in rapid changing technology environments.

Two key hypotheses guided the study.

**H1: Combining RL, topic modeling, and expert input enhances accuracy and speed in detecting technology changes.**

The findings showed that using expert-weighted keywords in iterative RL-based learning tracked progress in Quantum Key Distribution (QKD) and post-quantum cryptography.

**H2: The system balances exploration and exploitation when selecting topics.**

The results showed that adjusting Q-values, entropy, and topic divergence helps the model improve its knowledge and also reveals new research directions.

The method was tested over two iterations, each representing a year of progress. In each, the RL agent selected, evaluated, and refined topic distributions based on set policies. The second iteration showed the strength of RL and expert input. This improved precision and allowed for real-time adaptation to new developments in quantum security. The validation process confirmed the framework’s reliability by matching its insights with patents and recent research. A key strength of this approach is its scalability and adaptability. The RL agent continuously updates topic models. This keeps research trend detection current and responsive to changes in the scientific and technological fields. The system analyzes topic divergence, cosine similarity, and entropy changes. This lets it identify important areas and forecast emerging technologies.

This RL-driven method goes beyond quantum cryptography. It can boost technology foresight in many areas like market intelligence, AI healthcare startups, education, and biotechnology. Organizations can use this framework to detect technology changes early, improve R&D spending, and guide policy choices. Future research should aim to enhance real-time adaptability, cut expert bias with self-supervised learning, and include multilingual datasets. This will widen the framework’s use. The research shows how RL can change the knowledge integration process. It offers an adaptive, scalable, and data-driven way to find trends. As industries face rapid technology changes, this model provides a more automated, efficient, and insightful way to track and analyze innovation.

## Contributions to Knowledge

This thesis offers a hybrid Expert-Informed AI Learning framework and practical applications. It provides useful tool for researchers and practitioners working in adaptive technology monitoring.

* Domain Contribution: This thesis boosts technological intelligence and improves forecasting, focusing on R&D management for new technologies.
* Hybrid Framework Development: A new AI learning framework is created. It uses topic modeling, RL, and external knowledge from conference data. This helps make adaptive, data-driven decisions.
* Use of RL in Topic Modeling: The method uses reward-based optimization with RL. This guides topic selection by relevance, novelty, and coherence, marking a key advancement in the method.
* Expert-Informed Adaptation Loop: The model includes structured proxy feedback. This lets the system keep learning and adapting to changes. It is key for handling innovation when things are uncertain.
* Practical Validation: The framework is tested with a real-world case study in quantum communication and QKD. This shows its relevance and effectiveness for organizations in fast-paced innovation settings.
* Expanding Tech Mining Literature: This study builds on traditional tech mining methods (Antons et al., 2020; Porter, 2007). It focuses on a continuous, iterative learning process instead of a one-time analysis.

## Applicability to Other Domains

While the EILF developed in this research has been applied to a case study in quantum key distribution (QKD), its architecture is designed to be domain-agnostic and transferable to other emerging and high-impact technology areas. The core components, topic modeling, RL-based optimization, and structured external input, remain consistent, allowing the method to support real-time and dynamic detection of technological signals and emerging trends. For instance, in domains such as cybersecurity, or AI governance, early identification of critical weak signals or disruptive developments is essential for both strategic planning and threat mitigation.

However, to apply the method in such contexts, several elements require domain-specific customization. First, the method needs to set the initial aspect keyword, which must represent core concepts and indicators relevant to the new field, Second, the external input sources, including real-time alerts, expert reports, conference summaries, or intelligence feeds must be identified based on the relevant field. Finally, the reward function parameters should be determined, which may prioritize novelty, urgency, or risk-level depending on the application.

Despite these adjustments, the overall RL environment remains structurally unchanged. This balance between a stable design and flexible inputs helps our framework work well. It becomes a scalable and adaptive system that can detect changes in technology and provide insights. It responds quickly to rapidly changing information.

## Limitations

This study shows how effective RL-based topic modeling can be. However, this approach also has imitations of its own:

1. Expert dependence and potential bias

Reliance on expert-defined keywords for identifying aspects adds subjectivity. This may sway topic prioritization. Expert validation helps ensure research is relevant. However, it can also reinforce old biases and make it harder to discover new trends, even when we have an automatic expert-inform inputs. Future work should investigate self-supervised learning and adaptive keyword weighting to reduce the bias. This would lessen expert input while maintaining topic accuracy.

2. Computational complexity

The RL algorithm’s performance depends on dataset size and processing power. Larger datasets need significant computational resources, making real-time adjustments tough. Also, hyperparameter tuning and Q-value updates come with costs that affect efficiency as datasets grow. Using parallel RL architectures or better reward structures may help solve these issues later.

## Future Research

To tackle these limitations, we need to reduce reliance on experts and improve computational efficiency. Expert input is key to our framework and provides context and validates relevance. But relying on one predefined expert keywords can lead to scalability and consistency issues. Future research could ease this reliance. A semi-supervised method can generate and rank candidate keywords using learned and labeled models. The aim is not to replace expert input but to support it. This will reduce cognitive load and make the framework more adaptable and scalable across various domains. Furthermore, future studies can focus on self-supervised learning, scalable RL components, and real-time data integration. This will help create a more automated, efficient, and adaptive technology foresight system.

Several key areas need further exploration:

1. Algorithmic enhancements & reducing expert bias

One limitation of the current framework is its dependence on one source of expert-defined keywords. This can introduce bias and limit scalability. To reduce bias and boost diversity, multiple expert sources can join each iteration. They can help define weighted keywords and choose relevant documents. A shared glossary of key terms as a rich source of seed words for semi-supervised topic modeling, created or checked by several experts, can improve consistency, and reduce personal bias. Also, semi-supervised learning lowers expert bias by mixing a small set of expert-labeled external reports or documents for expert input with a larger group of unlabeled data. The labeling process can be conducted by companies’ managers like CEOs. This approach helps the model generalize beyond individual opinions. These methods could reduce the need for manual input. Also, testing different reward functions can help. For example, adaptive weighting can help adjust topic selection in real time. Using Deep RL (DRL) models can boost accuracy and efficiency. They enable better decision-making in complex, high-dimensional spaces.

2. Improving scalability and real-time adaptability

Improving the RL model to handle bigger datasets with less computer power could really enhance performance. Future work should explore Parallelized RL algorithms efficiently handle high-volume, high-dimensional text data, Integrate real-time data sources like live research publications, patents, and industry reports. This helps in adapting quickly to new technology trends, and adapt the model for multiple languages, working well beyond English.

3. Practical implementation and user accessibility

Wider adoption requires making RL-driven topic modeling more accessible to non-experts:

* Create easy-to-use interfaces for researchers and industry experts. This lets them interact with and understand the system's outputs without needing a lot of RL knowledge.
* Expanding real-world validation means using long-term case studies. This applies to fields like cybersecurity, biotechnology, and artificial intelligence. This helps us check if the model works well in different industries.
* Examining ethics and interpretability in automated trend forecasting helps to make AI insights clear and useful.

Future research should, therefore, target main areas including reducing reliance on experts and enhancing usability. This will help develop a fully automated, scalable, and easy-to-understand technology foresight system.

Availability of data and materials

The data and code used in this research are publicly available on GitHub. The repository holds datasets, figures, and tables. The dataset includes CSVs such as CTP1, CTP2, CTP3, DocCTP2, DocCTP3, etc., and the code encompasses the implementation of RL algorithms for topic modeling and analysis. The repository can be accessed at the following link: [GitHub Repository: RL.](https://github.com/alinazari1/RL) If you wish to replicate or build upon this research, the repository also provides the necessary pseudocode used in the experiments.

