PADERBORN UNIVERSITY

Draft

The Responsible AI Literacy (RAIL) Competency Model for Researchers

(Validation Version 0.9)

Stephan Drechsler

February 2026

Disclaimer for the RAIL Competency Model for Researchers

Current Status: Validation Phase (Pre-Publication)

This document presents the current draft of the **RAIL Competency Model for Researchers**. Please note that this model is currently undergoing formal validation (e.g., via Nominal Group Technique (NGT)) as part of my ongoing doctoral project. The results and the finalized framework have not yet been published in a peer-reviewed dissertation.

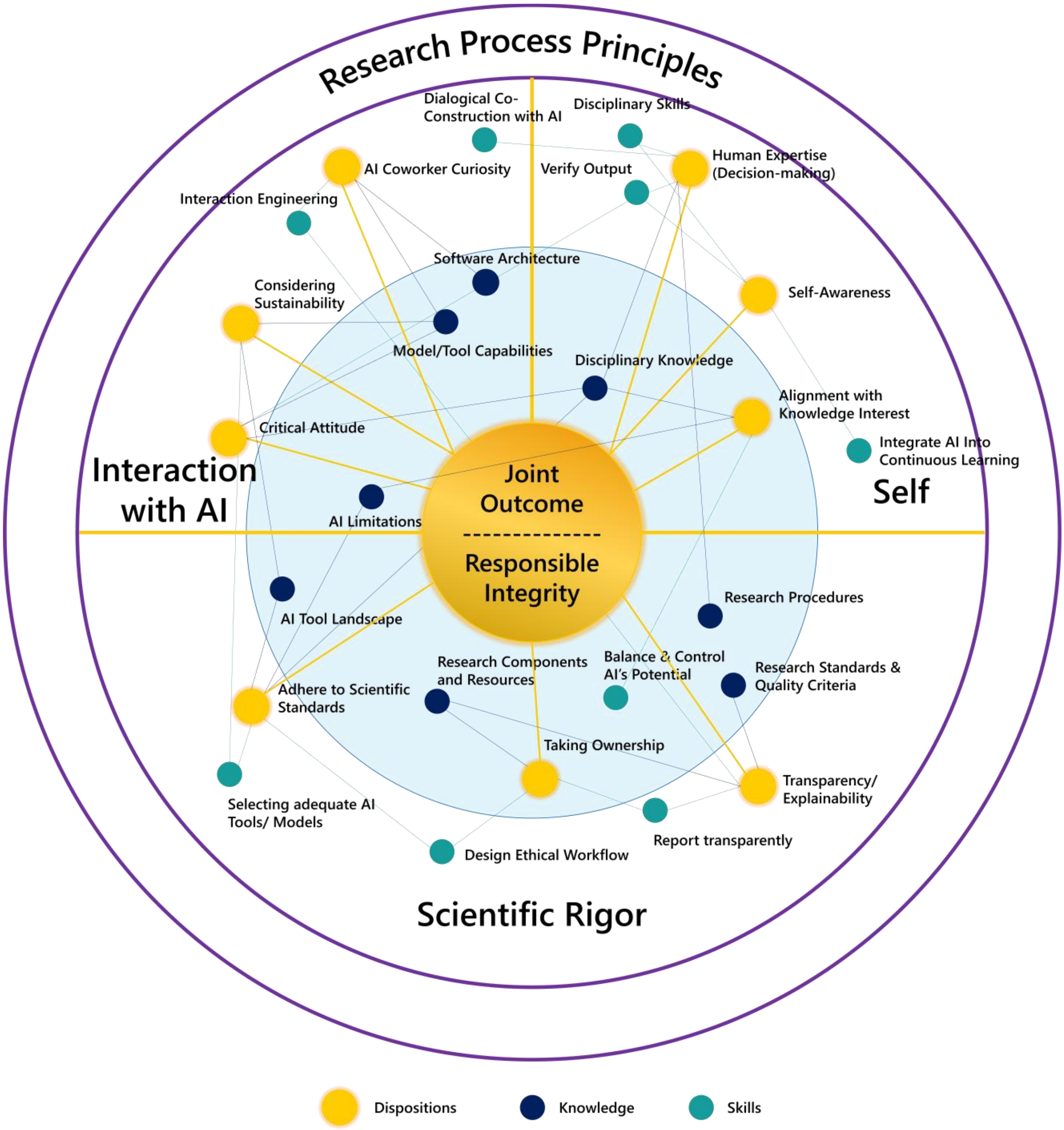
Note for Validation Experts: While the general public is subject to the 'No Derivatives' (ND) restriction of the CC BY-ND 4.0 license, registered validation experts are expressly permitted and encouraged to propose modifications, deletions, or additions to the model within the scope of the NGT sessions. To register as a validation expert, see the **Invitation: Expert NGT Session to Validate RAIL Researcher Model.**

Future Release Notice: The author is committed to Open Science principles. Upon successful completion of the validation phase and the official publication of the dissertation, the finalized version of the RAIL Researcher Competency Model will be re-released under a more permissive **Creative Commons Attribution 4.0 International (CC BY 4.0)** license to encourage widespread adoption and adaptation within the research community.

Contact & Feedback: If you are interested in using this model for research purposes or wish to provide feedback, please contact: *Stephan Drechsler, Paderborn University, Germany; stephan.drechsler@upb.de*

If you refer to this model in your work, please use the following citation format:

Drechsler, S. (2026). *The Responsible AI Literacy (RAIL) Competency Model for Researchers – (Validation Version 0.9)*. Paderborn University, Germany. https://doi.org/10.17619/UNIPB/1-2504


Research Process Principles
Dialogical Co-Construction with AI
Disciplinary Skills
AI Coworker Curiosity
Verify Output
Human Expertise (Decision-making)
Interaction Engineering
Software Architecture
Self-Awareness
Considering Sustainability
Model/Tool Capabilities
Disciplinary Knowledge
Alignment with Knowledge Interest
Critical Attitude
Integrate AI Into Continuous Learning
Interaction with AI
Joint Outcome
Responsible Integrity
Self
AI Limitations
Research Procedures
AI Tool Landscape
Research Components and Resources
Balance & Control AI's Potential
Research Standards & Quality Criteria
Adhere to Scientific Standards
Taking Ownership
Transparency/ Explainability
Selecting adequate AI Tools/ Models
Report transparently
Design Ethical Workflow
Scientific Rigor
Dispositions
Knowledge
Skills

Contents

Introduction

Why this competency model? "As AI continues to evolve, it promises to augment human creativity and ingenuity in unprecedented ways, fostering a new era of scientific innovation." (Padakanti et al., 2024, p.417), and I agree. However, recent developments in academia have led to a decline in academic integrity, as researchers have not been transparent about their use of AI in research (Kwon, 2025). One reason is that they fear their use of AI will not be accepted by fellow researchers, who may question their results. For further insights into this phenomenon, consult, for example, BaHammam (2025). Consistent with this, recent research indicates a need for researcher training in the use of (Gen)AI (Andersen et al., 2024). Frontiers Media (2025) also highlights that the lack of AI literacy fuels hesitancy and inconsistent use of AI in research, representing a training gap that is crucial for reviewers in the peer-review process. Moreover, they emphasize a trust gap, with 71% of researchers concerned about AI misuse by researchers and 45% concerned about misuse by publishers (Frontiers Media, 2025).

The Responsible AI Literacy (RAIL) competency model for researchers aims to contribute to the ethical development of AI4Science. The responsibility and integrity gap that the incorporation of AI into the research process leaves behind appears to cause tremendous harm to research integrity, undermining validity, reproducibility, and reliability.
Although the RAIL model was developed independently and not as an extension of existing frameworks like the European Competence Framework for Researchers (ResearchComp) or the living guidelines on the responsible use of generative AI in research, it can be meaningfully contextualized within both. The ResearchComp framework outlines broad researcher competencies, including cognitive abilities, ethical conduct, research management, and responsible data handling (European Commission, 2023), while the European Commission's living guidelines provide actionable recommendations to support the transparent and responsible use of generative AI in research (European Commission, 2025).
The RAIL model contributes to this landscape by offering a competency structure that integrates AI-related knowledge, skills, and responsible integrity dispositions grounded in theory and empirical evidence. In doing so, it does not claim lineage from this existing European ecosystem of research integrity and AI-responsibility initiatives but complements them conceptually: it operationalizes principles such as research integrity, transparency, and human-in-the-loop decision-making in AI-supported workflows, thereby helping researchers enact the expectations expressed in the framework and guidelines without being explicitly designed to extend them formally. Therefore, any alignment with the European framework or the guidelines should be understood as a contextual mapping rather than a direct derivation.
The RAIL researcher model is grounded in theory and empirical evidence. The empirical data stems from a document analysis of 52 scientific publications from 2020 to 2025, including papers and presentations, following PRISMA 2020 guidelines (Page et al., 2021). These publications serve as multi-perspective lenses on RAIL competencies, offering diverse insights through varied methodologies, disciplines, and research foci. Using Qualitative Content Analysis (QCA), I manually coded the documents in MAXQDA 24 for the research process steps, (explicit) knowledge, skills (abilities), responsible integrity dispositions, and AI literacy dimensions. Moreover, I employed co-occurrence analysis to identify the RAIL competencies. The latter method highlights connections between codes by analyzing the frequency with which competency dimensions and research tasks co-occur. This allowed me to map the structural dynamics of RAIL competencies (knowledge, skills, and responsible integrity dispositions) within research tasks. Hence, the RAIL model defines competency as

$$competency = \{knowledge, skills, responsible\ integrity(disposition)\}\ in\ a\ task(research\ process).$$

A similar definition of competency, with slightly different notation, appears in the Cc2020 Task Force (2020, p. 54). The three fundamental elements of competency are defined as:

- *Explicit knowledge* is defined as the declarative, factual, or conceptual information that a researcher can articulate, such as understanding how a specific AI model operates or the requirements for data quality in AI applications. Evidence of explicit knowledge appeared in the form of explanations, rationales, or definitions provided by the researchers when describing their approach.
- *Skills* refer to an individual's observable ability to perform specific tasks related to AI in the research process. This includes deploying an AI tool, validating outputs, troubleshooting errors, and integrating AI results into larger workflows. Skills are evidenced by descriptions of actions taken, procedures followed, or technical problems solved.

