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Competency Framework for AI in Construction: Shaping Learning Outcomes for the Next Generation

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The unprecedented adoption of artificial intelligence (AI) necessitates a systematic understanding of the core knowledge, skills, and abilities (KSAs)—hereafter referred to as competencies—required for AI implementation in the construction industry. Universities offering construction-related programs must acknowledge this transformation and develop curricula to ensure graduates are AI-proficient. These educational initiatives require a competency framework that delineates the essential KSAs for construction program graduates. However, such a framework is currently lacking. This paper addresses this gap by conducting a qualitative meta-analysis of significant AI training programs to develop a competency framework for guiding intended learning outcomes (ILOs) in construction education. Through comprehensive review, analysis, and synthesis of relevant sources, this study establishes a foundational framework that serves both as a catalyst for developing construction program intended learning outcomes (ILOs) and as a basis for scholarly discourse on framework refinement through industry engagement and needs assessment.

Keywords: Artificial intelligence, Intended learning outcomes, Curriculum development, Construction education, Digitalization

Introduction

The artificial intelligence (AI) implementation in construction reached USD 3.20 billion globally in 2023, with projections indicating growth from USD 3.93 billion in 2024 to USD 22.68 billion by 2032, representing a compound annual growth rate of 24.5% (Fortune Business Insights, 2024). Recent industry surveys report varying levels of AI adoption within construction firms, with one source indicating that 24% of professionals utilize AI for product development and marketing initiatives (Soto, 2024), while a Bluebeam study claims that 74% of construction managers have implemented AI solutions across various phases of their construction projects (Jones, 2024). According to Accenture's industry analysis, AI technologies present transformative opportunities for the construction sector through enhanced operational efficiency and cost optimization. Projections indicate that AI implementation could increase construction firms' profitability by 38% by 2035 through automated project management systems, machine learning-based safety protocols, and algorithmic resource optimization. However, successful AI integration necessitates significant capital investment in computational infrastructure, workforce restructuring considerations, and comprehensive technical training programs to enable personnel to effectively utilize AI-driven construction management systems (Accenture, 2017). Recent research indicates that AEC educators perceive AI literacy as one of the top computing-related competencies students need to develop in the next 5–10 years (Onatayo et al., 2024). The most viable long-term solution to address the shortage of construction professionals with AI competencies is establishing a sustainable pipeline of AI-ready graduates through redesigned university curricula and integrated AI-specific learning outcomes in construction-related programs. Assessing AI education requirements through the lens of employers and industry practitioners provides insights into post-graduation outcomes and enables measurement of learning outcomes in practical working environments. This approach also reveals the construction industry's specific requirements for AI competencies. However, a standardized competency framework for AI in construction-related education remains absent. This study advances the field by developing a comprehensive AI competency framework through two key approaches. First, it synthesizes established frameworks from related disciplines, drawing on their theoretical foundations. Second, despite the current scarcity of AI programs in construction-focused institutions, it analyzes these emerging initiatives to ensure domain relevance. The framework, developed through qualitative meta-analysis, provides a foundational structure that awaits empirical validation for construction contexts and subsequent adaptation across different regional settings.

