Human AI Collaboration in Strategic Competency Analysis for Future- Oriented Recruitment

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Abstract. Defining future competency requirements for recruitment calls for integrating role specific knowledge, organizational context, external developments, and human judgement. This study develops and evaluates a structured Human AI Collaboration Model for future oriented competency analysis. Using an iterative Design Thinking approach, an interactive prototype combining guiding questions, information sources, and generative AI prompts was developed and tested with five line managers, complemented by expert feedback from two consultants. The resulting approach is human initiated, AI augmented, and human evaluated. Initial findings indicate that structured Human AI collaboration can support systematic reflection on future competency requirements while highlighting the continuing importance of contextual human judgement.

Keywords: Competency Management; Future Skills; Strategic Job Analysis; Human-in-the-Loop; Human-AI Collaboration; AI-Supported Decision-Making; Recruiting

1 Introduction

Defining competency requirements for recruitment has become increasingly challenging as technological, economic, and societal developments continue to reshape jobs and the competencies required to perform them successfully. According to the World Economic Forum, approximately 39% of employees' core skills are expected to be transformed or become outdated by 2030 (World Economic Forum, 2025). Recruitment decisions therefore need to consider not only the requirements of a role today, but also how tasks and competency requirements may evolve in the future.

Strategic competency analysis goes beyond current role requirements by systematically considering how organizational priorities and anticipated external developments may reshape the competencies required for a role in the future (Singh, 2008). Insights from HR practice and discussions with line managers and practice partners provided the initial motivation for this study, suggesting that identifying future competency requirements can be challenging in day-to-day recruitment, with existing job descriptions or previous job advertisements often serving as a convenient starting point for defining role requirements. This creates a risk of reproducing established profiles rather than systematically considering how future developments may affect a role.

Generative artificial intelligence offers new possibilities for supporting this process (Dasaklis et al., 2026). However, identifying future competency requirements is inherently context dependent and requires managerial knowledge and judgement. The central question is therefore not whether AI can generate competency profiles, but how human expertise, relevant information sources, and generative AI can be combined to support future oriented competency analysis. Existing LLM applications in recruitment and selection predominantly focus on downstream activities such as resume screening, candidate matching and ranking, applicant assessment, and job advertisement generation (Dasaklis et al., 2026).

These applications typically operate on existing job descriptions, skill sets, or other representations of job requirements. Less attention has been paid to the preceding analytical task of systematically identifying and updating the requirements against which candidates are subsequently recruited and assessed. Against this background, this study develops and tests a structured Human in the Loop approach and addresses the following research question:

How can line managers use structured guidance, internal and external resources, and generative AI to identify current and future competency requirements for recruitment profiles?

2 Theoretical Background

2.1 Strategic and Future Oriented Competency Analysis

Traditional job analysis provides information about work activities, worker attributes, and the context in which work is performed (Sanchez & Levine, 2012). However, conventional approaches largely focus on jobs as they currently exist or have existed in the past, an assumption that becomes problematic as jobs and their requirements change (Singh, 2008). Strategic job analysis extends this perspective by incorporating anticipated organizational and environmental changes. Rather than treating future requirements independently from current work, prior approaches suggest first analyzing current tasks and requirements and subsequently revising them considering expected future changes (Singh, 2008; Ahmad & Alqaarni, 2023). This includes systematically considering internal and external developments and examining how these may alter future tasks and competency requirements.

A task-based perspective therefore provides an important link between present and future competency requirements. Current competency requirements can be derived from current tasks, while future requirements can be examined by considering how relevant developments may modify existing tasks, create new tasks, or make current tasks less relevant (Singh, 2008; Ahmad & Alqaarni, 2023).

Generic future skills frameworks can provide orientation regarding competencies that may gain importance across occupations and industries (e.g., World Economic Forum, 2025). For role specific recruitment, however, such broad framework needs to be contextualized by examining which developments and competencies are relevant to the particular role and organizational context. Accordingly, such an analysis requires line managers to connect different types of information, including current tasks and requirements, organizational priorities, technological developments, labor market changes, industry trends, and broader societal or regulatory developments.

The challenge therefore is not simply to identify relevant future trends or future skills, but to determine which developments are relevant for a specific role and translate their implications into concrete competency requirements.