- *Responsible Integrity Dispositions* are stable tendencies to act with, for example, honesty, accountability, and fairness. For instance, a stance toward transparency that influences how researchers approach ethical AI use, reporting, or decision-making in the research process. Indications may include statements about ethical considerations, caution, transparency, or acknowledgment of limitations when research actions were taken.

The qualitative content analysis began with deductive categories, such as research steps, knowledge, and skills, within the workplace environment framework, considering the subject areas of AI literacy identified by Pinski and Benlian (2024). Inductive categories were derived from these deductive categories, and responsible integrity dispositions were inferred, using Bayesian reasoning, from the co-occurrence of knowledge and skills within a research task, contextualized by the main ethical principles defined by Cuschieri (2022). In this approach, theoretical insights from existing literature were established as prior beliefs. Throughout the coding process, the identified indicators of knowledge and skills were evaluated based on their evidentiary weight (likelihood). By adopting this Bayesian approach, the analysis provides a transparent and rigorous justification for inferring the underlying latent construct from observable textual indicators.[1]
The competencies are represented as hypergraphs, in which each competency element is treated as a node. The connections of all relevant competency elements are called hyperedges. To enhance interdisciplinary connectivity in STEM research, a mathematical description of this competency is provided in the closing remarks.[2]

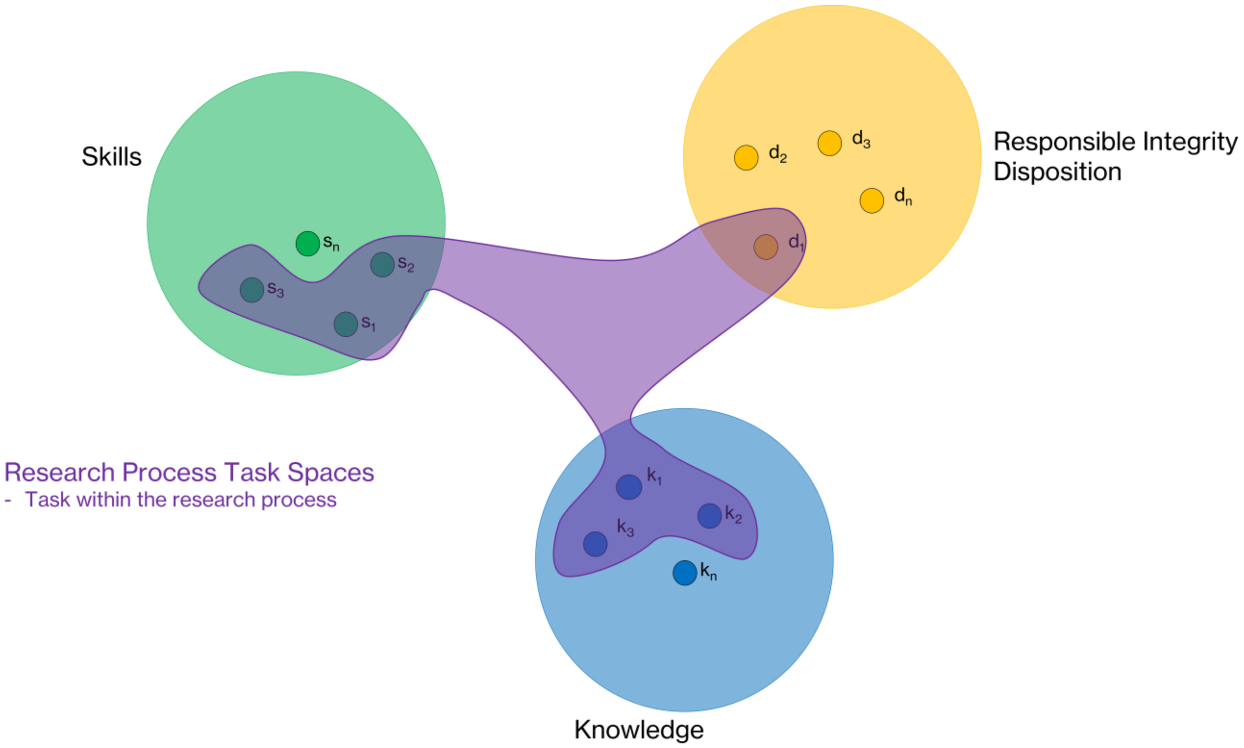


Figure 1: Exemplarity RAIL Competency Hypergraph

[1] Since dispositions are not directly observable, the identified responsible integrity dispositions are inferred from the actions (where knowledge and skills have been applied) using Bayesian reasoning. For more information on how to apply Bayesian Inference in social inquiry, please consult Fairfield and Charman (2022), e.g., pages 507-550 on test strength.

[2] Mathematical notation and technical terminology were refined using Gemini 3 Pro; The chapter was subsequently audited and verified for accuracy by a qualified mathematician.

For example, Figure 1 depicts a responsible integrity disposition (d_1) that, together with three skill nodes (s1, s2, s3) and three knowledge nodes (k1, k2, k3), constitutes the Exemplarity RAIL Competency Hypergraph for a task within the research process (purple area). The nodes have been abstracted into disjoint sets of knowledge, skills, and responsible integrity dispositions from the codes identified in the qualitative content analysis and its inference.
The most essential hypergraphs are illustrated on the title page, with centrality exceeding 5 percent, but without illustrating the purple hyperedge that links all necessary knowledge, skills, and dispositions for a task space. The hierarchy of hypergraphs was determined by the centrality of the responsible integrity disposition, which is postulated to serve as a moral compass guiding the application of knowledge and skills in action. Each hypergraph includes only hyperedges whose hypernodes exceed a modified z-score > 0, depending on the number of co-occurrences with the corresponding responsible integrity disposition and the total number of hypernodes in the hypergraph.

- $\mathrm{mzi} > 2$: primary hub,
- $0 < \mathrm{mz}_i < 2$: secondary core,
- $mz_i < 0$: statistical noise

The modified z-score (mz_i) is calculated using the following formula:

$$mz_i = \frac{0.6745 \times (x_i - \tilde{x})}{MAD}$$

Where:

- x_i is the hypernode for which the modified z-score will be calculated,
- $\tilde{x}$ is the median, and
- MAD is the median absolute deviation value, i.e. $MAD = \{|x_i - \tilde{x}|\}$.

Furthermore, the model contextualizes these competencies within the subject areas of AI literacy, as in Pinski & Benlian (2024). The competency statements presented on the following pages are formulated using the internationally recognized Action-Content-Purpose scheme.[3] For more information, consult, for example, the European handbook “Defining, writing, and applying learning outcomes” (Cedefop, 2017). In the following table, it is shown how the competency dimensions of the RAIL model relate to the competency formulation scheme:

Scheme Component	Description	RAIL Dimension
Action	This describes the specific, observable action expected of the researcher to integrate AI into research without compromising research integrity.	Here, the responsible integrity disposition serves as an allocator for a verb that reflects integrity-related actions in the research process, drawing on the set of knowledge- and skill-nodes identified in the document analysis.
Content	The Content specifies the subject matter, tools, theories, or specific knowledge and skills necessary to integrate AI into research without compromising research	Here, the identified categories of knowledge and skills constitute the content the researcher must acquire to

[3] This scheme corresponds to the German WAS-WOMIT-WOZU scheme of formulating learning outcomes (Reis, 2014; Wunderlich & Szczyrba, 2016).

	integrity, including which competency elements must be synthesized for the task.	integrate AI responsibly into specific research steps.
Purpose or Context	This describes the specific conditions, environment, or situation in which the action occurs. It provides the "where" or "for what" by defining the research context in which the competency is relevant, and stating with aspect of research integrity must be ensured by the researcher.	Here, the responsible integrity disposition, together with the research process task, contextualizes the action within the realm of research integrity.

