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Applying Job Design Criteria for Effective Human-AI Collaboration

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ABSTRACT

Human-AI collaboration often underperforms due to a lack of motivation-supportive system design. This paper proposes a framework grounded in work design theory – specifically the Job Characteristics Model (JCM) – to guide the development and evaluation of AI systems. We introduce qualitative evaluation anchors that translate core job design criteria into assessable aspects of AI-supported work. These anchors were developed through a theory-driven process that combines work design theory with recent literature on AI's impact on work characteristics. The goal is to foster intrinsically motivating and cognitively engaging human roles in AI collaboration, thereby enhancing overall human-AI team performance.

Keywords: Human-AI interaction design, Job characteristics model, Intrinsic motivation, Evaluation anchors, Work design

INTRODUCTION

While Artificial Intelligence (AI) technologies continue to evolve, human-AI collaboration in professional contexts often underperforms (Vaccaro et al., 2024). In many cases, humans tend to engage only superficially with AI-generated outputs, resulting in suboptimal decision quality (Buçinca et al., 2024). A key issue is that current AI systems are designed under the assumption that humans are naturally motivated to engage with AI outputs (Buçinca, 2024). However, motivation is not a fixed trait, but shaped by work design (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006; Parker & Grote, 2022). Many AI systems reduce human roles to merely accepting or rejecting outputs, which fosters passive human behavior, impedes learning and skill development, and can lead to overreliance on automation (Buçinca et al., 2021, 2025; Endsley, 2023; Parker & Grote, 2022).

To avoid this, the design of AI systems must actively support psychologically founded prerequisites that promote intrinsic motivation. This paper explores how such job design principles can be systematically integrated into AI design and evaluation. We propose theoretically grounded job design criteria and outline their qualitative operationalization for human-AI collaboration, as currently conceptualized within the HORIZON project AI4REALNET.

Chapter 2 outlines key challenges in current AI design. Chapter 3 presents the theoretical framework based on the Job Characteristics Model. Chapter 4 details the evaluation anchors as conceptual results. Chapter 5 discusses limitations and future directions.

Challenges in Current AI Design

Despite advances in AI, joint human-AI decision-making often underperforms compared to the best-performing individual, whether human or AI (Vaccaro et al., 2024). Endsley's (2023) *Ironies of AI* highlight how features intended to enhance system performance paradoxically undermine it. Many AI systems are opaque, making it difficult for humans to understand how outputs are generated. Simultaneously, humans tend to overestimate AI capabilities, leading to overreliance, where humans trust in AI outputs, even when suboptimal (Endsley, 2023). This amplifies automation bias – the tendency of humans to uncritically accept automation-generated outputs (Buçinca et al., 2021; Lee & See, 2004; Parasuraman & Manzey, 2010). Such effects are particularly problematic in professional high-stake contexts. Over time, they can impair learning and skill development, ultimately leading to deskilling (Buçinca, 2024; Buçinca et al., 2025).

Providing explainable AI (XAI) and interpretable models is a common response to these challenges (Schaffer et al., 2019), but remains insufficient as humans tend not to engage with it (Buçinca et al., 2024). One main reason for this lack of human engagement is the inappropriate allocation of tasks between humans and AI (Joe et al., 2015; Pritchett et al., 2014). Many systems allocate tasks based on technical feasibility rather than human strengths (Joe et al., 2015; Pritchett et al., 2014), leading to so-called ≪left-over≫ roles (Bailey, 1989; Parker & Grote, 2022), like system monitoring or handling exceptions (Feigh & Pritchett, 2014). These roles are cognitively demanding and psychologically unsuitable (Feigh & Pritchett, 2014), particularly as humans are ill-equipped to continuously monitor opaque, complex systems without active involvement (Yampolskiy, 2025).

To address this, AI design must move beyond a purely technology-driven approach and instead integrate psychologically founded principles that support intrinsic motivation to engage with AI. Therefore, we propose a work-design-based approach that ensures AI systems foster meaningful and cognitively engaging roles for humans. This approach builds on established job design theories and is outlined in detail in the following chapter.