2.2 Human AI Collaboration in Competency Analysis

Recent research indicates a shift from predominantly discriminative applications such as classification, matching, and ranking towards generative and interactive LLM applications embedded in HRM decision processes (Dasaklis et al., 2026). This development creates new opportunities for supporting managers in complex analytical tasks rather than merely automating predefined HR activities. From an augmentation perspective, the potential value of AI lies not necessarily in automating such tasks, but in combining complementary human and machine capabilities (Raisch & Krakowski, 2021).

A Human in the Loop perspective further emphasizes that human involvement can occur throughout the interaction with AI rather than being limited to the validation of final outputs. Interactive approaches are characterized by repeated human input and review, with humans taking different roles across the process (Mosqueira Rey et al., 2023). For strategic competency analysis, this suggests that human judgement should be embedded throughout the analytical process rather than applied only to a final AI generated competency profile. Whether technological or market development is relevant to a particular role, which tasks are likely to change, and which competencies should consequently be prioritized depend on organizational context, strategic choices, and role specific knowledge. Human judgement therefore remains essential.

The central design question therefore is not whether humans or AI should conduct strategic competency analysis, but how their respective contributions should be combined across different stages of the process. A Human in the Loop approach provides a useful perspective for such a combination by keeping human expertise and judgement involved. Recent reviews of LLM applications in HRM similarly emphasize the need to design Human in the Loop mechanisms that incorporate human oversight, feedback, and decision making throughout AI supported processes (Dasaklis et al., 2026). For strategic competency analysis, however, this raises the more specific question of how human and AI contributions should be allocated across the different stages of the analytical process.

While generative AI can support the exploration and structuring of information, generate alternative perspectives, and suggest possible implications of external developments, line managers contribute role specific and organizational knowledge, assess the relevance of these suggestions, and decide which implications should be translated into competency requirements. Recent research has consequently called for more explicit and empirically examined Human in the Loop designs in HRM applications (Dasaklis et al., 2026). However, limited attention has so far been paid to how such human and AI contributions can be systematically structured across the process of identifying current and future competency requirements.

3 Methodology

3.1 Research and Development Approach

Drawing on a Design Thinking approach (Plattner, Meinel & Leifer, 2011), the study developed and iteratively refined a practice-oriented process for future oriented competency analysis. The development addressed the practical challenge of enabling line managers to identify competency requirements for specific roles while considering both current requirements and anticipated future developments.

A key consideration was that the process should be applicable across different jobs and organizations of varying size and sector, while accommodating different levels of line manager experience in strategic job analysis and in the use of AI.

The development comprised several iterative cycles conducted by the authors. Initial iterations focused on the overall process, including its sequence of steps, guiding questions, and relevant information sources. Building on this process, subsequent iterations examined where generative AI could meaningfully support the analysis and focused on developing and refining prompts for these specific process steps.

The process was grounded in strategic job and competency analysis and translated this general methodological principle into a sequence of steps that can be applied by line managers to a specific recruitment case. Rather than prescribing a predefined set of future competencies,

the approach structures the analytical process through which role specific competency requirements are derived.

3.2 Prototype Development

Based on the iterative development process, a structured prototype was developed to support line managers in identifying current and future competency requirements for a specific recruitment case. The prototype was implemented as an interactive PDF that guides users through the competency analysis process and combines guiding questions, background information, relevant information sources, and prompts for generative AI support. The resulting process and Human AI Collaboration Model are presented in the Findings section.

For the AI supported elements of the prototype, two sets of prompts were developed. The first set consists of simple prompts formulated as guiding questions that line managers can also use for their own reflection without generative AI. When entered into a generative AI system, the same questions provide basic AI support for the respective analytical step. The second set consists of more detailed prompts that provide additional context, specify the analytical task, and structure the expected output in greater detail. This allows users to choose the level of AI support according to their needs and experience.

The prompts were iteratively developed and refined by the two authors using two different roles from their own context as test cases. Alternative prompt formulations were tested and revised throughout this process. The prompts were designed to build on information generated in previous stages where relevant, thereby maintaining the connection between organizational context, tasks, developments, and competency requirements.