RAIL Competencies

Human Expertise (Decision-Making)

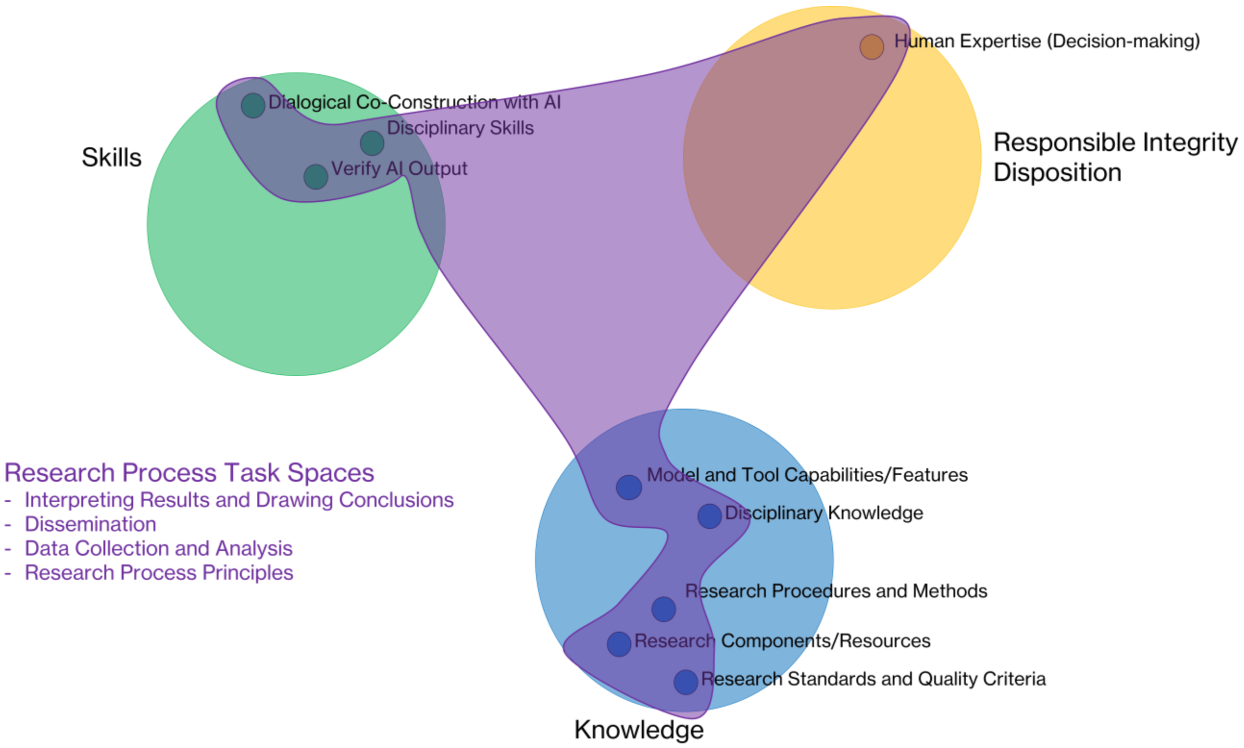


Figure 2: Human Expertise (Decision-Making) Competency Hypergraph

Human decision-making is central to the RAIL model because many knowledge and skills nodes are associated with this disposition. It clarifies the role of the human-in-the-loop principle, which is central to trustworthy AI and accountability in research (European Commission, 2025). Hence, it is also deeply rooted in the subject areas of Humans and Society as trust in human expertise or capabilities is valued. Moreover, it refers to AI models and their capabilities and limitations. At the time of writing (January 2026), machines have not yet become conscious and still cannot conduct complex, ethical research independently. Moreover, it emphasizes that human cognitive development is crucial, as AI outputs can be verified only when researchers draw on their disciplinary knowledge and skills. This highlights the role of cognitive development in researchers' professional development.

Scheme Compo-nent	Formulated Competency Statement
Action	**Implements** informed and responsible decision-making by applying professional judgement throughout the research lifecycle, consistently upholding established research principles and integrity.
Content	**Synthesizes** disciplinary knowledge, research methods, and an understanding of **AI model capabilities/limitations** to verify outputs critically and engage in **dialogical co-construction** without compromising methodological rigor.
Purpose	**Ensures** that research remains valid, trustworthy, and scientifically grounded, maintaining a framework in which **the human-in-the-loop** guides the research lifecycle (collection, analysis, interpretation of evidence, and dissemination) and AI enhances rather than replaces scholarly judgment.

AI Coworker Curiosity

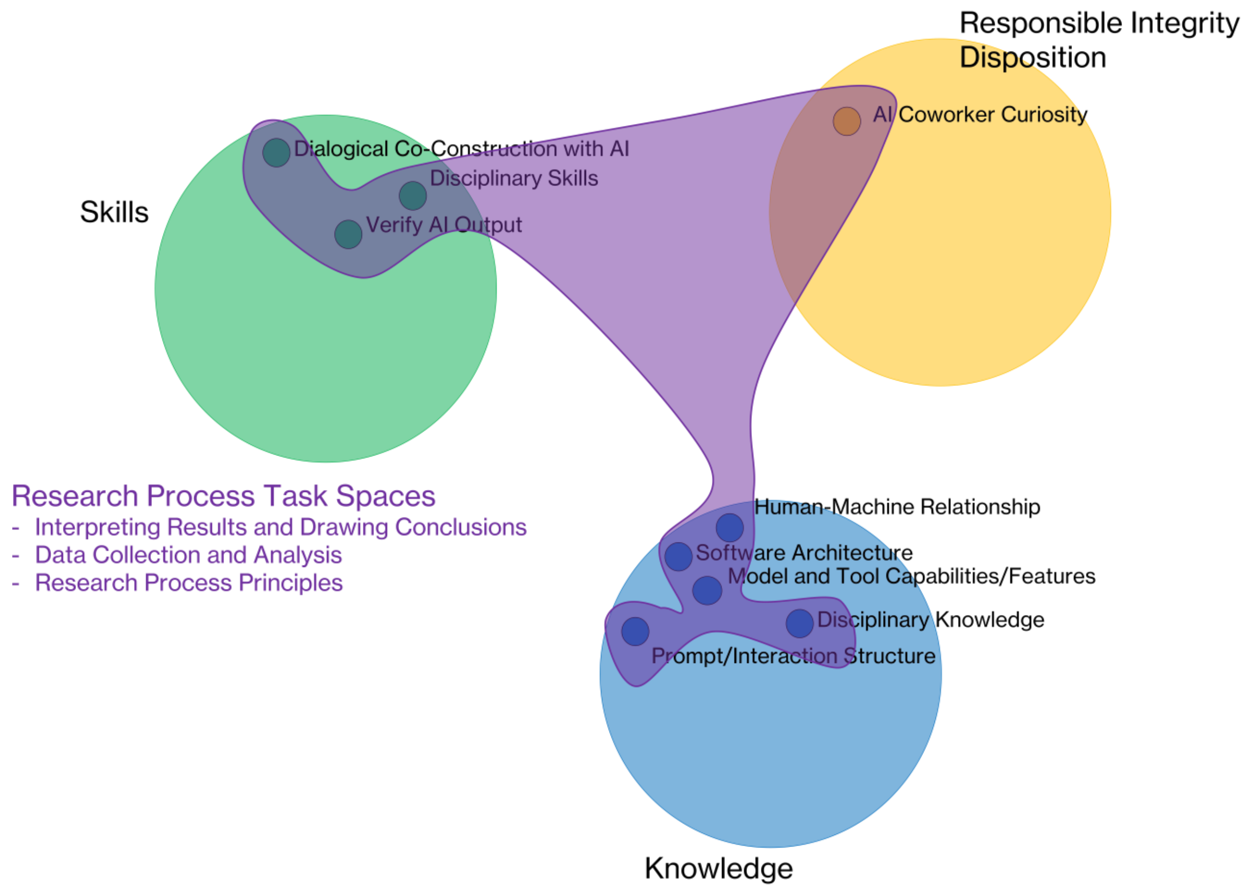


Figure 3: AI Coworker Curiosity Competency Hypergraph

This competency is deeply rooted in knowledge about AI and the stance to comprehend AI as a coworker, the researcher must familiarize him/herself with to effectively work together, considering not only AI's capabilities and limitations but also the design of software architecture and the structure of the human-machine relationship. Unlike general AI literacy, the competency of "AI Coworker Curiosity" emphasizes the human-machine relationship. The action is no longer about using this relationship but about strategizing its role within the research lifecycle. The content dimension incorporates technical hypernodes, such as “Software Architecture” and “Interaction Engineering”, treating them as factors in the partnership. Explicit knowledge of “Model/Tools Capabilities/Features” also encompasses the capabilities and features of agentic AI. As AI systems become more autonomous, it also becomes important to consider which parts of the research process and a researcher's life can be actively influenced. Recent advancements in agentic AI, such as the development of OpenClaw, raise multiple questions about how to approach these rapid changes and the uncertainty they entail (see, e.g., Meyer, 2026). The responsible integrity disposition of AI coworker curiosity is intended to activate researchers’ exploratory intentions and the knowledge and skills needed to address this uncertainty about your AI Coworker. The purpose dimension links these aspects to the research process, ensuring that the primary goal is a responsible and ethical workflow that produces accurate (joint) results.

Scheme Component	Formulated Competency Statement
Action	**Designs and strategizes** sophisticated interaction structures by managing the **Human-Machine Relationship** through continuous, iterative learning.
Content	**Synthesizes** deep knowledge of **Software Architecture**, **Prompt Structure**, and **Tool Capabilities** with practical skills in **Interaction Engineering** and **Dialogical Co-Construction**.
Purpose	**Ensures** the selection of adequate models and the creation of **Responsible/Ethical Workflows** to facilitate that AI-supported **Data Collection and Analysis** remain methodologically sound.