THEORETICAL FRAMEWORK – THE JCM AND ITS EXTENSION

The Job Characteristics Model (JCM) by Hackman and Oldham (1976) defines five core task characteristics – skill variety, task identity, task significance, autonomy, and feedback – that foster critical psychological states such as experienced meaningfulness, experienced responsibility, and knowledge of results. These criteria are particularly relevant in human-AI collaboration, as AI systems shape how tasks are structured and executed (Parker & Grote, 2022; Zhang et al., 2025), ultimately influencing motivation (Buçinca et al., 2024; Liu & Li, 2025).

To address the cognitive demands of AI-supported, knowledge-intensive work, we draw on Morgeson & Humphrey's (2006) extension of the

JCM, which includes knowledge characteristics such as job complexity, information processing, problem-solving, and specialization. Notably, they reclassified *skill variety* as a knowledge characteristic and complemented the task characteristics with *task variety*. These criteria reflect the degree of humans' active cognitive engagement – a key factor in preserving expertise and preventing deskilling over time (Buçinca et al., 2025; Liu & Li, 2025; Parker & Grote, 2022).

To translate these criteria into a practical tool for the design and evaluation of AI, we operationalized them as qualitative anchors in a theory-driven process: starting from core job design literature, we conducted a targeted review on how AI affects each characteristic and synthesized the insights. At this stage, however, the framework is conceptual and requires empirical validation. Semi-structured interview guides and observational protocols to validate these anchors will be developed at a later stage.

The following section presents the task characteristics, their relevance in the human-AI context and the corresponding anchors, followed by knowledge characteristics in the same logic.

EVALUATION ANCHORS FOR HUMAN-AI COLLABORATION

Task Characteristics

Task Significance is defined as "the degree to which the job has a substantial impact on the lives or work of other people, whether in the immediate organization or external environment" (Hackman & Oldham, 1976, p. 257). In AI-supported environments, perceived task significance may be diminished if meaningful aspects of a task are automated (Liu & Li, 2025). However, when AI takes over routine tasks, humans may focus more on value-adding activities. Table 1 presents anchors that capture how humans perceive both the significance of their own and the AI's contribution.

Table 1: Evaluation anchors for task significance.

High	Medium	Low
Humans recognize both, their own impact and the impact of AI on the overall performance, including the impact on others. AI makes this transparent. The task is perceived as significant for the overall performance.	Humans have a basic understanding of how their actions impact the overall performance, but the impact is not always obvious. AI makes it partly transparent. The task is perceived as partly significant for the overall performance.	Humans do not recognize the impact of their own work or the AI on the overall performance. AI is not able to make impacts transparent. The task is perceived as routine and without significant importance for the overall performance.

Task Identity refers to "the extent to which a job requires completing a 'whole' and identifiable piece of work" (Hackman & Oldham, 1976, p. 257). In AI-supported settings, workflows are often fragmented as automation takes over individual steps. As a result, humans may only engage with isolated parts of the process, making it harder to understand how their contribution fits into the final outcome (Liu & Li, 2025). When human roles are limited to monitoring or validating AI outputs, their connection to a complete task may weaken (Feigh & Pritchett, 2014; Joe et al., 2015; Parker & Grote, 2022). Table 2 presents evaluation anchors that assess the extent to which humans perceive their work as coherent and complete.

Table 2: Evaluation anchors for task identity.

High	Medium	Low
Humans are assigned a complete task (including planning, preparation, execution and follow-up tasks) and see how their work contributes to the whole. AI supports without fragmenting the process and by making contributions transparent.	Humans are involved in selected task steps. AI handles key steps and makes contribution partially transparent.	Humans only perform isolated actions without seeing how their input fits into a complete task. AI executes most of the process.

Task Variety is about performing a range of different activities (Morgeson & Humphrey, 2006; Stegmann et al., 2010). AI can either increase variety by taking over routine tasks or reduce it by narrowing human roles to repetitive functions (Brougham & Haar, 2018; Liu & Li, 2025). Table 3 provides evaluation anchors to assess whether humans engage in diverse activities or if AI restricts task variety.

Table 3: Evaluation anchors for task variety.

High	Medium	Low
Humans are confronted with different types of problems, decision-making situations and contextual conditions that require different strategies for action.	Humans are involved in various tasks, but these are only partially interrelated. AI supports task variety but lacks context or integration between tasks.	Humans mainly carry out unrelated tasks. Humans are mainly occupied with monitoring the AI, executing its instructions or selecting AI-generated options in a limited number of tasks.