A consistent Human in the Loop principle guided the development of the prototype. AI generated outputs were designed to serve as inputs for further human evaluation rather than as final results. Users are explicitly instructed to critically review the generated outputs, assess their fit with the specific role and organizational context, modify or reject suggestions where necessary, and add contextual information unavailable to the AI.

3.3 User Testing and Expert Feedback

The prototype was evaluated iteratively through user testing with five participants from different organizations and industries and expert feedback from two consultants from the project's practice partner, an assessment center consultancy. The latter provided expert feedback on the prototype from a professional recruitment and assessment perspective at two stages of its development. Their feedback focused on the structure, comprehensibility, and practical applicability of the prototype and was used to inform its further refinement.

User testing was conducted in two stages. One participant tested an early version of the prototype, providing initial user feedback that informed its further development. In a subsequent testing round, all five participants independently applied the penultimate version of the prototype to a real vacancy. The participants held managerial or senior professional roles across different functional areas, including real estate, organizational transformation, treasury, business operations, and project management, and represented organizations from the insurance, software, real estate services, and technology sectors. The five recruitment cases covered vacancies in learning and development, administration, materials and composites, underwriting and credit portfolio management, and strategic facility management. Participants were free to use generative AI tools of their choice and used ChatGPT, Perplexity, and Microsoft Copilot across the different cases.

The participants constituted a convenience sample and were selected to ensure relevant recruitment experience, either because they regularly recruited employees as part of their role or

had recently been involved in filling a vacancy. No additional instructions on how to use the prototype were provided, allowing the testing to assess whether the process and its guidance were sufficiently self-explanatory for independent use.

Following the application of the prototype, participants provided written feedback through a structured questionnaire with open ended questions. The questionnaire addressed comprehensibility of the language and terminology, the sequence and guidance provided by the process, the usefulness of the interactive PDF and its interaction with AI use, satisfaction with the resulting competency profile, time required to complete the process, and participants' willingness to use the approach for future competency analyses.

3.4 Data Analysis

The written feedback was analyzed using a structured, category-based approach. Responses were first organized according to the predefined dimensions of the questionnaire: comprehensibility and language, process guidance, interaction between the prototype and generative AI, perceived quality of the resulting competency profile, time required, and intention to use the approach.

Within each category, the authors compared responses across participants and identified recurring positive assessments, challenges, and suggestions for improvement. Where relevant, the number of participants mentioning a particular issue was recorded to indicate its occurrence across the sample. The identified issues were subsequently reviewed by both authors and used to inform further refinement of the prototype.

4 Findings

4.1 Human AI Collaboration Model for Future Oriented Competency Analysis

The development process resulted in a structured model of Human AI Collaboration for future oriented competency analysis (Figure 1). Building on strategic competency analysis and the Human in the Loop perspective, the model systematically combines human expertise, internal and external information, and generative AI. It is characterized by three principles: The approach is human initiated, AI augmented, and human evaluated.

The model structures future oriented competency analysis into a sequence of steps covering the definition of the organizational and role context, identification of current tasks and competency requirements, identification and assessment of relevant future developments, translation of these developments into changes in tasks and competency requirements, and final prioritization for the recruitment profile.

The starting point is the specific organizational and functional context including information about the role. Then the tasks associated with a particular role are identified and the competencies currently required to perform these tasks successfully are derived. This provides the basis for the subsequent future oriented analysis. Potentially relevant external and internal developments are identified and assessed regarding their implications for the role, its tasks, and consequently its competency requirements. The resulting current and future competency requirements are subsequently prioritized for the recruitment profile.

Central to the model is a task-based logic that connects present and future competency requirements: current competency requirements are derived from current tasks, while future competency requirements are derived by examining how relevant internal and external developments may modify existing tasks, create new tasks, or make existing tasks obsolete.

Generative AI provides targeted support throughout this process. Its contribution differs depending on the analytical stage and includes suggesting potentially relevant tasks, identifying

potentially relevant developments, supporting the translation from tasks into competency requirements, and structuring or refining results. AI generated outputs are not treated as final results but as inputs into further human reflection and evaluation.