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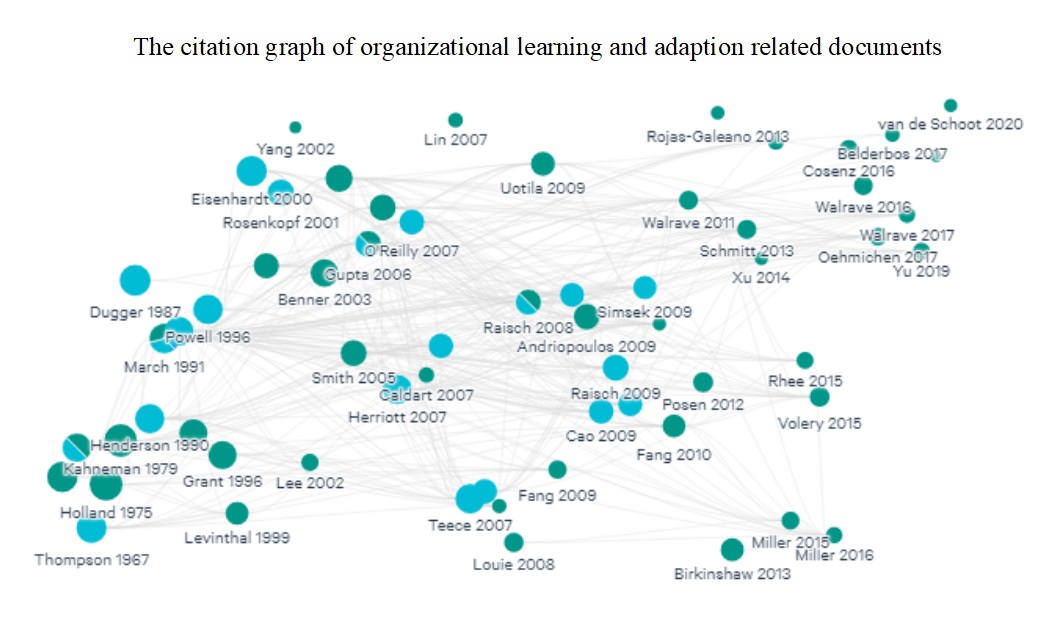
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Appendix A

Appendix A.1: This file contains the image “[ReviewRepository/Literature\_EE.jpg](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Images/Literature_EE_March1991.jpg),” a representation related to the literature review.



Appendix A.2: The image "[ReviewRepository/ReviewWordCloud.jpg](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Images/ReviewWordCloud.jpg)” provides a word cloud visualizing key terms from the literature review.

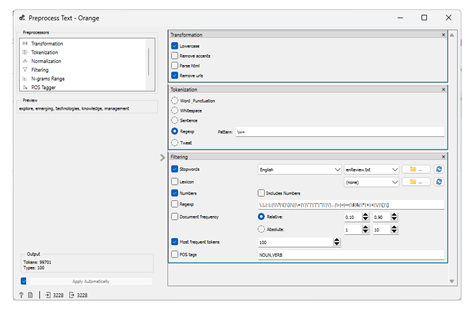
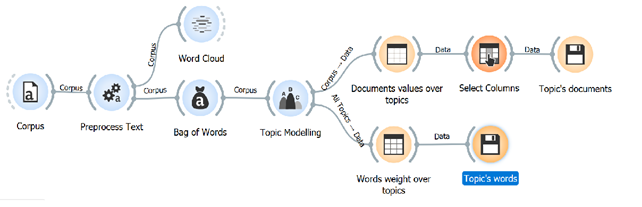


Appendix A.3: “[ReviewRepository/SourceTitle.csv](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Data/SourceTitle.csv)” is a CSV file listing the titles of sources included in the review.

Appendix A.4: “[ReviewRepository/Dataset2925.csv](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Data/Dataset2925.csv)” is a dataset file related to the research study.

Appendix A.5: “[ReviewRepository/enReview.txt](https://github.com/Exploring-Technology/ReviewRepository/blob/main/enReview.txt)” contains the text of the English-language review.

Appendix A.6: The image “[ReviewRepository/TopicModelingWorkFlow.png](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Images/TopicModelingWorkFlow.png)” outlines the workflow of the topic modeling process.

Appendix A.7: “[ReviewRepository/Document\_Topics\_values.csv](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Data/Document_Topics_values.csv)” contains data related to the document-topic values.

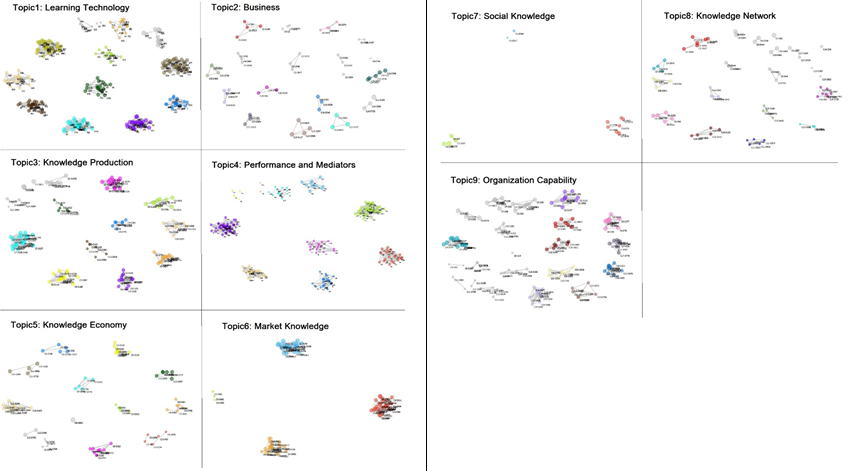
Appendix A.8: “[ReviewRepository/Words\_Topics\_values.csv](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Data/Words_Topics_values.csv)” lists words associated with topics from the analysis.

Appendix A.9: “[ReviewRepository/TopicClustersWorkflow.png](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Images/TopicClustersWorkflow.png)” illustrates the workflow of topic clustering.

Appendix A.10: “[ReviewRepository/TopicCluster.csv](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Data/TopicCluster.csv)” is a CSV file containing information about the topic clusters identified in the analysis.

Appendix A.11: “[ReviewRepository/Screening-NeuralNetworks.png](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Images/Screening-NeuralNetworks.png)” depicts the screening process for neural networks.”

Appendix A.12: “[ReviewRepository/TopicsClusters.jpg](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Images/TopicsClusters.jpg)” is an image that visualizes the topic clusters.



Appendix A.13: “[ReviewRepository/SampleData.csv](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Data/SampleData.csv)” is a CSV file containing a sample dataset.

Appendix A.14: “[ReviewRepository/ResultsInTabular.xlsx](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Data/ResultsInTabular.xlsx)” is an Excel file containing the results in a tabular format.

Appendix A.15: “[ReviewRepository/Cosine similarity Workflow.jpg](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Images/Cosine%20similarity%20Workflow.jpg)” provides a visual representation of the cosine similarity workflow.