Autonomy refers to the degree of freedom individuals have in scheduling their work, making decisions, and choosing how to perform tasks (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006; Stegmann et al., 2010). In AI-supported work environments, autonomy may be constrained when systems enforce workflows or prescribe decisions (Feigh & Pritchett, 2014; Levy et al., 2021; Liu & Li, 2025; Parker & Grote, 2022;

Schaap et al., 2023). At the same time, AI can also enhance autonomy by offering flexible, human-adaptable options. The following anchors in Table 4 reflect the extent to which humans retain autonomy when working with AI systems.

Table 4: Evaluation anchors for autonomy.

High	Medium	Low
Planning: Humans have complete control over the planning of the timing and sequence of their tasks. The AI is flexible and adaptable to individual plans. **Decision-making:** Humans are free to implement their own ideas or AI-supported solutions. They can make independent decisions on goals and courses of action. The AI can be fully overridden. **Method**: Humans have complete freedom to decide which strategy to use to complete the task. The AI is adaptable to different methods and individual preferences.	**Planning:** People have a certain amount of leeway when planning the time and sequence of their tasks. The AI's specifications regarding time and sequence can be partially adapted by humans. **Decision-making:** Humans choose between a limited number of AI-generated options. Their ability to implement self-developed ideas is restricted but not entirely blocked. **Method:** Humans can adjust their approach within a set of predefined methods to carry out the task. The AI allows limited customization.	**Planning**: The timing and sequence of human tasks are largely or completely determined by AI. Humans have hardly any scope to change these. **Decision-making:** The AI dedicates decisions or enforces predefined options. Humans have little or no say in implementing alternative or novel solutions, even if they have them. **Method:** The AI enforces a fixed way of completing a task. Humans follow predefined steps with no flexibility in choosing or adapting the strategy.

Feedback refers to "the degree to which carrying out the work activities required by the job results in the individual obtaining direct and clear information about the effectiveness of his or her performance" (Hackman & Oldham, 1976, p. 258). AI can enhance feedback through immediate, data-driven responses but may also present it in ways that are difficult to understand (Shin et al., 2024). Table 5 presents evaluation anchors that assess the clarity, immediacy, and comprehensibility of AI-generated feedback.

Table 5: Evaluation anchors for feedback.

High	Medium	Low
Humans receive direct, comprehensible and prompt feedback from the AI regarding their own performance.	Humans receive direct feedback from AI regarding their own performance, but it is only partially comprehensible and/or not prompt.	The feedback from the AI is not comprehensible or timely, which makes it difficult to assess their own performance.

Knowledge Characteristics

Skill Variety refers to the breadth of skills required to perform a job (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006; Stegmann et al., 2010). Depending on whether AI complements or replaces human skills, it can either increase skill variety by requiring the integration of diverse skills such as analytical and interpersonal skills, or reduce it by narrowing tasks to highly specialized routines (Liu & Li, 2025; Parker & Grote, 2022). Table 6 presents evaluation anchors that assess whether the AI-supported work context demands a broad range of human skills or restricts the variety of skills required.

Table 6: Evaluation anchors for skill variety.

High	Medium	Low
The humans' task requires a broad range of relevant knowledge and different relevant skills.	The humans' task requires a narrower range of skills and knowledge compared to without AI.	The humans' task does not require broad knowledge and different skills. The tasks are very specialized.

Problem Solving refers to "the degree to which a job requires unique ideas or solutions" (Morgeson & Humphrey, 2006, p. 1323). While AI can support decision-making by offering insights and alternatives (Levy et al., 2021; Salimzadeh & Gadiraju, 2024), it may also foster overreliance and reduce opportunities for independent problem-solving (Buçinca et al., 2021; Schaffer et al., 2019; Vaccaro et al., 2024). As a result, humans risk becoming passive recipients rather than active contributors, which may lead to a gradual loss of expertise (Buçinca, 2024; Buçinca et al., 2025; Parker & Grote, 2022). Table 7 presents evaluation anchors that assess the extent to which individuals can independently develop solutions versus relying on predefined AI-generated options.

Table 7: Evaluation criteria for problem solving.