Contextual background

Artificial Intelligence (AI) integration in construction represents a technological advancement focused on implementing computational intelligence systems to enhance construction operations. The field encompasses machine learning algorithms, computer vision systems, and natural language processing applications that optimize critical processes including project planning, risk assessment, scheduling, supply chain operations, quality control, and safety protocols. Market growth is primarily driven by demands for operational efficiency, cost optimization, enhanced workplace safety, and environmental sustainability across construction projects (Fortune Business Insights, 2024). Despite the benefits of implementing AI technologies, companies and practitioners in the civil engineering and construction sectors face challenges in adopting these innovations. A primary obstacle is the necessity of accessing employees with the relevant technical skills and expertise required for effectively utilizing AI systems. Research indicates that limited skills and competencies in AI present a significant barrier to the successful adoption of AI technologies within the construction sector. Studies underscore the urgent need for targeted training and educational initiatives to address this skills gap and adequately equip the workforce for the demands of an AI-driven construction industry (Siriwardhana & Moehler, 2024). Formal education programs are essential in equipping construction professionals with the knowledge and skills required for effective AI integration. This necessity is further supported by calls for a comprehensive “remodeling” of university curricula to better prepare students for the AI-driven demands of the industry (Mian et al., 2020). Construction educators increasingly recognize AI literacy as a critical competency for students to develop within the next 5–10 years (McCord et al., 2024), necessitating a comprehensive competency framework tailored to the construction domain, as discussed next. The development of AI competencies in construction education has been predominantly shaped by private sector training programs, which primarily emphasize technical proficiency in proprietary AI platforms. While these programs provide operational knowledge, they often neglect critical discourse on AI's broader implications for learning and professional practice (UNESCO, 2024). Furthermore, existing AI frameworks and strategic roadmaps typically present generalized approaches that fail to address the context-specific requirements and unique challenges faced by construction practitioners (Siriwardhana & Moehler, 2024). The absence of scientifically-validated frameworks for integrating AI-related content into higher education curricula represents a significant gap in construction education. This deficiency is particularly critical given the increasing adoption of AI technologies in construction practices. A rigorously developed, research-based competency framework is essential to guide the systematic integration of AI education in construction programs. Such a framework would ensure that students develop not only technical proficiency but also the critical thinking skills necessary to evaluate and implement AI solutions within the complex socio-technical environment of construction projects.

Synthesis of relevant research

The development of AI competency programs in higher education institutions has emerged as a critical initiative, though these efforts have largely progressed independently without standardized frameworks for construction-specific applications. A comparative analysis of prominent programs reveals diverse approaches to AI education in construction. Stanford University's "CEE329" course presents a comprehensive overview of AI applications across the architecture, engineering, and construction (AEC) industry, strategically focusing on practical applications such as design optimization, scheduling, documentation, safety, and project monitoring. Notably, this course's accessibility to students without prior AI knowledge demonstrates an inclusive approach to technological integration in construction education (CIFE, 2018). The University of Florida's "DCP 4300" 'AI in the Built Environment' takes a different approach, offering specialized training that bridges theoretical concepts with real-world applications for design, construction, and planning students. This introductory program's emphasis on practical scenarios provides students with tangible understanding of AI implementation in construction contexts (University of Florida, 2024). Carnegie Mellon University's "MS in AI Engineering-Civil Engineering" program demonstrates a comprehensive curriculum structure, integrating advanced technical competencies in machine learning and deep learning with critical considerations of engineering ethics and policy frameworks (Carnegie Mellon University, 2024). This holistic approach specifically addresses the evolving technological demands within civil engineering practice. In contrast, the CIB-funded program at Politecnico di Milano emphasizes a more targeted technical focus, concentrating primarily on practical machine learning methodologies and their applications in civil engineering contexts (CIB, 2024). The University of Illinois at Urbana-Champaign adopts a research-oriented approach through its graduate seminar series (CEE 595), facilitating in-depth exploration of AI applications specifically within construction scenarios (The Grainger College of Engineering, 2024).

This diversity in programmatic approaches reflects the broader industry recognition of AI's transformative potential in civil engineering. It also reveals a spectrum of approaches, from introductory exposure to advanced specialization, reflecting the industry's evolving needs for AI expertise at various levels. Various international organizations have developed comprehensive AI competency frameworks, though these frameworks predominantly focus on general applications rather than industry-specific implementations in construction. UNESCO's "AI Competency Framework for Students" establishes 12 competencies across four dimensions—human-centered mindset, ethics of AI, AI techniques and applications, and AI system design. While these competencies provide valuable foundational knowledge, they do not address the specific technical requirements and operational constraints inherent in construction projects and civil engineering applications. Similarly, UNESCO's "AI Competency Framework for Teachers" and their "Guidance for Generative AI in Education and Research" offer broad guidelines for educational integration of AI technologies. However, these frameworks lack specific considerations for engineering education and practical implementation in construction-related disciplines, where AI applications range from structural optimization to construction safety monitoring. The "Beijing Consensus on Artificial Intelligence and Education" emphasizes inclusive AI development but does not address the unique challenges of implementing AI within the complex, project-based nature of construction operations (UNESCO, 2024). Beyond UNESCO's educational focus, industry-oriented frameworks such as the "Competency Model Approach to AI Literacy" (Faruqe et al., 2021), and the "AI-Oriented Competency Framework for Talent Management" attempt to bridge the general workforce skills gap