Human judgement therefore remains embedded throughout the process. Line managers provide role specific and organizational knowledge, assess the relevance and plausibility of AI generated suggestions, add information unavailable to the AI, and decide which elements should be retained, modified, or rejected. Particularly when assessing future developments, managers need to determine whether a suggested development is actually relevant to their organization and role and what consequences it may have for future tasks and competency requirements. Human involvement is therefore not limited to validating a final AI generated competency profile but occurs repeatedly throughout the analytical process.

Importantly, generative AI is not treated as equivalent to the information sources used in the analysis. Internal sources such as organizational strategy or information about transformation projects and external sources such as industry reports and market statistics provide additional evidence and orientation. Generative AI supports the exploration, structuring, and processing of this information but does not replace the underlying internal and external evidence.

Figure 1 summarizes the resulting model as a repeated sequence of human input, AI supported exploration, and critical human evaluation across the competency analysis process.

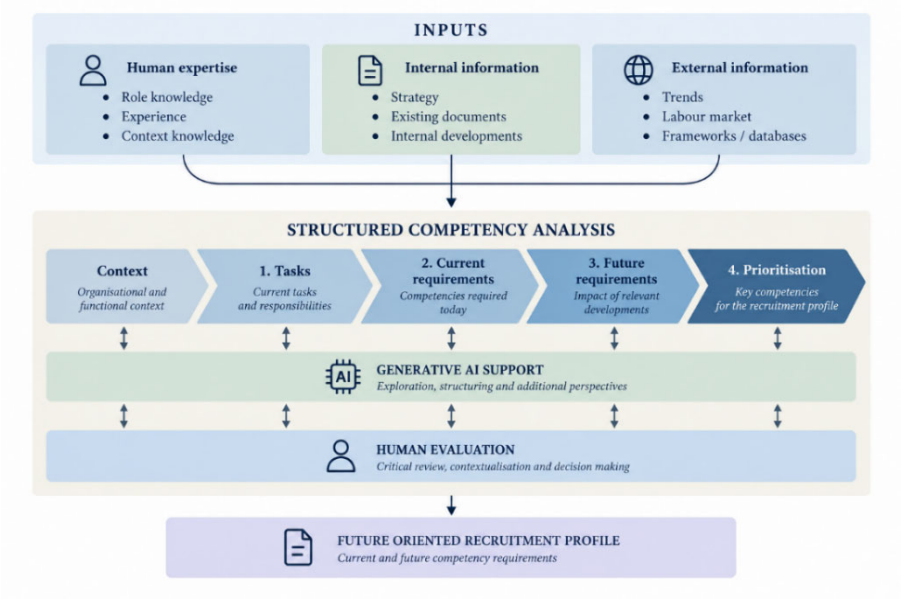


Fig. 1. Conceptual Model of Human AI Collaboration in Future Oriented Competency Analysis

4.2 Initial Evaluation of the Prototype

Overall, the line managers evaluated the prototype positively and considered the structured process helpful for identifying competency requirements. Three main themes emerged from the feedback: the value of structured guidance for future oriented analysis, the complementary role of generative AI and human judgement, and usability challenges related to the current implementation.

Structured guidance and future orientation. Participants particularly valued the stepwise structure of the process. The sequence encouraged them to move beyond existing job profiles

and systematically consider internal and external developments that might affect the role. One participant described how working through the individual steps led to several substantive corrections of the initial assumptions about the role, including a shift from operational to strategic requirements and the reconsideration of specific competencies as interface rather than functional requirements. The iterative process was perceived as encouraging users to challenge intermediate results instead of moving directly from initial information to a final competency profile. At the same time, some feedback indicated that parts of the process were repetitive and could be further streamlined.

AI support and human judgement. Participants generally perceived the AI generated suggestions as useful for broadening their perspective and identifying aspects they might otherwise have overlooked. The future oriented stages were particularly highlighted as providing additional perspectives. However, the testing also showed the importance of continued human evaluation. In individual cases, AI outputs omitted context specific requirements or produced overly broad and generic lists that required manual supplementation, reduction, or prioritization. More detailed prompts were perceived as producing more precise outputs than the simpler prompts, although the availability of two prompt versions also created uncertainty about which version to use. These observations provide initial support for the human evaluated principle of the proposed model: AI generated outputs can support the analysis, but contextual assessment and final decisions remain with the line manager.