Adherence to Scientific Standards

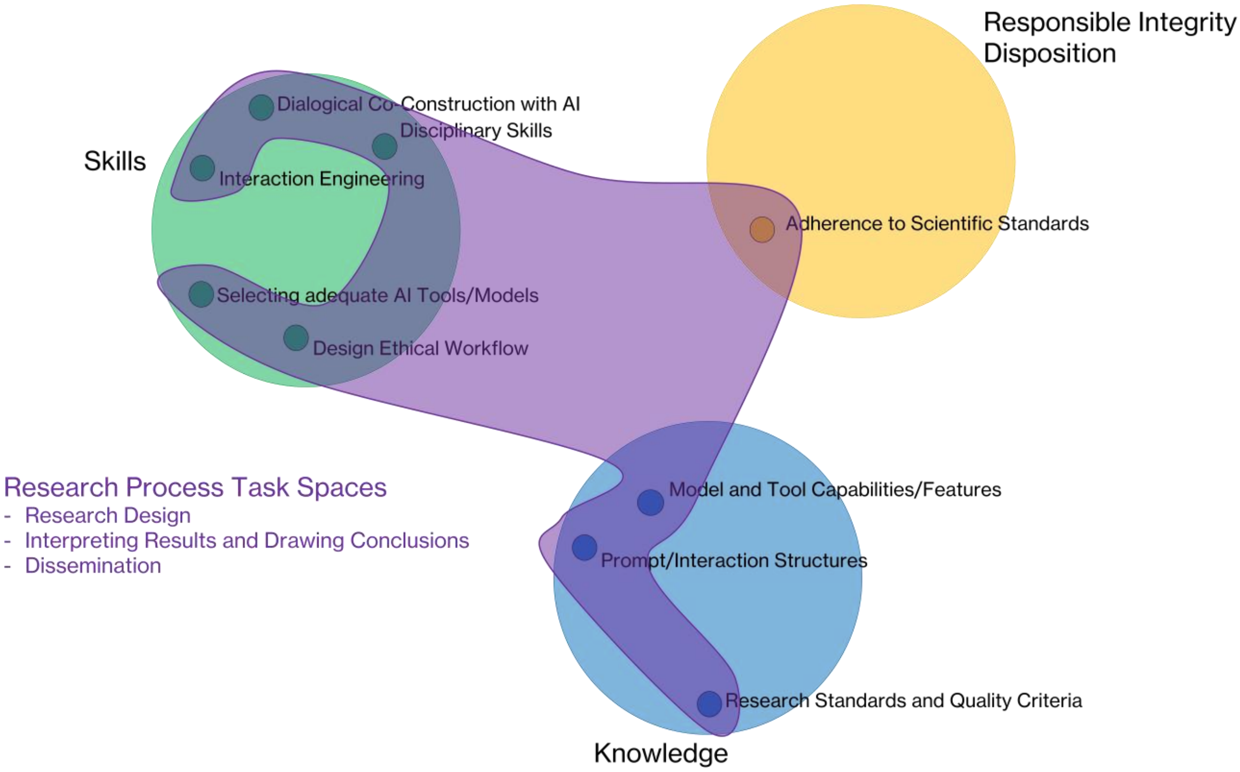


Figure 4: Adherence to Scientific Standards Competency Hypergraph

The commitment to scientific standards as a primary filter for AI-assisted activities is deeply rooted in society's trust in researchers and science itself. The formulation of this competency emphasizes that the knowledge of "Prompt Structures" and "Model Features or Capabilities" is not just for efficiency but a requirement for meeting scientific quality criteria. The purpose highlights that the goal of "Interaction Engineering" is to design a workflow that protects the scholarly nature of the research design and the subsequent dissemination of research results. In this context, it should be highlighted that this competency is also linked to a smaller competency that is not part of the main RAIL model: Data Protection.

Scheme Component	Formulated Competency Statement
Action	**Critically maintains** professional rigor to sustain scientific rigor throughout the entire research lifecycle, including **Research Design**, dissemination, and the interpretation of results.
Content	**Synthesizes** an understanding of **Research Standards and Quality Criteria** with technical knowledge of **Prompt/Interaction Structures** and **Model Capabilities** to apply **disciplinary skills** effectively.
Purpose	**Ensures** that the integration of AI through **Interaction Engineering** and **Dialogical Co-Construction** results in a **Responsible/Ethical Workflow** that sustains scientific validity and integrity.

Taking Ownership

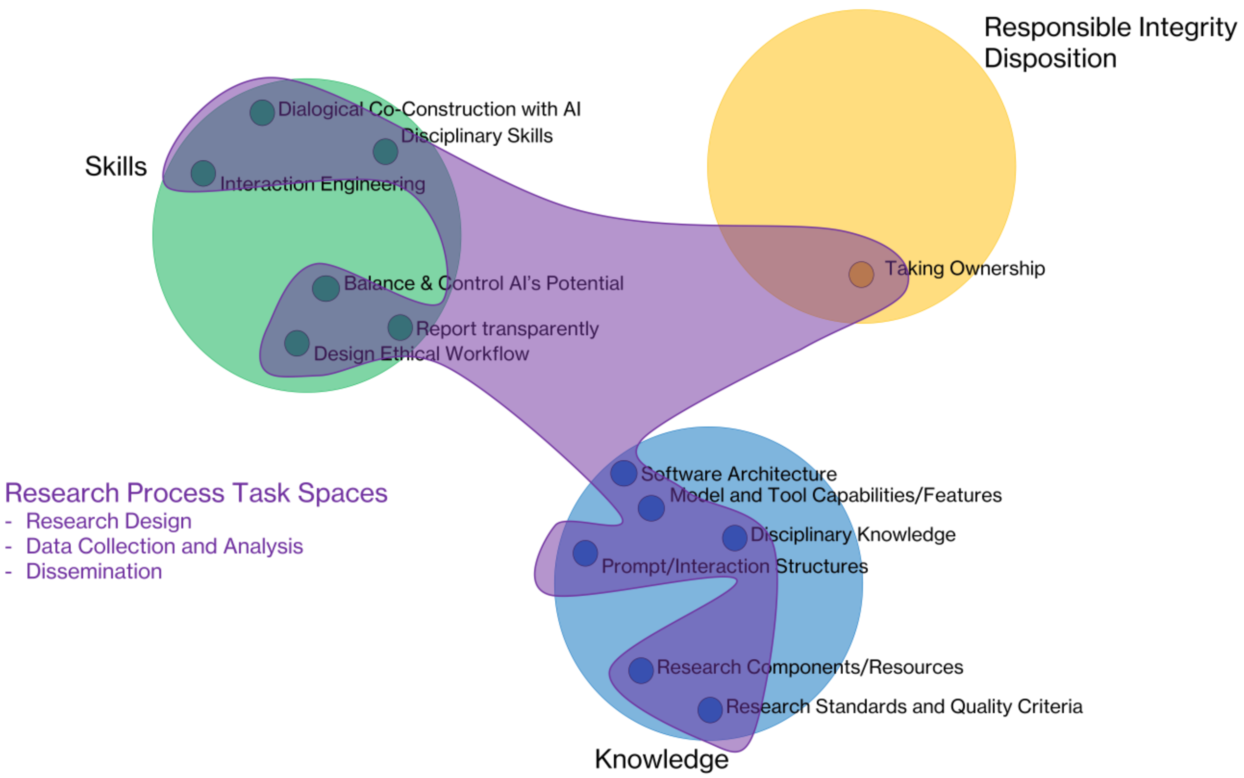


Figure 5: Taking Ownership Competency Hypergraph

While "AI Coworker Curiosity" focuses on the partnership between the researcher and AI in the research process, "Taking Ownership" emphasizes the researcher's role as the ultimate controller, balancing and managing AI's potential. This competency highlights that society still trusts human expertise and puts researchers' agency over automation. The inclusion of "Report transparently" in the skills dimension emphasizes that ownership entails accountability for how AI was used in the research process. Ranging from "Research Components and Resources" to "Software Architecture", this competency requires a broad knowledge base to prevent the researcher from becoming a passive user of the technology. In the context of workplace learning, Rausch (2025) notes that human ownership of the problem-solving process is also crucial for leveraging the learning opportunities offered by AI systems. In science, the problem-solving perspective is paramount because research begins with problems rather than observations, leading researchers to be characterized as 'problem-solvers' by Karl Popper (Thornton, 2023).

Scheme Component	Formulated Competency Statement
Action	**Acknowledges full accountability and agency** by balancing and controlling AI's potential throughout the research process, ensuring that human judgment remains the primary authority in high-stakes decisions.
Content	**Synthesizes** deep **Disciplinary Knowledge** and **Software Architecture** awareness with the ability to **Report Transparently** and design **Responsible/Ethical Workflows** that mitigate the risks of model features and limitations.
Purpose	**Ensures** that **Research Design**, **Data Collection**, and **Dissemination** are not merely automated but are actively directed by the researcher to maintain the credibility and personal responsibility inherent in scholarly work.