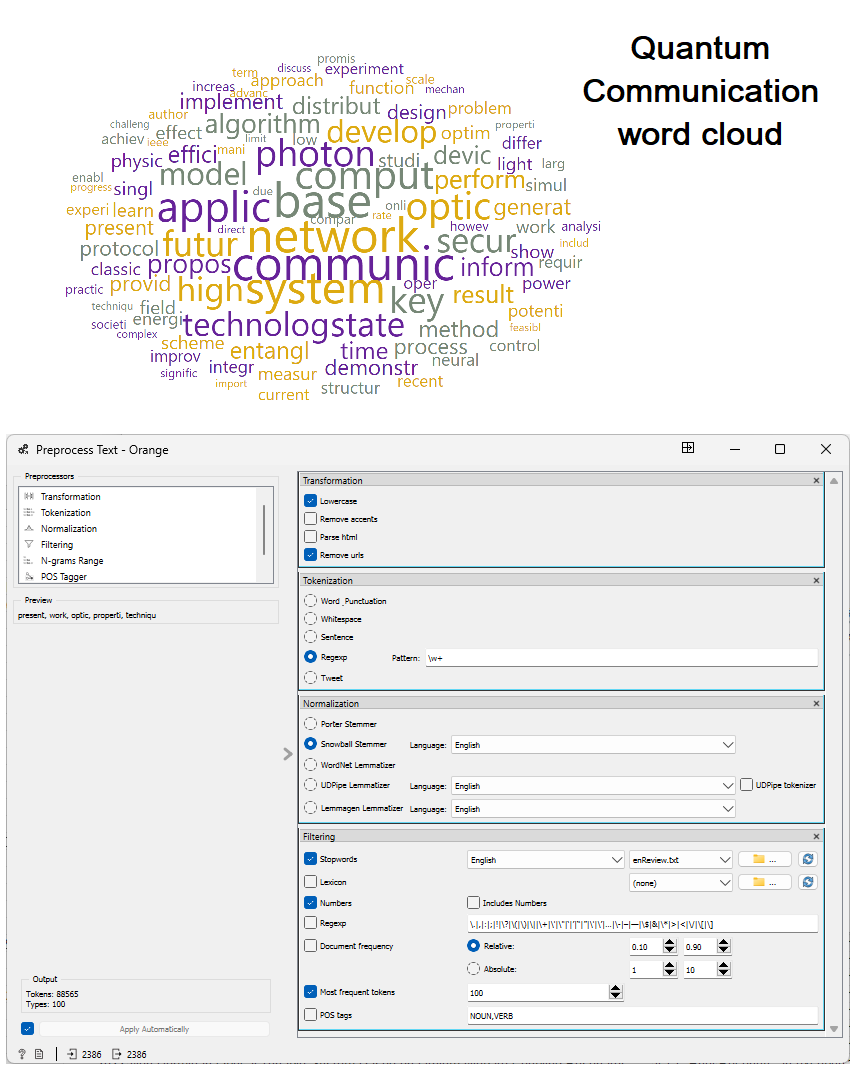


Appendix A.16: “[ReviewRepository/Data/ReviewDocuments.csv](https://github.com/Exploring-Technology/ReviewRepository/blob/main/Data/ReviewDocuments.csv)” is a dataset file containing the reviewed documents.

Appendix B

Appendix B.1: “[ProjectRepository/QuantumArticles.csv](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Data/QuantumArticles.csv)”is a CSV file containing articles related to quantum research.

Appendix B.2: “[ProjectRepository/QWordCloud.png](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Images/QWordCloud.png)” visualizes a word cloud from the quantum research articles.



Appendix B.3: “[ProjectRepository/WOSScopus2386.csv](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Data/WOSScopus2386.csv)” is a CSV file with data from the WOS and Scopus databases.

Appendix B.4: **“**[ProjectRepository/The project Journals and Conferences.csv](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Data/The%20project%20Journals%20and%20Conferences.csv) “ lists journals and conferences related to the project.

Appendix B.5: **“**[ProjectRepository/WOSCorpus\_Project\_TopicDocsOver70.csv](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Data/WOSCorpus_Project_TopicDocsOver70.csv)” contains topic documents with over 70 references from the WOS corpus.

Appendix B.6: “[ProjectRepository/ProjectSampleData.xlsx](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Data/ProjectSampleData.xlsx) “is an Excel file containing the sample data for the project.

Appendix B.7: “[CTP1&2 Similarity Matrix (first iteration)](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Results/CTP1%262.csv) “ presents the similarity matrix for CTP1 and CTP2 in the first iteration.

Appendix B.8: “[35 Test Documents (first iteration)](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Results/QCrypto23.csv) “ contains 35 test documents from the first iteration.

Appendix B.9: **“**[DocsCTP2 Similarity Matrix (first iteration)](https://github.com/Exploring-Technology/ProjectRepository/blob/main/Results/DocsCTP2.csv) “ presents the similarity matrix for CTP2 in the first iteration.

Appendix B.10: [Corpus Data](https://github.com/alinazari1/RL/blob/main/P2_Corpus.csv): A small dataset of documents published by 2022, collected from online libraries and screened for relevance.

Appendix B.11: [CTP1 - Initial Topic Model (First Iteration)](https://github.com/alinazari1/RL/blob/main/P2_CTP1.csv): This section contains the initial topic model created during the first iteration.

Appendix B.12: [Aspect’s Text and Keywords](https://github.com/alinazari1/RL/blob/main/P2_Aspects.csv): A compilation of aspect texts and their associated keywords.

Appendix B.13: [Quantum. Tech](https://www.alphaevents.com/events-quantumtechus): Details related to quantum technologies as part of the dataset.

Appendix B.14: [CTP2 - Protocol Aspect Topic Model](https://github.com/alinazari1/RL/blob/main/P2_CTP2.csv): The protocol aspect topic model generated during the analysis.

Appendix B.15: [CTP3 - Security Aspect Topic Model](https://github.com/alinazari1/RL/blob/main/P2_CTP3.csv): The security aspect topic model created as part of the analysis.

Appendix B.16: [CTP1 & CTP2 - Similarity, ADNS, and Entropy Changes](https://github.com/alinazari1/RL/blob/main/P2_CTP1%262.csv): Metrics for CTP1 and CTP2, focusing on similarity, ADNS, and entropy changes.

Appendix B.17: [CTP2 & CTP3 - Similarity, ADNS, and Entropy Changes](https://github.com/alinazari1/RL/blob/main/P2_CTP2%263.csv): Metrics for CTP2 and CTP3, focusing on similarity, ADNS, and entropy changes.

Appendix B.18: [QCrypt2023 - Conference Papers Derived Dataset (First Iteration)](https://2023.qcrypt.net/accepted-papers/): A set of documents derived from QCrypt2023 conference papers, used to calculate expected rewards in the first iteration.

Appendix B.19: [QCrypt2024 - Conference Papers Derived Dataset (Second Iteration)](https://2024.qcrypt.net/accepted-papers/): A set of documents derived from QCrypt2024 conference papers, used to calculate expected rewards in the second iteration.

Appendix B.20: [DocCTP2 - Similarity of CTP2 Topics with QCrypt2023 Documents](https://github.com/alinazari1/RL/blob/main/P2_DocCTP2.csv): Analysis of similarity between CTP2 topics and QCrypt2023 documents.

Appendix B.21: [DocCTP3 - Similarity of CTP3 Topics with QCrypt2024 Documents](https://github.com/alinazari1/RL/blob/main/P2_DocCTP3.csv): Analysis of similarity between CTP3 topics and QCrypt2024 documents.