High	Medium	Low
The humans develop their own ideas or solutions and can react creatively to unforeseen situations. AI does not provide solutions.	The development of human ideas or solutions is restricted because the AI proposes solution options. However, these can be adapted.	Humans have little opportunity to develop or apply their own ideas or solutions. AI provides fixed solutions with minimal room for customization.

Job Complexity refers to the degree to which a task is mentally demanding or difficult (Morgeson & Humphrey, 2006; Stegmann et al., 2010). While AI may simplify operational tasks, it can simultaneously increase cognitive load through requirements such as monitoring, exception handling, and adaption to AI-generated outputs (Buçinca et al., 2025; Feigh & Pritchett, 2014; Levy et al., 2021). In this way, AI tends to shift complexity rather than reduce it. Table 8 presents evaluation anchors that assess the cognitive demands placed on humans.

Table 8: Evaluation anchors for job complexity.

High	Medium	Low
Humans engage in sustained mental effort, applying judgment, practice, and adaptive thinking. The complexity stems from the task itself and is experienced constructive challenging. AI provides clear and relevant output without unnecessary mental effort.	Humans apply some cognitive effort, mainly through reviewing AI suggestions or applying predefined rules.	The task is cognitively under- or overchallenging. Humans either passively monitor AI outputs or face results that are too complex to interpret. In both cases, the task lacks constructive cognitive activation.

Information Processing refers to "the degree to which a job requires attending to and processing data or other information" (Morgeson & Humphrey, 2006, p. 1323). AI can support this function by pre-filtering data, but may also undermine it by fully pre-processing information, turning humans into passive recipients (Buçinca, 2024). As such, the human role in information processing is a critical factor in maintaining cognitive engagement and preserving expertise. Table 9 presents evaluation anchors that assess the extent of human involvement in interpreting and integrating information.

Table 9: Evaluation anchors for information processing.

High	Medium	Low
Humans actively search, analyse, and integrate information. AI provides structured but unprocessed data and may support understanding through simulations. Interpretation remains a human task.	Humans process pre-filtered information selected by the AI. Some interpretation is needed, but the system steers attention and framing.	Humans consume fully processed AI outputs. Information is final, and little to no analysis or interpretation is required.

Specialization refers to "the extent to which a job involves performing specialized tasks or possessing specialized knowledge and skill" (Morgeson & Humphrey, 2006, p. 1324) and reflects whether human expertise remains essential or is increasingly replaced by automated processes in AI-supported work environments. AI may foster specialization by taking over routine tasks, enabling humans to concentrate on expert-level activities (Brougham & Haar, 2018; Liu & Li, 2025). However, this criterion is critical when it results in low skill variety. Table 10 presents evaluation anchors that assess whether human tasks require in-depth domain expertise to perform their tasks or whether AI systems reduce the need for specialization.

Table 10: Evaluation anchors for specialization.

High	Medium	Low
The task requires in-depth knowledge in a specific area to perform the task effectively. AI handles routine work.	A certain amount of specialized knowledge and skills are required, but most of the time general knowledge is sufficient.	Specialized knowledge is not required. General knowledge is sufficient, as AI handles the expertise by solving problems.

Together, these evaluation anchors represent an initial step toward a structured conceptual framework for assessing whether AI systems support or hinder motivational and cognitive engagement in human-AI collaboration.

CONCLUSION

Despite technological advancements, human-AI collaboration continues to face critical challenges such as overreliance (Endsley, 2023), automation bias (Buçinca et al., 2021; Lee & See, 2004; Parasuraman & Manzey, 2010), and poorly aligned task allocation that often overlooks human strengths and weaknesses (Joe et al., 2015; Pritchett et al., 2014). Current solutions like XAI fail to address the root problem: the lack of motivation-supportive interaction design, which is a prerequisite for meaningful human engagement with AI systems (Buçinca et al., 2024). To address this, we introduce an initial conceptual step toward a design and evaluation framework grounded in work design theory. Specifically, we apply and adapt criteria from the Job Characteristics Model (Hackman & Oldham, 1976) and its extension (Morgeson & Humphrey, 2006) to the context of AI-supported work. The resulting evaluation anchors offer a structured approach to assessing key motivational job characteristics in AI system design.

LIMITATIONS AND OUTLOOK

A key limitation of this work is the lack of empirical validation of the evaluation anchors. To address this, semi-structured interview guides and observational protocols are currently being developed to operationalize and test the framework in real-world settings.

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