Transparency and Explainability

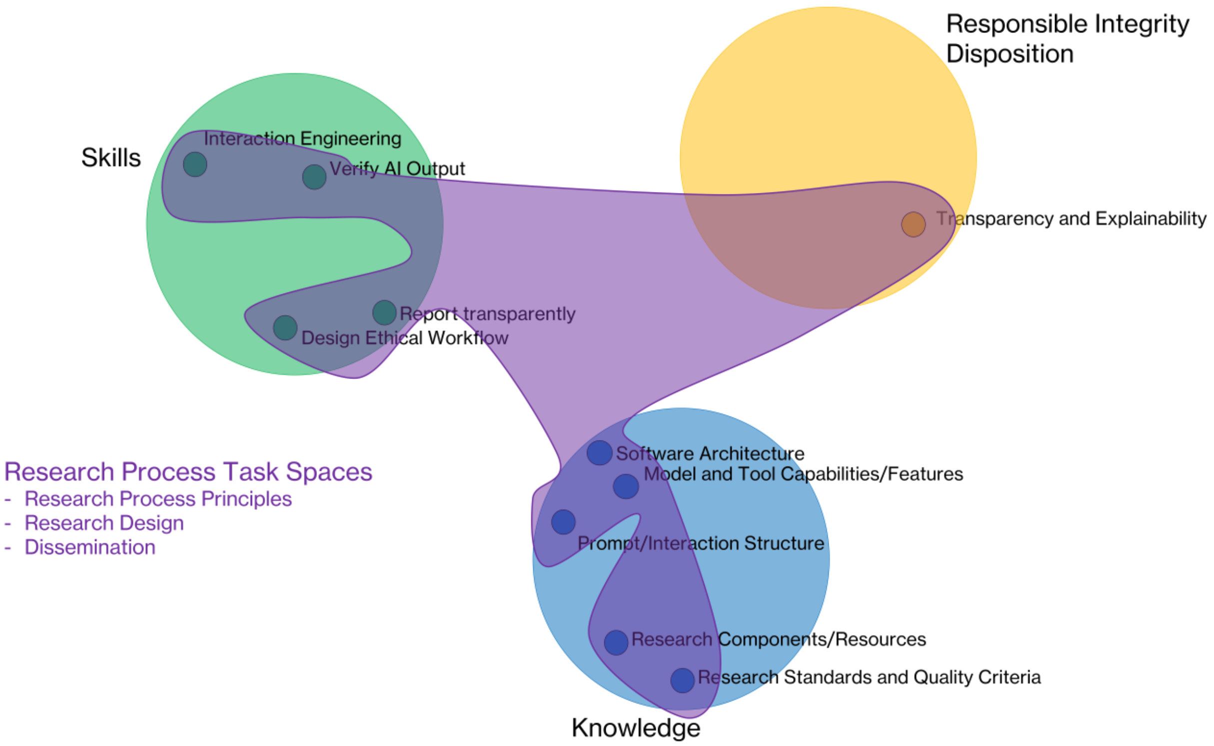


Figure 6: Transparency and Explainability Competency Hypergraph

Unlike "Taking Ownership," which focuses on control, the competency of “Transparency and Explainability” focuses on the visibility of that control. The Action requires making the "invisible" interactions with AI visible to the scientific community. You could describe it as an audit trail that the researcher must follow. The Content dimension emphasizes understanding “Software Architecture” not only for use but also to explain why a model might have produced a specific result. The Purpose links back to the Research Process Principles and Dissemination, ensuring that AI assistance does not become an opaque layer that obscures scientific truth.

Scheme Component	Formulated Competency Statement
Action	**Reveals and communicates** the logic behind AI-assisted research steps by actively documenting the decision-making process from design through dissemination.
Content	**Synthesizes** technical insights into **Software Architecture** and **Prompt/Interaction Structures** with the ability to **Verify AI Output** and **Report Transparently** on the use of research components.
Purpose	**Ensures** that the research remains accountable and interpretable, allowing peers to understand how **Interaction Engineering** and **Model Capabilities** influenced the **Research Design** and results.

Alignment with Own Knowledge Interest

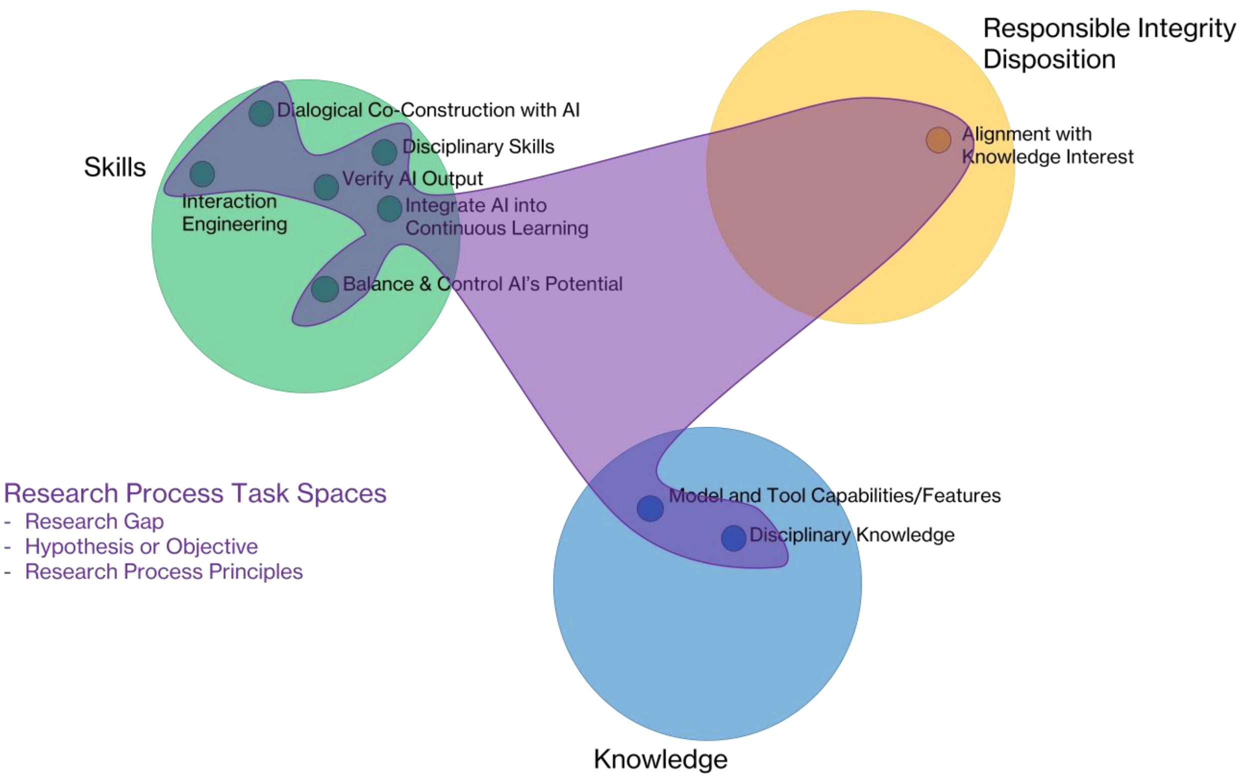


Figure 7: Knowledge Interest Alignment Competency Hypergraph

Unlike purely technical or regulatory competencies, this competency centers on the researcher's originality. The Action is about steering the AI toward a specific "Research Gap" rather than following a generic path. The Content highlights that "Dialogical Co-Construction" is the mechanism for aligning the AI's broad capabilities with the researcher's specific disciplinary skills, while leveraging “Interaction Engineering,” which incorporates techniques such as prompt or context engineering and model fine-tuning. The Purpose emphasizes that the researcher must "Integrate AI into Continuous Learning" to ensure the tool remains an extension of their own intellectual curiosity and scholarly "Objectives", and therefore serves the control of direction.

Scheme Component	Formulated Competency Statement
Action	**Designs and supervises** the AI-supported research path by strategically identifying a **Research Gap** and defining the core **Hypothesis or Objective**.
Content	**Synthesizes** deep **Disciplinary Knowledge** and **Model Capabilities** with practical skills in **Interaction Engineering** and **Dialogical Co-Construction** to verify AI outputs against personal scholarly goals.
Purpose	**Ensures** that the research remains intrinsically motivated and intellectually grounded, utilizing the ability to **Balance and Control AI's Potential** so that technology serves the unique knowledge interests of the researcher and society.

Critical Stance toward AI

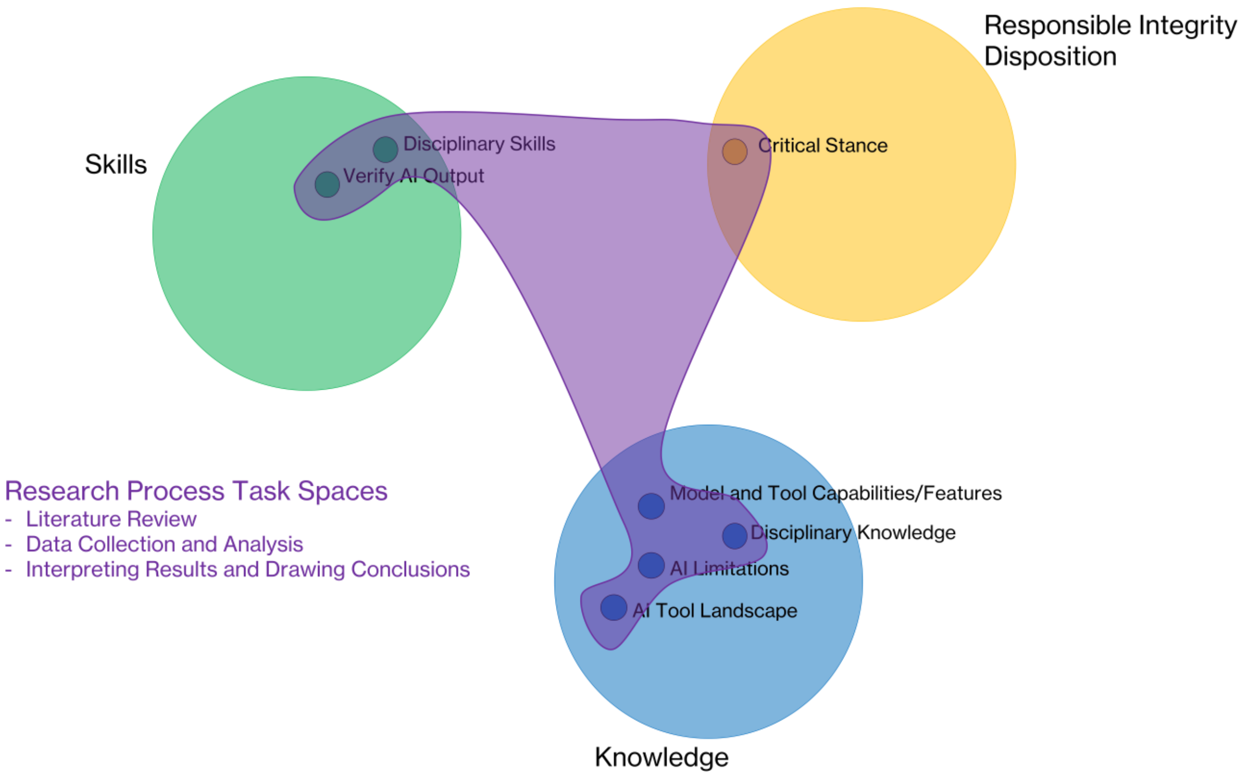


Figure 8: Critical Stance Competency Hypergraph

The “Critical Stance toward AI” transforms professional scepticism into a competency. The Action emphasizes that a critical attitude is not passive; it is the active performance of maintaining a reflective stance during every step of the research process. The Content highlights that the researcher cannot be critical without knowing the broader context. This includes the "AI Tool Landscape" and specific "AI Limitations" that might affect a particular field of study. The Purpose links these critical skills directly to the final step of the research process before communicating results, "Interpreting Results and Drawing Conclusions," ensuring that the researcher’s disciplinary skills and judgement remain the final filter for what is accepted as scientific truth. In this context, it should be highlighted that this competency is also linked to a smaller competency that is not part of the main RAIL model: Test for biases.

