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WIP: Teaching What AI Can't Do: A Task-Level Roadmap for the Future of Engineering Education

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WIP: Teaching What AI Can't Do: A Task-Based Analysis of Human Complementarity in Engineering Work

1. Abstract

This Work-in-Progress (WIP) paper investigates how artificial intelligence (AI) may reshape engineering work through a task-based analysis of nationally standardized occupational descriptions. Rather than forecasting job displacement or evaluating specific AI tools, this study examines how AI may interact with the tasks that define engineering practice across disciplines. Guided by human capital complementarity theory, we analyzed task descriptions from the U.S. Department of Labor's O*NET database for engineering occupations. Using qualitative content analysis, each task was coded according to its likely relationship with AI as substitutable, augmentable, complementary, or emergent. Preliminary findings indicate that AI is more often positioned as augmenting or complementing engineering work than replacing it. Augmentable tasks were most common in analytical and modeling-intensive activities, where engineers remained responsible for interpreting outputs and validating results. Complementary tasks were prominent in integrative work, emphasizing human judgment, coordination, and accountability. In contrast, substitutable and emergent tasks were less common. These findings suggest that the enduring value of engineers' work lies not only in technical execution, but in interpretation, judgment, and responsibility. As such, engineering education should increasingly prepare students to critically engage AI-generated outputs, integrate technical and contextual considerations, and exercise professional judgment in complex practice.

2. Introduction.

This Work-in-Progress (WIP) paper explores a task-based approach to examining engineering work in the context of Artificial Intelligence (AI). Rather than predicting job futures or evaluating specific AI tools, we analyze nationally standardized task descriptions for engineering roles to examine how AI relates to different components of engineering work. Artificial intelligence is increasingly embedded in engineering practice, reshaping how engineers analyze data, design systems, and make decisions. Advances in generative models, simulation tools, and automated analytics now perform many activities that have long been central to engineering work, including numerical analysis, modeling, and technical documentation. Recent national reports characterize AI as a general-purpose technology that reorganizes work primarily through task reconfiguration rather than wholesale occupational replacement, with important implications for how human expertise is exercised across professions (Committee on Automation and the U.S. Workforce: An Update et al., 2025). In parallel, federal initiatives led by the National Science Foundation emphasize the need for workforce and educational systems to adapt to AI-enabled contexts by rethinking how technical expertise, judgment, and responsibility are developed through education and training (National Science Foundation, 2020, 2022).

Despite these calls, much of the published work on AI in engineering education remains oriented toward classroom-level applications, competency-specific education, and adoption for research, rather than toward systematic examination of how engineering work itself is being restructured (Berdanier, 2016; Harris & Kittur, 2024; Katz, 2019; Menekse, 2023) Research on engineering practice suggests that engineering work is composed of heterogeneous and evolving task repertoires rather than stable job roles (Trevelyan, 2014; Mazzurco et al., 2021). From this perspective, understanding AI's implications for engineering education requires attention to tasks rather than job titles.

Accordingly, this study is guided by the following research question: How do nationally standardized task descriptions across engineering disciplines reflect the ways AI may reshape engineering work? Leaning on Human Complementarity Theory (Acemoglu & Autor, 2011), we use this analysis to examine whether a task-based analysis can provide a useful empirical foundation for identifying enduring forms of human contribution and informing future engineering education research.

3. Engineering Work as Task-Based Practice.

Based on existing research, engineering work can be viewed as a task-based practice. While engineering practice involves problem solving and the application of specialized knowledge, it is fundamentally the intentional integration of these elements toward meaningful ends (Sheppard et al., 2007). Empirical studies further show that engineers coordinate interdependent tasks and people, with many outcomes realized through others' contributions, highlighting engineering as both a technical and social discipline (Trevelyan, 2007). Qualitative research on workplace engineering problems depicts engineers operating in complex, uncertain contexts characterized by conflicting goals, multiple solution strategies, non-engineering constraints, distributed knowledge, and inherently collaborative work (Jonassen et al., 2006). Together, these findings support framing engineering work through the lens of coordinated tasks, emphasizing that tasks provide a primary means of describing and studying what engineers do.

Studies of engineering practice consistently show that professional engineering work extends well beyond technical analysis to include coordination, communication, negotiation, and responsibility for outcomes (Trevelyan, 2014). A synthesis of research on engineering work across disciplines similarly identifies recurring activity categories such as design, problem solving, collaboration, and decision-making (Mazzurco et al., 2021). These findings align with practice-based perspectives in engineering education, which conceptualize expertise as participation in patterned forms of activity rather than possession of isolated skills (Johri et al., 2014; Stevens et al., 2008). Other studies have explored the integration of the social and technical aspects of engineering, finding that engineering work frequently requires engineers to link technical expertise with social interactions (Jesiek et al., 2018). This task-centered view challenges role-based discussions of engineering practice and instead suggests that engineering expertise and how it will be impacted by AI requires attention to what engineers do, rather than specific titles.

Human Complementarity Theory. This study draws on task-based theories of technological change, which argue that technologies reshape work by reallocating tasks between humans and machines rather than eliminating entire occupations (Acemoglu & Autor, 2011). From this perspective, the central question is not whether AI replaces engineers, but how engineering work is reconfigured and where human contribution remains essential. Per the framework, tasks may be substituted, meaning they can be performed largely by automated systems; complementary, in that technology enhances rather than displaces human involvement; augmented, where technology generates information for interpretation; or emergent associated with oversight, governance, or responsibility for technological systems (Acemoglu & Restrepo, 2018, 2020). This theoretical framework has seldom been used in engineering education beyond anchoring the importance of human-technology integration in the context of the fourth industrial revolution (Cheville et al., 2018; Liu & Brunhaver, 2025; Oh et al., 2020; Ulutan, 2019). Thus, we argue that human capital complementarity provides a novel lens for examining what engineering classrooms should prioritize and how engineering education should be structured in the age of AI.