Usability and opportunities for refinement. The main challenges concerned the practical interaction with the prototype rather than its underlying analytical logic. Participants identified the switch between the interactive PDF and external AI systems, repeated transfer of information, and selection between different prompt versions as potential sources of friction. Suggestions for further development included clearer guidance on prompt selection, greater standardization of outputs, reducing repetitive steps, and stronger integration of AI into the guided process. The reported completion time for the line managers ranged from approximately 30 to 45 minutes, with one participant indicating that a faster application could take around 15 minutes. Four of the five line managers explicitly stated that they would use the approach for future competency analysis.

The two consultants provided an additional expert perspective. While they considered the process systematic and conceptually useful, they similarly questioned whether the current interaction design was sufficiently streamlined for direct use by line managers. Their feedback particularly emphasized the need to reduce lengthy AI outputs and simplify the interaction between the structured process and generative AI.

5 Discussion and Implications

This study explored how structured guidance, relevant information sources, human expertise, and generative AI can be combined to support line managers in identifying current and future competency requirements for recruitment. The resulting model conceptualizes this process as human initiated, AI augmented, and human evaluated. Initial user testing suggests that the value of this approach lies not only in the information generated by AI, but particularly in the structured and iterative process through which managers arrive at a competency profile.

A key contribution of the proposed approach is its process orientation. Rather than starting with generic future skills or asking generative AI to produce a future oriented competency profile directly, the analysis starts from the specific organizational context and current tasks. Future competency requirements are subsequently derived by considering relevant internal and external

developments and their implications for the role and its tasks. This process logic is consistent with strategic job analysis approaches that connect current tasks and requirements with anticipated organizational and environmental changes (Singh, 2008; Ahmad & Alqaarni, 2023). The user testing provides initial indications that this stepwise approach can encourage reflection and lead managers to reconsider or refine initial assumptions about a role.

The findings also illustrate the complementary roles of human judgement and generative AI. AI generated suggestions broadened perspectives and provided additional input, particularly when considering future developments, but they also omitted context specific requirements or generated overly broad lists. Human involvement was therefore required not only to validate a final result, but throughout the process to contextualize, challenge, supplement, and prioritize AI generated suggestions. This supports an augmentation rather than automation perspective on Human AI collaboration (Raisch & Krakowski, 2021) and illustrates how a Human in the Loop approach (Mosqueira Rey et al., 2023) can be operationalized in a specific HR decision process.

From a practical perspective, the prototype provides line managers with a structured way to conduct future oriented competency analysis without requiring them to develop the analytical process themselves. The two levels of prompts allow the guiding questions to be used either for managerial reflection or with more detailed generative AI support. However, the testing also revealed a tradeoff between analytical structure and ease of use. While participants generally valued the stepwise process, repeated switching between the interactive PDF and external AI systems and some repetitive steps created friction. Future development should therefore focus on simplifying the interaction while preserving the points at which managers are explicitly required to reflect on and evaluate intermediate results.

The study has several limitations. The prototype was tested with a small convenience sample of five line managers, supplemented by feedback from two consultants, and the findings should therefore be considered exploratory. Participants used different generative AI systems and applied the prototype to different roles, which reflects realistic use but limits comparability across cases. Furthermore, the study examined participants' perceptions of the process and resulting profiles rather than independently assessing the quality or predictive validity of the identified competency requirements. Future research could disentangle the effects of structured guidance and AI support by comparing unstructured human analysis, structured analysis without AI, and structured Human AI analysis.

6 Conclusion

Identifying future competency requirements is a context dependent analytical task that cannot be reduced to generating a list of future skills or prompting an AI system for a competency profile. This study proposes a structured Human AI Collaboration Model that combines human expertise, internal and external information, and targeted generative AI support across the competency analysis process. The approach is human initiated, AI augmented, and human evaluated. Initial user testing indicates that its potential value lies particularly in supporting systematic reflection on how future developments may affect roles, tasks, and competency requirements, while keeping contextual evaluation and decision making with the line manager. The findings provide a starting point for further research on how structured guidance and generative AI can jointly support future oriented competency management.

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