Appendix C

Appendix C.1

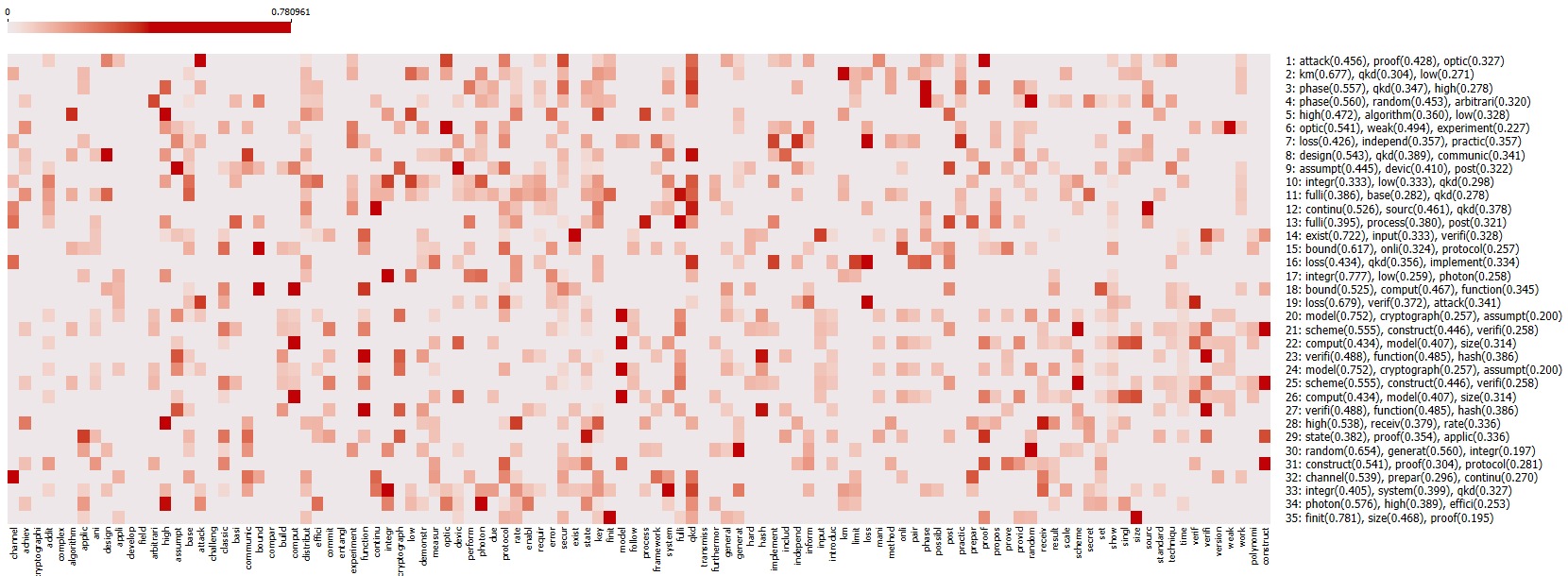


Figure 43: Keyword Distribution Heatmap of Protocol Advances in QCrypt 2023 Papers

Appendix C.2

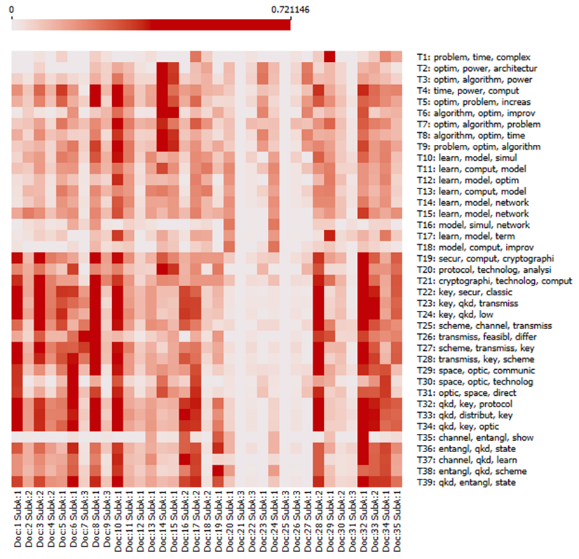


Figure 44: Mapping QCrypt2023 Papers to CTP2 Topics

Appendix C.3

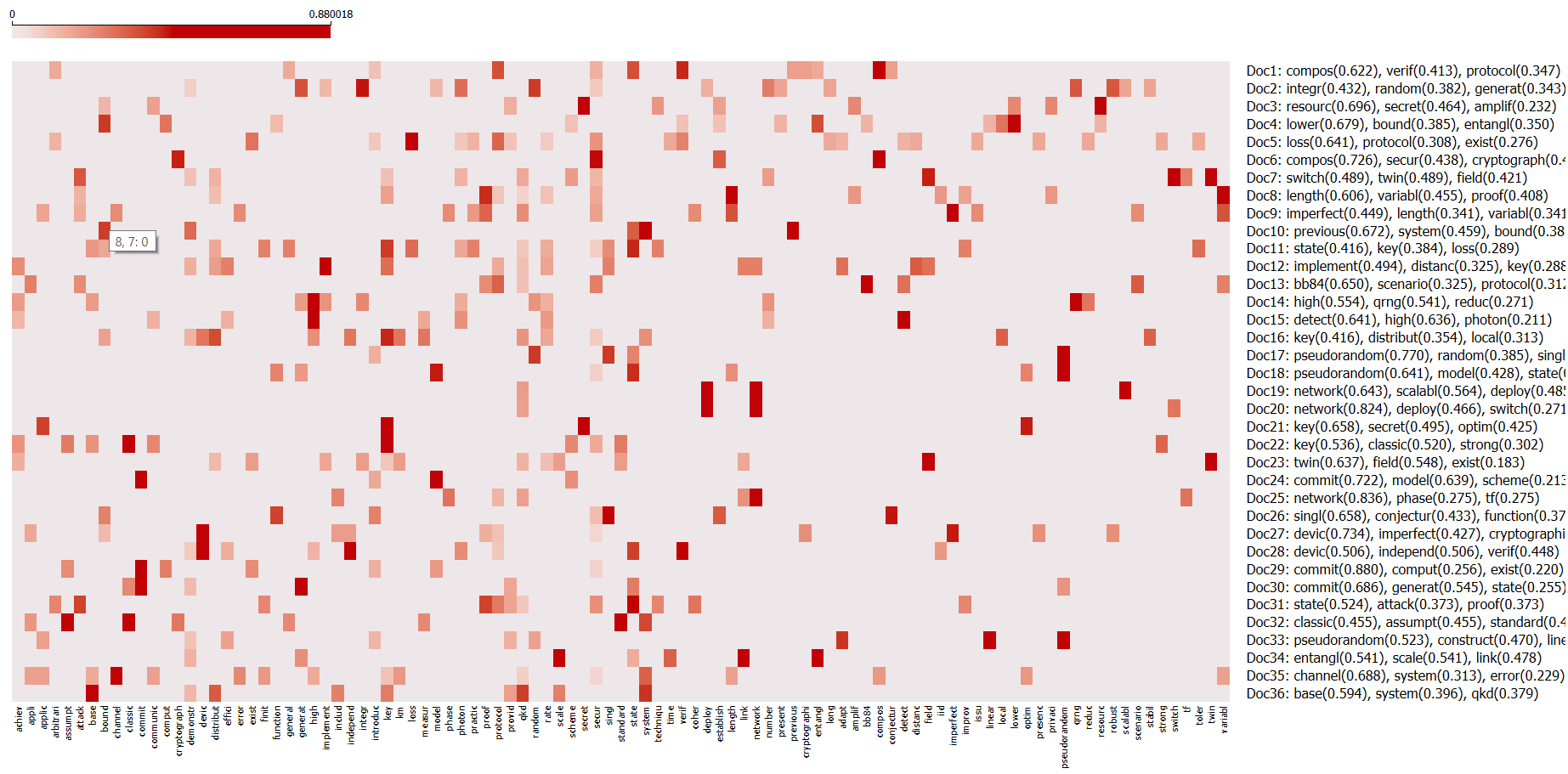


Figure 45: Keyword Heatmap of Security Protocol Advancements in QCrypt 2024 Papers