Scheme Component	Formulated Competency Statement
Action	**Maintains a critically reflective and evaluative stance** by constantly questioning the validity of AI-generated content through the application of professional skepticism.
Content	**Synthesizes** deep **Disciplinary Knowledge** with knowledge of the AI Tool Landscape, with a focus on **Model Capabilities/Features** and inherent **AI Limitations**.
Purpose	**Ensures** that **Literature Reviews**, **Data Collection and Analysis**, and the final **Interpretation of Results** are verified against disciplinary standards to prevent the uncritical adoption of biased or erroneous machine outputs.

Self-Reflectiveness

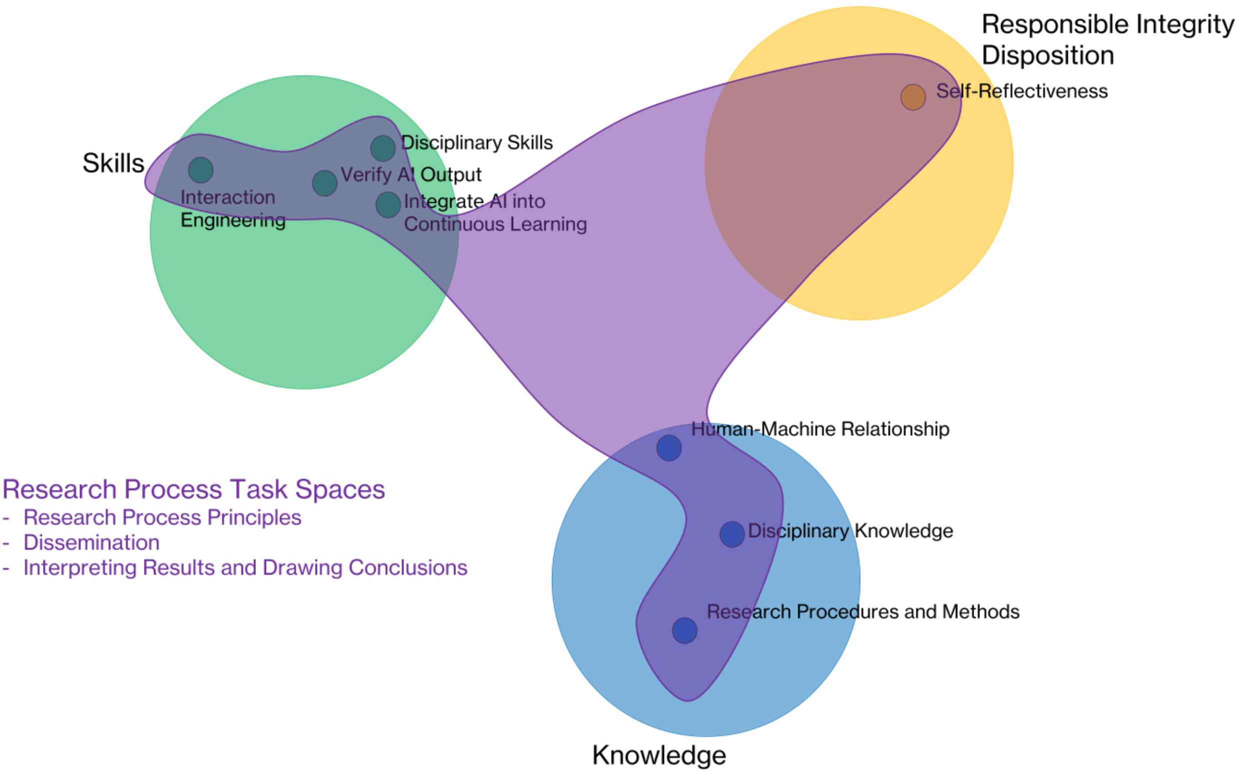


Figure 9: Self-Reflectiveness Competency Hypergraph

The competency of “Self-Reflectiveness” concerns the researcher's perception of their professional role and agency. The action of this competency centers on the researcher’s internal monitoring of their relationship with the technology. It is about recognizing one’s own strengths and vulnerabilities when paired with an AI partner. It could be understood as an internal feedback-loop. The Content highlights that self-reflectiveness is driven by "Continuous Learning". By mastering "Interaction Engineering," the researcher maintains control over how their input shapes the AI's utility and how the AI, for example, can function as a critical reviewer, providing feedback for consideration. The Purpose links back to "Interpreting Results and Drawing Conclusions". This ensures that the researcher does not lose their scholarly voice or professional identity to automation, even while using advanced AI tools.

Scheme Component	Formulated Competency Statement
Action	**Adopts and observes** the personal role and agency within the **Human-Machine Relationship** to ensure that professional growth and self-correction remain central to the research process.
Content	**Synthesizes** deep **Disciplinary Knowledge** and familiarity with **Research Procedures/Methods** with the ability to **Verify AI Output** and **Integrate AI into Continuous Learning** through active **Interaction Engineering**.
Purpose	**Ensures** that the researcher maintains a clear distinction between machine assistance and human intellect during **Dissemination** and the **Interpretation of Results**, upholding the core **Research Process Principles**.

Considering Sustainability

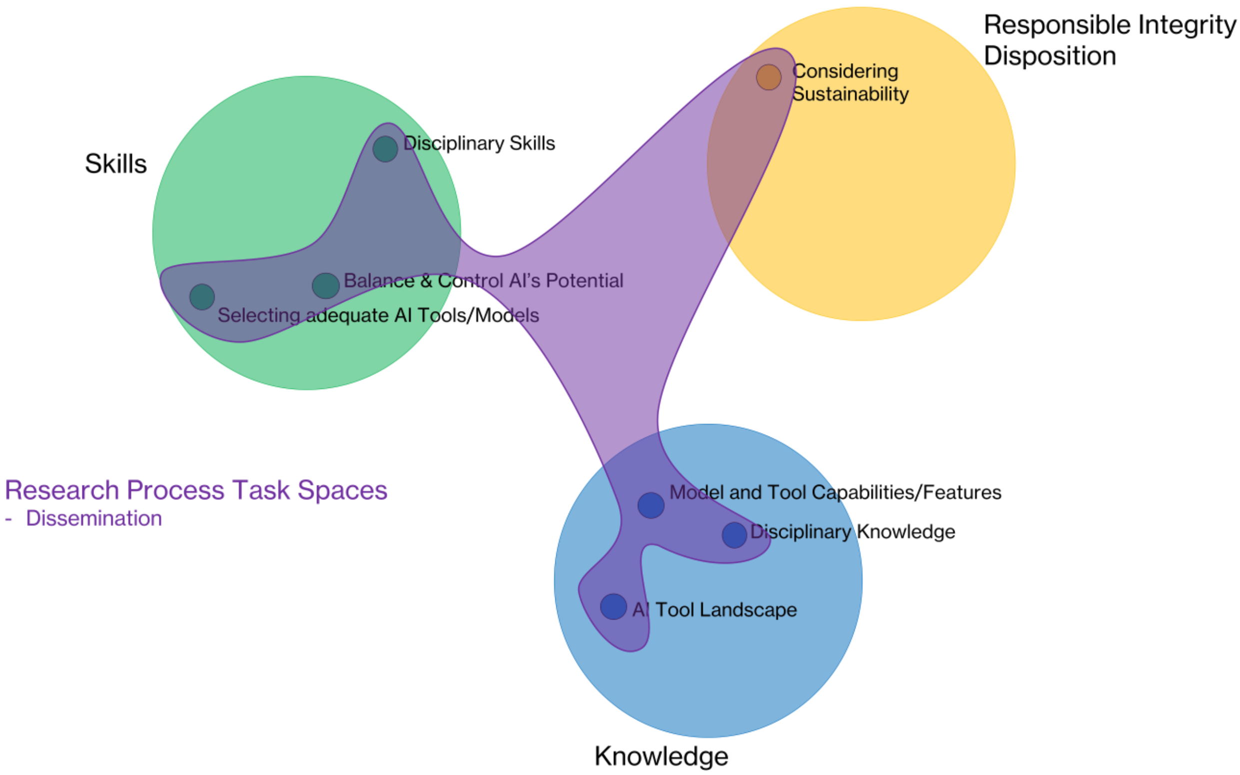


Figure 10: Considering Sustainability Competency Hypergraph

This competency emphasizes the skill of strategically "Selecting/Choosing adequate Tools/Models", specifically through the lens of sustainability, balancing high-performance needs with ethical resource consumption. This includes the role of AI companies with different ecological footprints. By including the "AI Tool Landscape" in the content dimension, the competency requires the researcher to look beyond the individual prompt and understand the broader infrastructure and resource consumption (e.g., energy costs) associated with different AI architectures. The Purpose links back to the Research Process (Purple zone), highlighting that "Considering Sustainability" is a core component of modern scientific integrity, for which the researcher must be held accountable when sharing results with the global community.