(Bharathithasan & Srinivasan, 2024). While these frameworks effectively address broad technical and non-technical competencies, they fall short in addressing construction-specific requirements, such as integration with Building Information Modeling (BIM), automated equipment operation, and real-time project monitoring systems. While each program contributes uniquely to AI education in construction, the lack of standardization across institutions suggests an opportunity for developing specialized AI competency frameworks that specifically address the unique challenges and requirements of the construction industry, including considerations for site safety, regulatory compliance, and project delivery methods.

Research methods

This study employed an explanation-building approach through a comprehensive theoretical literature review, following the typology proposed by Paré et al. (2015). This methodological framework was chosen because it provides prescriptive guidelines for industry practitioners while synthesizing theoretical foundations into practical applications. The review methodology specifically aimed to identify, analyze, and contextualize AI competency principles within the construction industry's real-world environment. The selection of a theoretical literature review approach was particularly appropriate for examining AI competency in construction, as this emerging field benefits from the systematic synthesis of disparate information into comprehensive frameworks. This methodological choice enables the development of prescriptive guidelines with direct applicability to industry practices, while addressing the current gaps in knowledge integration (Pawson et al., 2005). The review followed a two-phase methodology. The first phase analyzed existing AI training courses and competency frameworks across disciplines. The second phase employed a snowballing literature search technique (Pawson et al., 2005) to identify related publications, yielding 30 relevant works on AI competency, including specific sources addressing AI training in construction domains. The identified resources were systematically screened using predefined criteria. Academic papers, research articles, books, book chapters, and technical reports were retained if they demonstrated direct relevance to the fundamental aspects of AI education, competency development, or learning theory. Materials lacking this direct relevance were excluded from the analysis. This selective process ensured the final collection of sources effectively informed the definition of AI competency in construction. Comprehensive details of the selection criteria and analyzed sources are documented in Appendices A and B.

This study defines AI competency in construction as encompassing both emerging Large Language Models (LLMs) and established AI methodologies. While LLMs have transformed capabilities in unstructured data tasks such as documentation and semantic analysis, comprehensive AI competency extends to structured data methods, including supervised learning for progress tracking and cost prediction. This expanded scope addresses the full spectrum of construction industry needs, combining operational proficiency in LLMs with technical expertise in traditional machine learning approaches to deliver integrated solutions across diverse construction challenges in line with Liu et al. (2024). The paper adopts a competency definition and framework structure aligned with UNESCO's AI competency framework for students (UNESCO, 2024). This framework was selected over alternative structures due to UNESCO's status as a leading international non-commercial organization and its objective of providing a global reference for core AI competencies that can inform national and institutional framework design. Following UNESCO's approach, competency is defined through three fundamental pillars: knowledge, skills, and values. The framework's structure is organized as a matrix, as depicted in Figure 1. The framework matrix comprises nine competency blocks formed by intersecting the three interlinked AI competency pillars with three progression levels. The three pillars—knowledge, skills and values—are interdisciplinary and extend beyond particular AI tools or domains. While knowledge and skills are important components of AI competency, education systems must also ensure that students acquire the values needed to examine and understand AI critically, considering its ethical, social, and technical dimensions. Therefore, educators must move beyond technical skills to equip students with values associated with an ethical and human-oriented mindset (UNESCO, 2024).