Appendix C.4

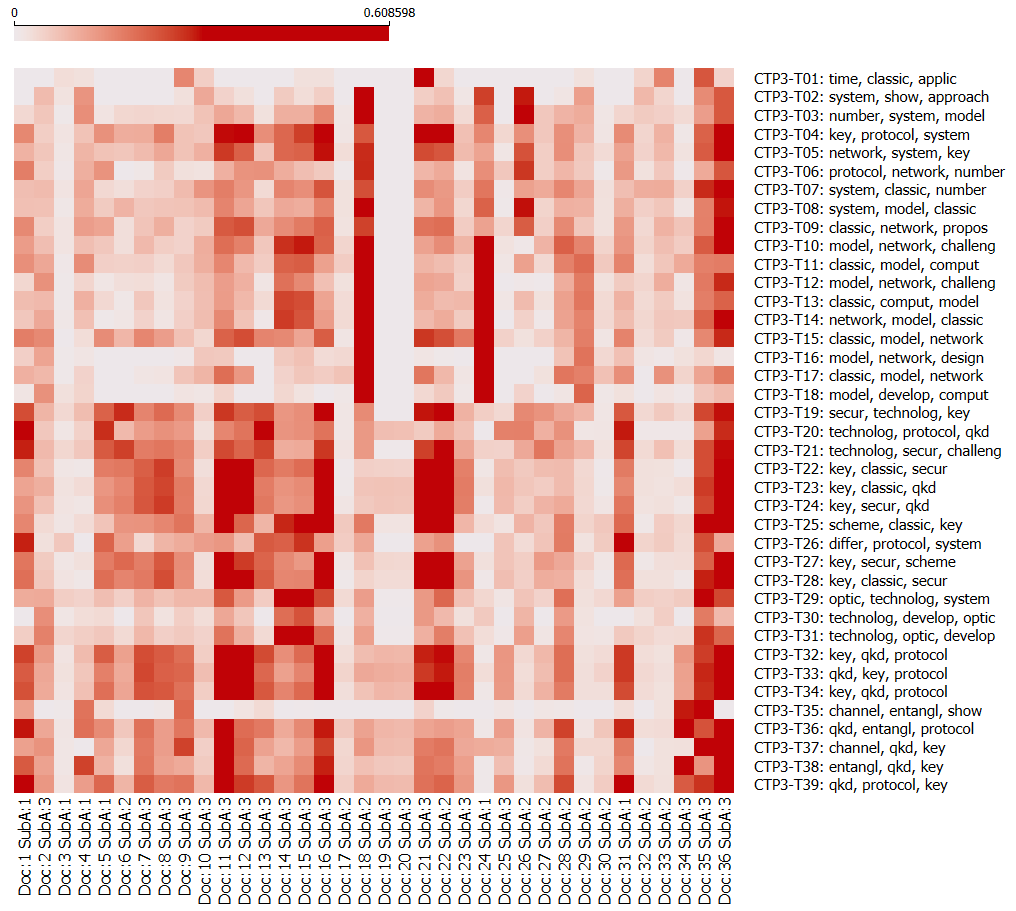


Figure 46: Mapping QCrypt2024 Papers to CTP3 Topics

Appendix C.5

Detailed Pseudocode from Table 6: The proposed overall algorithm

|  |  |  |
| --- | --- | --- |
| **Phases/Steps //Step description** | | |
| ***Phase 1: Data Collection*** |  | |
| 1: SK ← define\_search\_keywords (domain) *// Define search keywords specific to the research domain with input from domain experts.* | | |
| 2: C ← build\_corpus (SK) *// Collect documents using defined keywords, followed by text preprocessing to create a refined corpus.* | | |
| ***Phase 2: Topic Model Analysis***  *// Initial Topic Model*  3: TM ← LDA(C) *// Apply LDA to the corpus to generate the initial topic model.* | | |
| 4: CTP1 ← Initial Topic Model (TM) *// Use the generated topic model as the starting point (CTP1).*  CTP2 ← None *// only in first iteration* | | |
| *// Initial Topic Model Development and Refinement* | | |
| 5: AText ← Aspect\_Identification (Domain Expert notes) *// Identify aspect-related keywords based on expert input; in this research, we gather aspect-related keywords using this method: 1-* ***Text Collection:*** *Collect text from targeted resources like reports, conferences, or workshops. 2-* ***Preprocessing****: Clean text using tokenization, stop-word removal, and lemmatization. 3-* ***Keyword Extraction****: Apply TF-IDF to rank terms by importance within the conference corpus. 4- Keep important terms with high* ***TF-IDF scores****. Focus on the top 100 of these terms. Also, remove general terms like "algorithm" and "application."; Papers → Preprocessing → Cleaned text → TF-IDF →*{"secure protocol" (0.89), "entanglement distribution" (0.76)}*.* | | |
| 6: AT ← Weighted\_Aspect\_Keywords (AText) *// Assign weights to the keywords based on TF-IDF scores. Normalize weights to emphasize high-priority terms.* | | |
| 7: ATM ← get\_AspectTM (CTP1, AT) *// Refine the initial topic model (CTP1) by incorporating the aspect-based keywords to generate the Aspect Topic Model (ATM).* | | |
| 8: CTP2 ← ATM *// Assign the refined model as CTP2 for comparison with CTP1.* | | |
| *// RL Component: Evaluating Topic Novelty with RL*  9: current\_state ← compare\_models(CTP1, CTP2) *// Create topic similarity, divergence, entropy changes and topic absolute difference between CTP1 and CTP2 to calculate future rewards for finding suitable action.* | | |
| 10: action ← find\_topics (current\_state) *// Select an action (topic(s)) based on approximate future rewards of topics.* | | |
| 11: new\_state ← adjust\_topic\_model\_with\_new\_state (action, CTP2, new\_keywords, new\_documents)  *// Transition to a new state by incorporating new keywords and documents.* | | |
| 12: reward ← calculate\_reward(new\_state, action) *// Calculate topics reward with new related documents to validate the selected topics.* | | |
| 13: RL\_Model ← update\_RL\_model(action, reward) *// Update the RL model's policies and hyperparameters based on the calculated rewards and selected topics.* | | |
| // Analysis & Validation  14: VR ← compare\_topic\_models(CTP1, CTP2) *// Conduct heatmap analysis to compare changes and alignments in CTP1 and CTP2.* | | |
| 15: Patterns\_Novelty ← Technology\_Vision (QCrypt23 or 24 with CTP2\_Allwords) *// Analyze the selected topics and their alignment with new documents by examining their associations to uncover novel insights or patterns in the domain.* | | |
| 16: fine\_tuned\_topics = fine\_tune\_topics (CTP1&2, DocsCTP2, Patterns\_Novelty) *// Further refine topics based on insights from analysis and patterns in DocsCTP2 or DocsCTP3; evaluate the results and selection process with examine word trends and documents association with the selected topic(s) in each iteration.*  // Iteration Management & Transition | | |
| 17: CTP1 ← CTP2  18: CTP2 ← new\_state | | *// Replace CTP1 with the previous iteration’s CTP2 to prepare for the next iteration. Assign the current refined model to CTP2 for further iteration*. |
| // Iteration/Episode Control - guided by performance metrics such as F-score, precision, recall, and timeliness to refine topic models.  If (Patterns\_Novelty)  End Episode 🡪 **Final Topic Model**  Else  Proceed to Step 5 | | *// Stop the process if significant novel patterns are identified. Otherwise, continue with the iterative process by reinitiating from Step 5.* |