Scheme Component	Formulated Competency Statement

Action	**Evaluates and promotes** the long-term viability and ethical footprint of AI integration by critically assessing the resource-intensiveness of chosen digital methodologies.
Content	**Synthesizes** an expansive view of the **AI Tool Landscape** and **Model Capabilities/Features** with specialized **Disciplinary Knowledge** and skills to navigate the environmental and social impacts of technology.
Purpose	**Ensures** that the researcher can effectively **Balance and Control AI's Potential** during **Dissemination**, selecting adequate tools that align with sustainable research practices without compromising scholarly rigor.

Summary of the Framework

Competency Area	Action (Performance & Complexity)	Content (Knowledge, Skills & Tools)	Purpose (Context & Integrity)
Human Decision-making	**Implements human decision-making** by applying professional judgement, upholding research principles.	Synthesizes **disciplinary knowledge and skills**, and an understanding of **AI capabilities/limitations**, while engaging in **dialogical co-construction**.	Ensures that the researcher is the **human-in-the-loop** throughout the research lifecycle, so that the research remains valid and trustworthy.
AI Coworker Curiosity	**Designs and strategizes** interaction structures by managing the Human-Machine Relationship through iterative learning.	Synthesizes knowledge of **Software Architecture and Prompt Structure** with **Interaction Engineering** skills.	Ensures the selection of appropriate models and tools, the creation of **Responsible/Ethical Workflows** to facilitate methodologically sound **Data Collection & Analysis**.
Adherence to Scientific Standards	**Critically maintains** professional rigor to sustain scientific rigor throughout the entire research lifecycle,	Synthesizes an understanding of **Research Standards** with technical knowledge of **Model Capabilities** to apply **Disciplinary Skills** effectively.	Ensures that the integration of AI through **Interaction Engineering** yields a workflow that maintains scientific rigor.
Taking Ownership	**Acknowledges accountability and agency** by balancing and controlling AI's potential, retaining authority in high-stakes decisions.	Synthesizes **Disciplinary Knowledge** and **AI capabilities** with the ability to **Report Transparently,** mitigating the risks of model limitations and biases.	**Ensures** that **Data Collection & Analysis,** as well as **Dissemination**, are actively directed by the researcher rather than passively automated.
Transparency & Explainability	**Reveals and communicates** the logic behind AI steps by documenting the decision-making process.	Synthesizes knowledge of Model capabilities and **Software Architecture** with the ability to **verify AI Outputs** and report transparently to explain specific research outcomes influenced by **AI.**	**Ensures** research remains interpretable, allowing peers to understand how AI influenced the **Research Design** and results.
Alignment with Knowledge Interest	**Designs and supervises** the research path by identifying ethical, original gaps and defining core objectives.	Synthesizes **Dialogical Co-Construction** and **Interaction Engineering** to align **Model Capabilities** with specific **Disciplinary Skills** and goals.	**Ensures** technology serves the researcher's unique **Hypothesis or Objective**, keeping work intellectually grounded.
Critical Stance toward AI	**Maintains a reflective and evaluative stance** by constantly questioning AI content validity through professional skepticism.	Synthesizes deep **Disciplinary Knowledge** with knowledge of the **AI Tool Landscape**, with a focus on **Model Capabilities/Features** and inherent **AI Limitations**.	**Ensures the interpretation of Results** is verified against disciplinary standards, preventing the uncritical adoption of bias.
Self-Reflectiveness	**Adopts and observes** personal agency within	Synthesizes the ability to **verify AI Output** and **integrate AI into**	**Ensures** the researcher retains their scholarly voice during the

	the Human-Machine Relationship to ensure self-correction.	**Continuous Learning** while distinguishing human versus machine roles.	**Dissemination** and **Interpretation of Results**.
Considering Sustainability	**Evaluates and promotes** the ethical footprint of AI by assessing the resource-intensiveness of methodologies.	Synthesizes the knowledge of the **AI Tool Landscape** and the ability to **select tools** that balance **Model Capabilities** with environmental impact.	**Ensures Dissemination** choices align with sustainable practices without compromising the rigor of the **Research Process**.

Closing Remarks

Open Science and Open-Source

Although this competency hypergraph did not meet the inclusion criteria for the main model, it is still worth noting its existence.

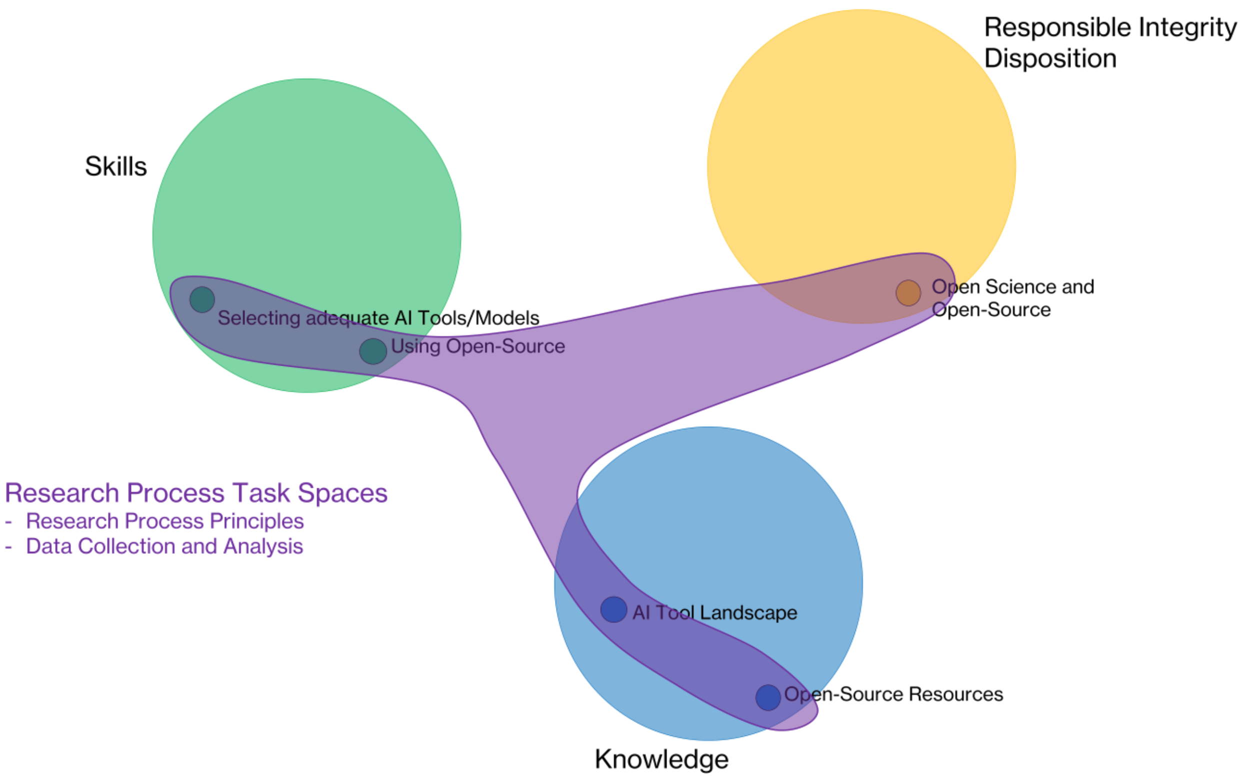


Figure 11: Open Science and Open-Source Competency Hypergraph

The competency “Open Science and Open-Source” aims for greater visibility and the associated benefits. The Action shifts from individual tool use to a broader commitment to transparency. It involves an active choice to use and contribute to the "Open-Source" ecosystem rather than relying solely on proprietary "black-box" models that most often do not disclose their training data and processes. The Content highlights that "Selecting adequate Tools/Models" is not just about performance, but also about finding resources that enable peer verification and accessibility (Open Science). The Purpose links these technical choices back to "Research Process Principles". This ensures that the use of AI actually supports the core tenet of Open Science: making the process as open as the results.

Scheme Component	Formulated Competency Statement
Action	**Promotes and practices** transparent research by prioritizing accessible methodologies and utilizing community-driven digital resources throughout the data lifecycle.
Content	**Synthesizes** knowledge of the **AI Tool Landscape** and Open-Source Resources with the practical skills of **Using Open-Source** software and **Selecting/Choosing adequate Tools/Models**.
Purpose	**Ensures** that Data Collection and Analysis are conducted in alignment with Research Process Principles, **fostering a collaborative environment** where research remains reproducible and scientifically open.

Evolving Nature

The RAIL model should be understood as evolving and adaptable across scientific disciplines. Its representation as a network of hypergraphs should emphasize its dynamic nature, in which hypernodes can emerge or disappear over time, as science, society, humans, and AI change.

Interdisciplinary Cross-Compatibility

The RAIL Researcher model is structured as a Tripartite Hypergraph $H = (V, E)$. This structure is not static but evolves over time as a function of scientific, technological, and societal change. This mathematical framework allows the model to remain flexible across different scientific disciplines while maintaining a rigorous core structure.

Vertex Set V

Let V be the finite set of all possible **competency elements**. To maintain formal separation between competency dimensions, V is partitioned into three disjoint sets:

- V_K $(Knowledge)$: The partition of explicit knowledge, where $V_K = \{k_1, k_2, \dots, k_n\}$.
- V_S (Skills): The partition of observable abilities, where $V_S = \{s_1, s_2, \dots, s_m\}$.
- $V_D(Dispositions)$: The Responsible Integrity Disposition partition, where $V_D = \{d_1, d_2, \dots, d_j\}$.

The global vertex set is the union of these partitions: $\mathrm{V} = \mathrm{V_K} \cup \mathrm{V_S} \cup \mathrm{V_D}$, satisfying the condition $\mathrm{V_K} \cap \mathrm{V_S} \cap \mathrm{V_D} = \emptyset$.