4. Methods.

We conducted a qualitative document analysis (Bowen, 2009) of engineering task descriptions drawn from the U.S. Department of Labor's O*NET database(U.S. Department of Labor, Employment and Training Administration, 2024). O*NET provides standardized descriptions of occupational tasks developed through expert input and is widely used in workforce research and policy analysis. In this study, task descriptions are treated as institutional representations of engineering work rather than direct observations of practice.

Data Selection and Analysis. We identified occupations containing the term "engineer" and limited the dataset to occupations requiring ABET accreditation per the database. The resulting dataset included task statements spanning multiple engineering disciplines. The unit of analysis was the individual task statement. Analysis, thus far, has proceeded in two stages. In the first cycle, task statements were coded according to their relationship to AI using four categories derived from task-based theories of technological change (as shown in Table 1). Augmentation was included as an analytic refinement to capture hybrid task relationships observed during coding, consistent with recent applications of task-based frameworks to AI-mediated work (Acemoglu & Restrepo, 2020).

Table 1. First Cycle Coding Framework

Code	**Operationalization**
Substitutable	Tasks that could plausibly be performed largely by AI systems with minimal human involvement.
Emergent	Tasks that arise in response to AI adoption, such as oversight, governance, or responsibility for automated systems.
Complementary	Tasks where AI may support work, but human involvement remains central to task execution or decision-making
Augmentable	Tasks in which AI performs portions of the work while human engineers retain responsibility for interpretation, validation, or subsequent action.

Following first-cycle a priori coding, analytic memos focused on identifying patterns in the form of human contribution emphasized across tasks, such as interpretation, judgment, or accountability (Miles et al., 2014). Coding was conducted by multiple researchers trained in qualitative methods using a shared codebook, with discussion used to resolve ambiguities and refine shared understanding (Tracy, 2010).

5. Limitations

As a WIP, this study offers an initial empirical examination of how AI may relate to engineering work through a task-based lens. The findings should therefore be interpreted as exploratory rather than definitive. Rather than directly capturing how AI is currently being used in engineering workplaces, this study relies on nationally standardized task descriptions as a structured proxy for examining how AI may relate to different forms of engineering work. This limitation is especially important given that occupational databases may not yet fully reflect the evolving role of AI in engineering practice. For example, the limited identification of emergent tasks across disciplines may indicate that formal task descriptions lag behind workplace change, rather than that AI-enabled work is absent.

6. Preliminary Findings.

Across engineering disciplines, patterns in AI–task relationships consistently surface distinct forms of human contribution. In particular, we found that at a high level (1) augmentable tasks foreground interpretation, (2) complementary tasks foreground judgment, and (3) substitutable and emergent tasks are a minority across engineering disciplines. These patterns are visible in the distribution of task statements across disciplines and in the language used to describe what engineers are expected to do. These findings describe disciplinary task lists and thus do not predict forthcoming experiences of any individual engineer or role. By examining how tasks are distributed and described across disciplines, this analysis highlights recurring forms of human contribution that engineering education must prepare students to enact across a range of professional contexts.

Substitutable and Emergent Tasks. Substitutable tasks constituted a small share of the dataset and were largely routine or procedural. Emergent tasks were rare, with only a small number of task statements explicitly referencing AI-related oversight or governance. This limited representation likely reflects a lag in how standardized task descriptions capture rapidly evolving AI-related work rather than the absence of such work in practice.

Complementary Tasks. Complementary tasks were prominent in integrative and coordination-oriented work. These tasks emphasized judgment under constraint, coordination across stakeholders, and responsibility for outcomes. Examples included evaluating design alternatives, ensuring regulatory compliance, overseeing construction or maintenance activities, and communicating technical information to diverse audiences. Even when AI could provide supporting information, task descriptions framed humans as accountable decision-makers.

Augmentable Tasks. Augmentable tasks were especially prominent in modeling-intensive and analytical activities. These tasks frequently involved generating, reviewing, or analyzing simulations, estimates, or test results. While AI tools could plausibly support or accelerate these activities, task descriptions consistently positioned engineers as responsible for interpreting outputs, validating assumptions, and determining implications for design or performance. This pattern suggests that AI shifts human effort toward interpretation and sensemaking rather than eliminating technical engagement.

7. **Conclusion and Future Work**.

These preliminary findings suggest that engineering work, as institutionally represented, is primarily characterized by augmentation and complementarity rather than substitution. Interpretation, judgment, and responsibility were identified as recurring forms of human contribution across disciplines. As a work in progress, this study demonstrates the potential of task-based analysis as a method for examining engineering work in AI-mediated contexts. However, task descriptions alone cannot capture how engineers or educators interpret and enact these tasks.

Next steps will extend this analysis by examining how engineering faculty and industry stakeholders interpret AI-related task structures, with particular attention to how workplace expectations are translated into curricular priorities, professional formation, and discipline-specific conceptions of preparedness. This next phase will help clarify whether the patterns identified in occupational task descriptions are reflected in lived practice and educational decision-making, while also informing how engineering education can respond to AI-mediated work in ways that preserve meaningful human contribution rather than simply adapting to technological change.

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