Appendix C.6

Table 18: Comparative Analysis of LLM-Based Tools and the Proposed Framework

|  |  |  |  |
| --- | --- | --- | --- |
| ****Feature**** | ****LLMs**** | ****Our RL-Based Method**** | ****Advantage Description**** |
| **Expert Input** | Prompt gives indirect control, but lacks structure (most use others content) | Structured expert input drives learning and refinement | Our method uses expert input to shape learning explicitly and transparently. |
| **Iteration Mechanism** | No structured memory between sessions | Each iteration builds on the last (a graph of states) | Enables cumulative improvement over time. |
| **Exploration vs. Exploitation** | Implicit, no user control (e.g., type " **unusual, creative,** and **alternative** perspectives..." hoping to get more creative responses) | Explicit ε-greedy or other strategies available (e.g., set learning rate, ε = 0.2, so 20% of the time the system explores new topic paths) | Allows fine-tuned control of discovery vs. known patterns. |
| **Exploration Boost** | "**unusual, creative,** and **alternative** perspectives … " or prompt hacks | Adjustable via parameters (e.g., ε) | Systematic, not trial-and-error prompting. |
| **Transparency** | Black-box; internal logic is hidden | Visibility into decisions (e.g., Q-values and related documents) | Clear, explainable decisions with references at the same time. |
| **Consistency** | Same prompt may yield different outputs over time | Deterministic based on policy/state (can be back to previous state and run new technology trend) | Reproducible and reliable outcomes in the topic models (states) graph. |
| **Goal Orientation** | Short-term, based on each prompt and more individual and provide general content unless somebody dig into the exploring process | Long-term reward and objective-driven (e.g., 3 month research projects) | Optimizes towards contextual strategic goals. |
| **Topic Modeling** | Emergent and unstructured | Built-in and refined over time | Topic models are aligned with organizational needs. |
| **Customization to Domain** | Requires custom fine-tuning or prompts | Integrated with expert input and rewards (expert feedback) | Out-of-the-box alignment with domain knowledge. |
| **Feedback Integration** | Weak and mostly forgotten after sessions | Real-time feedback shapes learning | Improves over time with expert reinforcement. |
| **Output Interpretability** | Outputs lack rational trace | Scored, weighted, interpretable outputs | Supports understanding and decision-making. |
| **Expert-Guided loop Role** | Passive prompt writers | Active shaper of rewards and learning path | Enables collaboration and co-design. |
| **Ease of Use** | Very easy; consumer-level interface | Slightly more complex but guided process | Simple once integrated, with domain-friendly workflow. |
| **Data Privacy & Control** | Data sent to external services | All local/in-house processing; Receiving external data | Ensures confidentiality and regulatory compliance. |
| **Data Ownership** | Controlled by the platform | Owned by team/org | Keeps strategic value internal. |
| **Collaboration & Knowledge Sharing** | No shared model or policy across users | Shared rules, rewards, and learning framework | Encourages organizational learning and alignment. |
| **Consistency Under Data Noise** | Sensitive to prompt changes or noisy inputs | Robust learning over noisy environments | Reliable even with evolving input data. |

Appendix C.7

Table 3: Correlation Between Review Questions, Sub-Questions, Clusters, and Topics

\* T?C?: Topic Number and Cluster (subtopic) Number.