The Hyperedge Set E

In this model, a competency is not an isolated skill but a functional connection. Formally, it is represented as a hyperedge $e \in E$, where $e \subseteq V$, that links nodes from different partitions. To be a valid RAIL Competency, a link must satisfy the Tripartite Requirement: it must connect at least one element from Knowledge, one from Skills, and one from Dispositions. A valid RAIL competency requires a link across all three partitions to ensure a full competency integration:

$$e \cap V_K \neq \emptyset, e \cap V_S \neq \emptyset, e \cap V_D \neq \emptyset$$

This condition ensures that "doing" (Skill) is always informed by "knowing" (Knowledge) and guided by "responsible integrity" (Disposition).

The Logical Mapping

The model uses a logical mapping to relate real-world work to specific researcher attributes:

- **Research Task ($\boldsymbol{T}$):** Represents a specific real-world research task within the research process.
- **Task Requirements ($\boldsymbol{V_T}$):** For any specific research task T, there exists a subset of vertices $V_T \subseteq V$ necessary to successfully perform task T.
- **Sociocultural-space-time context ($\boldsymbol{\Omega}$):** encompasses all relevant elements of socioculture, for example, institutions, laws and regulations, the current state of AI technology, disciplinary scientific standards, and ethical norms.

This logical mapping is sensitive to the sociocultural-space-time context (Ω):

$$V_T \leftarrow Mapping(T, \Omega)$$

As AI technology evolves or scientific standards change, the mapping $V_T \leftarrow M(T, \Omega)$ is updated to reflect new requirements, ensuring the model stays current without changing its underlying structure.

Effective Competency

The researcher's actual capacity to perform a task is defined as the **Effective Competency $\boldsymbol{C(T)}$**. This is the set of valid hyperedges ($\boldsymbol{e}$) whose elements are entirely contained within the task requirements ($\boldsymbol{V_T}$):

$$C(T) = \{e \in E \mid e \subseteq V_T\}$$

If the mapping for a task $\boldsymbol{T}$ results in no valid tripartite connections ($\boldsymbol{C(T)} = \emptyset$), the model identifies a "competency gap". This indicates that, while the researcher may possess the knowledge or skills, they lack the integrated "RAIL" connection required for responsible research.

Dynamic Properties and Functional Emergence

The model treats competency as a local emergence driven by the mapping logic. This introduces dynamic properties that explain how the model adapts over time.

- **Functional Dependence:** The composition of $\boldsymbol{V_T}$ also depends on the context Ω. If the context changes (e.g., a new AI regulation is introduced), the logical mapping updates $\boldsymbol{V_T}$, potentially requiring new nodes, or fewer nodes for the same task $\boldsymbol{T}$.
- **Competency Gaps:** If the intersection of the existing hyperedges and the task requirements is empty ($\boldsymbol{C(T)} = \emptyset$), the researcher faces an "Incompetency Condition." This indicates a competency gap where the researcher may possess isolated knowledge or skills but lacks the integrated RAIL connection required for the specific task.
- **Temporal Evolution (Non-Persistence):** The competency model is **non-persistent**. Because scientific standards and AI capabilities ($\boldsymbol{\Omega}$) evolve from time $\boldsymbol{t_1}$ to $\boldsymbol{t_2}$, the requirements for a task $\boldsymbol{T}$ also shift:

$$V_T(t_1) \neq V_T(t_2)$$

Consequently, a researcher considered competent at t_1 may require new connections at t_2 to maintain effective competency ($C(T, t_2)$). This property implies the necessity of continuous (workplace) learning.

Call for Validation

At the beginning of 2026, the RAIL model remains in the validation phase. Therefore, ongoing evaluation, feedback, and validation are necessary to sustain its development. The first validation phase runs from February to July 2026. At least three Nominal Group Technique (NGT) sessions with expert researchers who use AI in their work are conducted as the first validation step. The expert feedback will be used as data for further improvement and model validation. Expert researchers from all scientific disciplines are welcome to participate.

References

Andersen, J., Degn, L., Graversen, E., Horbach, S., Schmidt, E., Schneider, J., & Sørensen, M. (2024). *Generative Artificial Intelligence (GenAI) in the research process – a survey of researchers' practices and perceptions*. OSF. https://doi.org/10.31235/osf.io/83whe

BaHammam, A. S. (2025). The Transparency Paradox: Why Researchers Avoid Disclosing AI Assistance in Scientific Writing. *Nature and Science of Sleep*, *17*, 2569–2574. https://doi.org/10.2147/NSS.S568375

Cc2020 Task Force. (2020). Computing Curricula 2020: Paradigms for Global Computing Education. ACM. https://doi.org/10.1145/3467967

Cedefop. (2017). *Defining, writing and applying learning outcomes: A European handbook* (European Centre for the Development of Vocational Training, Hrsg.). Publications Office. https://doi.org/10.2801/797160

Cuschieri, S. (2022). Understanding Research Ethics. In S. Cuschieri (Hrsg.), A Roadmap to Successful Scientific Publishing: The Dos, the Don'ts and the Must-Knows (S. 27–34). Springer International Publishing. https://doi.org/10.1007/978-3-030-99295-8_2

European Commission. (2025, April). *Living guidelines on the RESPONSIBLE USE OF GENERATIVE AI IN RESEARCH*. https://research-and-innovation.ec.europa.eu/document/download/2b6cf7e5-36ac-41cb-aab5-0d32050143dc_en?filename=ec_rtd_ai-guidelines.pdf

Fairfield, T., & Charman, A. E. (2022). Social Inquiry and Bayesian Inference: Rethinking Qualitative Research. Cambridge University Press. https://doi.org/10.1017/9781108377522

Frontiers Media. (2025). *Unlocking AI's untapped potential—Responsible innovation in research and publishing*. https://www.frontiersin.org/documents/unlocking-ai-potential.pdf

Kwon, D. (2025). Science sleuths flag hundreds of papers that use AI without disclosing it. *Nature*, *641*(8062), 290–291. https://doi.org/10.1038/d41586-025-01180-2

Meyer, M. (February 3, 2026). *New AI Assistant OpenClaw Acts Like Your Digital Servant, but Experts Warn of Security Risks.* In: CNET. https://www.cnet.com/tech/services-and-software/from-clawdbot-to-moltbot-to-openclaw/

Padakanti, S., Kalva, P., & Kommidi, V. R. (2024). AI in Scientific Research: Empowering Researchers with Intelligent Tools. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *10*(5), Article 5. https://doi.org/10.32628/CSEIT241051012

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ (Clinical Research Ed.), 372, n71. https://doi.org/10.1136/bmj.n71

Pinski, M., & Benlian, A. (2024). AI literacy for users – A comprehensive review and future research directions of learning methods, components, and effects. Computers in Human Behavior: Artificial Humans, 2(1), 100062. https://doi.org/10.1016/j.chbah.2024.100062

Rausch, A. (2025). Artificial intelligence for informal workplace learning: A problem-solving perspective. Frontiers in Organizational Psychology, 3. https://doi.org/10.3389/forgp.2025.1555429

Reis, O. (2014). Kompetenzorientierte Prüfungen. Prüfungstheorie und Prüfungspraxis. In A. Gutge-Wickert & U. Kessler (Hrsg.), *Die homöopathische Behandlung chronischer Krankheiten. Kongressband* (S. 47–52).

Thornton, S. (2023). Karl Popper. In E. N. Zalta & U. Nodelman (Hrsg.), The Stanford Encyclopedia of Philosophy (Winter 2023). Metaphysics Research Lab, Stanford University. https://plato.stanford.edu/archives/win2023/entries/popper/

Wunderlich, A., & Szczyrba, B. (2016). *Learning-Outcomes ‚lupenrein' formulieren*. https://www.th-koeln.de/mam/downloads/deutsch/hochschule/profil/lehre/steckbrief_learning_outcomes.pdf

Invitation: Expert NGT Session to Validate RAIL Researcher Model

Dear Expert,

I am reaching out to **invite you** to join a unique opportunity to engage in thoughtful discussion and exchange ideas with fellow experts on the competencies essential for today's responsible AI-literate (RAIL) researchers. Your experience and insights are highly valuable in a Nominal Group Technique (NGT) session to review, discuss, and validate this model alongside other experts, thereby shaping the ethical development of AI4Science.

Session details:

- **Duration:** ca. 90 minutes
- **Format:** [virtually via Zoom]
- **Group size:** 4-9 experts
- **Date:** January to July 2026 **(please get back to me via e-mail, or answer survey: https://umfragen.uni-paderborn.de/index.php/753161?lang=en)**

You will have the option to receive a ***certificate of participation*** from Paderborn University in recognition of your role as an expert panelist.

To ensure the integrity of the RAIL Researcher model during this validation phase, it is currently shared under a CC BY-ND 4.0 license. However, **by registering as a validation expert, you are explicitly granted permission and encouraged** to propose modifications, deletions, or additions throughout the NGT session. Your critical feedback will be used as data and is exactly what this process requires to move toward the final Open Access release (CC BY 4.0).

If you have any questions or would like further details about the session or my research, please do not hesitate to reach out – I am happy to provide more information. Additionally, if you know colleagues who may be interested in joining, please share this invitation or let me know, and I would be glad to connect with them.

Best,
Stephan

Stephan Drechsler, M.A.
Research Associate
Educational Management and Research in Further Education

PADERBORN UNIVERSITY

Warburger Str. 100
33098 Paderborn
Germany
Office TP6.2.310
Telephone +49 5251 60-5212
E-Mail stephan.drechsler@uni-paderborn.de
Web www.uni-paderborn.de/en/person/26915

Link to the Registration Survey