\* Cluster words are stems of verbs or nouns with different forms.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Topic** | **Cluster - Top Three Words** | **Focus on** |  |  |  |  |  |  |  |  |  |  |  |  |
| **Question A. What are the most relevant concepts of knowledge integration in OL?** | | | **A1** | **A2** | **A3** | **B1** | **B2** | **B3** | **B4** | **C1** | **C2** | **C3** | **C4** | **No. of Docs** |
| Topic 1: Learning Technology | T1C1: knowledge, integr, social | Model of knowledge integration | ü | ü | ü |  |  |  |  |  |  |  |  | 1 |
| Topic 3: Knowledge Production | T3C11: industri, design, path | Product design link to competitiveness | ü |  | ü | ü |  |  |  |  |  | ü |  | 1 |
| Topic 4: Performance and Mediators | T4C8: perform, mediat, knowledge | The balance of EE influence firms' innovation | ü |  |  |  |  |  |  |  |  |  |  | 47 |
| Topic 6: Market Social Knowledge | T6C1: social, knowledge, adopt | Predict the performance of open innovation equity investment using classification techniques | ü |  |  |  |  |  |  |  |  |  |  | 22 |
| T6C2: social, learn, economi | Impact of trusting leadership on SMME marketing innovation | ü |  |  |  |  |  |  |  |  |  |  | 27 |
| Topic 7: Social Knowledge | T7C3: knowledge, intern, market | Explore the impact of external institutional pressure | ü |  |  |  |  |  |  |  |  |  |  | 4 |
| Topic 8: Knowledge Network | T8C3: network, industri, knowledge | Promote the performance of innovation with collaboration in knowledge management in industries. | ü |  | ü |  |  |  |  |  |  |  |  | 3 |
| Topic 9: Organization Capability | T9C1: theori, organiz, capabl | The impact of knowledge sources on radical and incremental innovation. | ü |  |  |  |  |  |  |  |  |  |  | 7 |
| T9C11: theori, knowledge, organ | Explore central tensions to achieve ambidexterity | ü |  | ü |  |  |  | ü |  |  |  |  | 2 |
| T9C17: organiz, organ, futur | Organization's ability in its management of today's business demands. | ü |  |  |  |  |  |  |  |  |  |  | 6 |
| T9C19: organ, organiz, integr | Identify the antecedents that facilitate structural, sequential, and contextual ambidexterity | ü |  |  |  |  |  |  |  |  |  |  | 7 |
| T9C6: knowledge, capabl, integr | Exploring different innovation capability - clustering | ü |  |  |  |  |  |  |  |  |  |  | 9 |
| **Question B. What models or frameworks have been developed?** | | | **A1** | **A2** | **A3** | **B1** | **B2** | **B3** | **B4** | **C1** | **C2** | **C3** | **C4** | **No. of Docs** |
| Topic 1: Learning Technology | T1C10: system, knowledg, technolog | Highlight concepts, mechanisms, and points of reference for actors who might wish to develop farmer innovation tracking |  |  |  | ü | ü | ü | ü |  |  |  |  | 51 |
| T1C11: learn, system, technolog | Develop a conceptual framework for extending the benefits of strategically balancing exploitation and exploration. |  |  |  | ü |  |  | ü |  |  |  | ü | 36 |
| T1C12: learn, technolog, applic | Identify the most active and influential solutions in innovation research. |  |  |  | ü |  | ü | ü |  |  |  |  | 36 |
| T1C13: technolog, applic, learn | Absorbing and assimilating tacit and disembodied knowledge of technologies via technology learning. | ü |  | ü | ü |  | ü | ü |  |  |  |  | 25 |
| T1C14: learn, technolog, system | Explore the evolutionary trajectories of technological innovation | ü |  |  | ü |  |  | ü |  |  |  |  | 51 |
| T1C2: capabl, knowledg, chang | Explore innovation capability in geographic business networks |  |  |  | ü |  | ü | ü |  |  |  |  | 3 |
| T1C3: busi, technolog, author | Explore the mechanisms underpinning open innovation success | ü |  |  |  | ü | ü | ü |  |  |  |  | 1 |
| T1C9: manag, adopt, chang | Analyze how internal-driven management innovation take shape to improve teaching and learning | ü |  |  | ü | ü | ü | ü |  |  |  |  | 11 |
| Topic 2: Business | T2C10: busi, enterpris, organ | Digital business transformation | ü |  |  | ü | ü | ü | ü |  |  |  | ü | 5 |
| T2C13: busi, process, chang | Explore the evolutionary and development of cross-boundary innovation models | ü |  |  |  |  | ü | ü |  |  |  | ü | 4 |
| T2C14: busi, industri, model | Business models in process industries | ü |  |  | ü | ü | ü | ü |  |  |  |  | 4 |
| T2C16: busi, enterpris, social | Fertile settings for innovative and entrepreneurial activities | ü |  |  | ü |  |  |  |  |  |  |  | 3 |
| T2C19: busi, enterpris, valu | Digitalization affects the evolution of business models across contexts | ü |  |  |  | ü | ü | ü |  |  |  |  | 3 |
| T2C2: enterpris, busi, social | Critically assesses Western views on the social economy | ü |  |  | ü |  |  | ü |  |  |  | ü | 3 |
| T2C3: busi, valu, system | How circular entrepreneurs engage with the institutional structures in designing business models |  |  |  | ü | ü | ü | ü |  |  |  | ü | 1 |
| T2C4: busi, market, social | Concept of sustainability and the role of social enterprise |  |  |  | ü | ü | ü | ü |  |  |  | ü | 3 |
| T2C5: busi, model, enterpris | Business model focusing on market competition | ü |  |  | ü |  |  | ü |  |  |  | ü | 2 |
| Topic 3: Knowledge Production | T3C12: industri, applic, increas | Revolutionise the application and delivery of IT using Cloud Computing | ü |  |  | ü |  |  | ü |  |  |  | ü | 6 |
| T3C13: product, industri, design | Incremental innovations |  |  |  | ü | ü |  |  |  |  |  | ü | 6 |
| T3C2: posit, resourc, knowledg | Examine the enablers and barriers influencing international knowledge transfer | ü |  |  |  |  | ü |  |  |  |  |  | 6 |
| T3C5: product, technolog, market | Application of tacit knowledge | ü |  |  | ü | ü | ü | ü |  |  | ü |  | 13 |
| Topic 4: Performance and Mediators | T4C1: innov, impact, mediat | Investigating key factors such as employees' knowledge sharing, innovation passion, absorptive capacity and risk-taking behaviour on workplace innovation | ü |  |  | ü |  |  | ü |  |  | ü |  | 11 |
| T4C9: perform, mediat, organiz | Examine the role of intermediate knowledge mechanisms |  |  |  |  | ü | ü | ü |  |  | ü | ü | 22 |
| Topic 5: Economic Knowledge Development | T5C10: compani, economi, strategi | Managerial ties impact firm business model innovation |  |  |  |  | ü |  | ü |  |  |  | ü | 10 |
| T5C12: compani, busi, technolog | Seek new opportunities outside their traditional technology domain | ü |  |  |  |  | ü | ü |  |  | ü |  | 2 |
| T5C13: compani, economi, product | Globalization, competitiveness, and the knowledge-based economy |  |  |  | ü | ü |  |  |  | ü |  |  | 6 |
| T5C2: economi, compani, resourc | Digital innovation in platform ecosystems |  |  |  |  |  | ü |  |  |  |  |  | 5 |
| T5C3: economi, emerg, capabl | Financial inclusion and socioeconomic development | ü |  | ü | ü | ü | ü | ü |  |  |  | ü | 5 |
| T5C6: compani, busi, organ | Some aspects of innovation | ü |  |  | ü |  | ü | ü |  |  |  | ü | 8 |
| T5C9: busi, compani, exist | Digital innovation and circular business model innovation |  |  |  | ü | ü |  | ü |  |  | ü | ü | 5 |
| Topic 6: Market Social Knowledge | T6C3: social, context, understand | Social entrepreneurship | ü |  | ü | ü |  |  | ü |  |  |  | ü | 3 |
| Topic 7: Social Knowledge | T7C1: design, inform, market | Tacit knowledge in embedded in the marketplace |  |  |  | ü |  |  |  |  |  |  |  | 2 |
| T7C2: knowledg, inform, theori | Communities of social entrepreneurs | ü |  | ü | ü |  |  | ü |  |  |  |  | 7 |
| Topic 8: Knowledge Network | T8C10: network, enterpris, case | Ambidexterity in the management of policy networks |  |  |  | ü | ü | ü | ü |  |  |  |  | 2 |
| T8C19: network, inform, valu | Dynamic comparative analysis of interorganizational innovation networks |  |  |  |  | ü | ü | ü |  |  | ü | ü | 4 |
| T8C20: network, organ, system | Exploring the role of gatekeepers in innovation networks and their ability to overcome cognitive |  |  | ü |  |  | ü | ü |  |  |  | ü | 2 |
| T8C7: network, social, knowledg | Interrogation of tacit knowledge | ü |  |  | ü | ü | ü | ü |  |  |  |  | 5 |
| T8C8: network, knowledg, applic | Explore effects of open innovation and big data analytics on reflective knowledge exchange | ü |  |  | ü | ü |  | ü |  |  |  |  | 1 |
| Topic 9: Organization Capability | T9C10: organiz, organ, capabl | The classic trade-off between exploration and exploitation |  |  |  |  | ü | ü | ü |  | ü |  | ü | 3 |
| T9C14: organ, capabl, process | Examine the influence of entrepreneurial leadership on innovations of firms |  |  |  |  |  | ü | ü |  |  |  | ü | 7 |
| T9C15: organiz, path, influenc | Explore pivotal roles in the innovation process | ü |  |  | ü | ü | ü | ü |  |  |  | ü | 10 |
| T9C16: capabl, organ, process | Explore IT managers perceptions |  |  |  |  |  | ü | ü |  |  |  | ü | 6 |
| T9C18: organ, organiz, knowledg | Examine organizational learning types | ü |  |  | ü |  |  | ü |  |  |  |  | 8 |
| T9C20: integr, organ, knowledg | Learning to innovate in new ways | ü |  |  |  |  | ü | ü |  |  |  |  | 10 |
| T9C4: organ, organiz, literatur | Emerging markets | ü |  |  | ü | ü | ü | ü |  |  |  |  | 12 |
| T9C9: path, relat, organ | Career paths affect innovation capacity | ü |  |  | ü | ü |  |  |  |  |  |  | 2 |
| **Question C. What models have used dynamic machine/ RL techniques?** | | | **A1** | **A2** | **A3** | **B1** | **B2** | **B3** | **B4** | **C1** | **C2** | **C3** | **C4** | **No. of Docs** |
| Topic 1: Learning Technology | T1C4: learn, strategi, import | Emerging market firms' innovation strategy | ü |  |  | ü |  |  | ü |  |  | ü | ü | 3 |
| T1C5: learn, perform, manag | Uncover the mediating mechanisms in employees' digital creativity | ü |  |  |  |  |  |  |  |  | ü |  | 4 |
| T1C6: learn, system, applic | Overview of financial econometrics, mathematics, statistics, and machine learning |  |  |  |  |  |  |  | ü |  |  |  | 2 |
| T1C7: system, learn, technolog | Emerging toolsets of machine learning |  |  |  | ü |  |  | ü |  |  | ü | ü | 10 |
| T1C8: learn, applic, technolog | Exploration vs. exploitation dilemma | ü |  |  | ü |  |  |  |  | ü | ü |  | 29 |
| Topic 2: Business | T2C1: busi, resourc, differ | Explore entrepreneurship and success factors to drive business to resilience and stability and achieve competitive advantage | ü |  |  |  |  |  | ü |  |  |  | ü | 4 |
| T2C11: busi, technolog, factor | Cooperation factor for business innovation | ü |  |  |  |  |  |  |  |  |  | ü | 1 |
| T2C12: busi, process, author | Explore the role of the digitalization phenomenon in the development of innovative business models |  |  |  |  |  |  | ü |  |  |  | ü | 3 |
| T2C15: enterpris, busi, model | Emerging technology for digital capabilities |  |  |  |  |  |  |  |  |  |  | ü | 4 |
| T2C17: busi, enterpris, network | Business model innovation to obtain competitive advantages |  |  |  |  |  |  |  |  |  |  | ü | 4 |
| T2C18: busi, market, model | Explore the emergence of business model for digital innovation projects |  |  |  |  |  |  |  |  |  |  | ü | 2 |
| T2C6: busi, market, intern | International business models |  |  |  |  |  |  |  |  |  |  | ü | 4 |
| T2C7: busi, enterpris, capabl | Create and capture value | ü |  |  |  |  |  |  |  |  |  | ü | 3 |
| T2C8: social, enterpris, role | The role of enterprise in social innovation |  |  |  |  |  |  |  |  |  |  | ü | 1 |
| T2C9: busi, learn, enterpris | Transforming business intelligence |  |  |  |  |  |  |  |  |  |  | ü | 2 |
| Topic 3: Knowledge Production | T3C1: product, social, market | Explore the interplay of corporate social responsibility |  |  |  |  |  |  | ü |  |  |  | ü | 3 |
| T3C10: product, industri, technolog | Cluster-based technological innovation | ü |  |  |  |  |  | ü |  |  |  | ü | 9 |
| T3C14: product, industri, howev | AI-based models to understand and transparent the most sought-after innovations |  |  |  |  |  |  |  |  | ü |  |  | 5 |
| T3C3: product, knowledg, develop | Assessing service and signaling competences in manufacturing firms' productivity | ü |  |  |  |  |  | ü |  |  | ü | ü | 9 |
| T3C4: product, industri, enterpris | Enhance exploratory innovation outcomes through business partner management | ü |  |  |  |  |  |  |  |  | ü | ü | 12 |
| T3C6: product, market, perform | Examine economy through social ties, innovation behavior | ü |  |  |  | ü |  |  |  |  |  | ü | 14 |
| T3C7: product, perform, knowledg | Examine the relationship between the attributes of market knowledge and particular types of innovation | ü |  |  |  |  |  |  |  |  |  | ü | 21 |
| T3C8: product, industri, market | Examine the role of market power in driving innovation and productivity | ü |  |  |  | ü |  | ü |  |  | ü | ü | 12 |
| T3C9: product, market, relationship | Exploring the linkages between organisational ambidexterity and Human Resource Management | ü |  |  |  |  |  |  |  |  | ü |  | 7 |
| Topic 4: Performance and Mediators | T4C10: perform, mediat, knowledg | Effect of performance-based rewards on radical innovations | ü |  |  |  |  |  |  |  |  | ü | ü | 28 |
| T4C2: perform, capabl, mediat | Understanding the factors to advance green |  |  |  |  |  |  |  |  |  | ü | ü | 23 |
| T4C3: mediat, perform, relationship | Exploring the link between open innovation, customer knowledge management and radical innovation |  |  |  |  |  |  |  |  |  | ü | ü | 42 |
| T4C4: organiz, perform, effect | The dimensions of organizational culture and organizational performance | ü |  |  |  |  |  |  |  |  | ü | ü | 2 |
| T4C5: mediat, perform, exist | Balancing exploitation and exploration to achieve sustainable success |  |  |  | ü |  |  | ü |  |  | ü | ü | 4 |
| T4C6: organiz, perform, mediat | Innovation trajectories to achieve and sustain competitive advantage |  |  |  |  |  |  |  |  |  | ü | ü | 16 |
| T4C7: perform, organiz, posit | Explore the linkage between organizational boundary flexibility and innovation performance | ü |  |  |  | ü |  | ü |  |  | ü | ü | 13 |
| Topic 5: Economic Knowledge Development | T5C1: economi, compani, knowledg | Knowledge sharing for successful collaboration between companies and external communities. |  |  |  |  |  |  |  |  |  |  | ü | 4 |
| T5C11: compani, innov, organ | Company resilience as new knowledge and human capital |  |  |  |  |  |  |  |  |  |  | ü | 4 |
| T5C4: economi, compani, busi | Ambidextrous leadership factor in the success of emerging market firms' venturing into advanced economies |  |  |  |  |  |  |  |  |  |  | ü | 6 |
| T5C5: compani, context, market | The linkages between disruptive innovation and sustainable entrepreneurship |  |  |  |  |  |  |  |  |  |  | ü | 8 |
| T5C7: economi, compani, industri | Systematically develop and sustain profitable innovation pipelines |  |  |  | ü |  |  |  |  |  |  | ü | 5 |
| T5C8: compani, enterpris, innov | Undeniable and strategic element for competitiveness | ü |  |  |  |  |  | ü |  |  |  | ü | 1 |
| Topic 6: Market Social Knowledge | T6C4: social, market, busi | Investigation of organising of social innovation with the perspective of dynamic capabilities and social transformation. | ü |  |  | ü |  |  | ü |  |  | ü | ü | 23 |
| Topic 8: Knowledge Network | T8C1: network, social, knowledg | Enhancing the adoption of social networking tools to increase knowledge sharing practices |  |  | ü |  |  |  |  |  |  | ü |  | 3 |
| T8C11: network, valu, product | Explore challenges for digital innovation |  |  |  | ü |  |  | ü |  |  | ü | ü | 2 |
| T8C12: network, knowledg, organ | Innovation is the driving force of human progress |  |  |  |  |  |  |  |  |  |  | ü | 5 |
| T8C13: network, industri, knowledg | Organizations' network capital |  |  |  |  |  |  |  |  |  |  | ü | 4 |
| T8C14: network, indic, relationship | Intra-firm employee network dynamics and their consequences for firm exploratory innovation |  |  |  |  |  |  |  |  |  | ü | ü | 1 |
| T8C15: network, technolog, intern | Growth in Global trade volume and the strongest development potential |  |  |  |  |  |  |  |  |  |  |  | 1 |
| T8C16: network, knowledg, perform | The formation and evolution mechanism of technological innovation network |  |  |  |  | ü |  |  | ü |  | ü |  | 4 |
| T8C17: network, knowledg, organ | Explore the effects of collaboration network on innovation in nanotechnology. |  |  | ü |  |  |  |  |  | ü |  |  | 4 |
| T8C18: network, organiz, adopt | Explore the relationship between network role, territorial location and the adoption of transgressive styles |  |  |  |  |  |  |  |  |  | ü | ü | 3 |
| T8C2: network, industri, resourc | Effective way to promote industrial innovation |  |  |  |  |  |  |  |  |  | ü | ü | 3 |
| T8C21: network, learn, valu | Collective reputation cognition as enterprise's perception of the general rules of reputation evaluation |  |  |  |  |  |  |  |  |  | ü | ü | 5 |
| T8C22: intern, network, learn | Network searching and motivation for learning |  |  |  |  |  |  |  | ü |  |  |  | 1 |
| T8C23: network, enterpris, perform | Growth of enterprises with knowledge co-creation |  |  |  |  |  |  |  |  |  |  | ü | 4 |
| T8C4: network, key, knowledg | Green finance and the intensity of environmental regulation |  |  |  |  |  |  |  |  |  |  | ü | 3 |
| T8C5: network, intern, social | Knowledge diffusion in online courses |  |  |  |  |  |  |  |  |  | ü | ü | 4 |
| T8C6: network, product, organ | Understand existing and emerging innovation networks |  |  |  | ü | ü |  | ü | ü | ü |  | ü | 1 |
| T8C9: network, resourc, enterpris | Explore the resource development process |  |  |  |  |  |  |  |  |  |  | ü | 2 |
| Topic 9: Organization Capability | T9C12: capabl, process, role | Organisation's e-learning in the development of dynamic capabilities. |  |  |  |  |  |  |  |  |  | ü | ü | 4 |
| T9C13: capabl, learn, organ | Exploration of new possibilities and the exploitation of old certainties in organizational learning |  |  |  |  |  |  |  |  |  | ü | ü | 6 |
| T9C2: capabl, knowledg, resourc | Knowledge governance mechanisms relevant for innovation | ü |  |  |  |  |  |  |  |  |  | ü | 10 |
| T9C21: organ, chang, capabl | The dynamic capabilities in uncertain environments |  |  |  |  |  |  |  |  |  | ü | ü | 7 |
| T9C3: capabl, level, differ | Explore the differences in transformational leadership's influences on each aspect of innovation capability |  |  |  |  |  |  | ü |  |  |  | ü | 7 |
| T9C5: knowledg, organiz, manag | Assess the role of a collaborative culture in the organization's knowledge management process | ü |  |  |  |  |  |  |  |  |  | ü | 4 |
| T9C7: capabl, knowledg, role | Explore the influence of transformational leadership on innovation capability | ü |  |  |  |  |  |  |  |  | ü | ü | 7 |
| T9C8: learn, organiz, organ | Organizational learning with forgetting |  |  |  |  |  |  |  |  | ü | ü | ü | 1 |
| **9** | **121** |  | **60** | **1** | **11** | **41** | **28** | **29** | **55** | **4** | **7** | **36** | **74** | **1010** |

1. [Q-learning Topic Selection for Topic Modeling Script](https://github.com/alinazari1/RL/blob/main/README.md) [↑](#footnote-ref-1)
2. [Q-values in DocCTP2](https://github.com/alinazari1/RL/blob/main/P2_DocCTP2.csv) [↑](#footnote-ref-2)