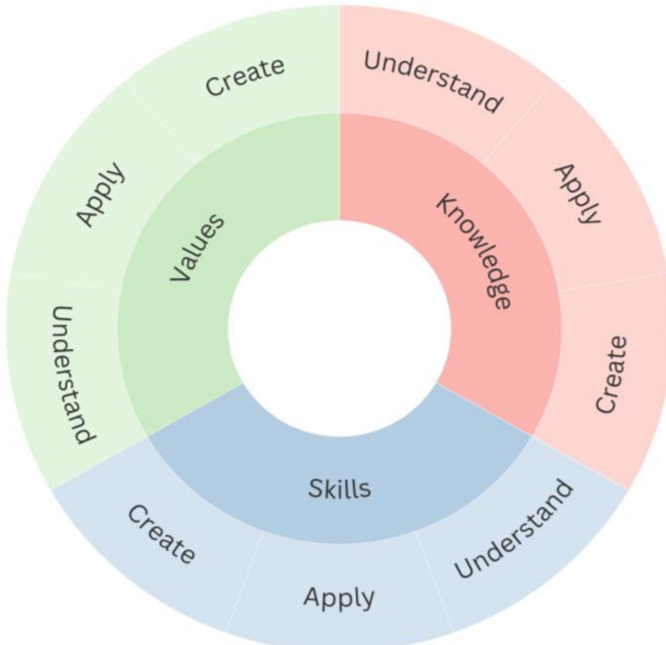

Figure 1. The competency framework structure and blocks

The three progression levels—understand, apply, and create—reflect increasing proficiency in AI engagement. The **understand** level establishes foundational concepts and ethical considerations, while the **apply** level focuses on transferring these competencies to solve complex problems in varied contexts. The **create** level advances to innovation and implementation of AI solutions while evaluating their societal impact (Biggs & Tang, 2011). This structure facilitates spiral learning, enabling systematic competency development across educational stages.

From sources to the framework

The framework construction process is illustrated in Figure 2, with each stage detailed in subsequent sections.

Sources

The review analyzed a diverse collection of 30 documents, categorized by their institutional origins and thematic focus. In terms of institutional classification, five documents (16.7%) are formal competency frameworks, including UNESCO's AI frameworks for students and teachers, The Alan Turing Institute's business framework, Concordia University and Dawson College's framework, and the SFIA 9 Framework. University courses and programs constitute the largest category with 13 documents (43.3%), spanning institutions such as Stanford, ETH Zurich, Harvard, and the University of Florida, among others. Commercial and industry-oriented sources account for four documents (13.3%), including MinnaLearn's course, Civils.ai's qualification program, and Zigurat's construction course. The remaining eight documents (26.7%) are academic papers and research articles analyzing various aspects of AI competencies and implementation. Regarding thematic focus, 17 documents (56.7%) specifically address AI applications and competencies in construction-related fields, architecture, and the built environment, demonstrating a strong sectoral emphasis in the literature.

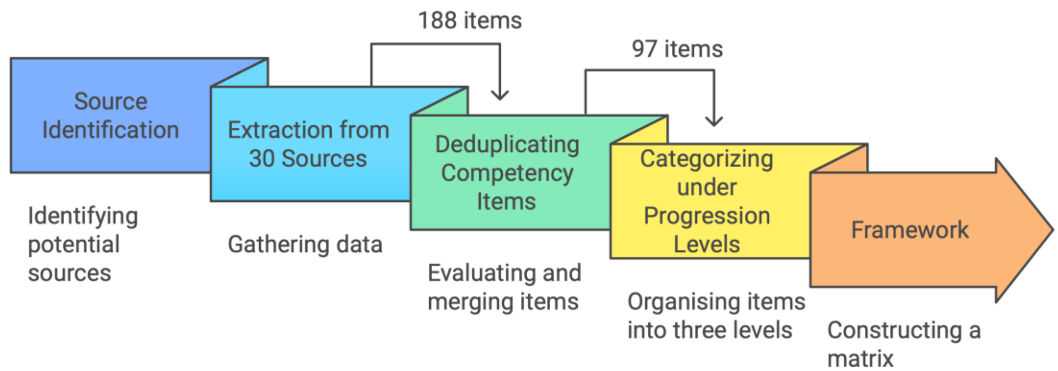

Figure 2. The competency framework development process

These include specialized programs like Stanford's CEE329 course and IAAC's Master in AI for Architecture & Built Environment. The remaining 13 documents (43.3%) focus on generic AI skills and competencies applicable across sectors, such as UNESCO's frameworks and the National Science Foundation's report on AI workforce development. This distribution reflects a balanced representation between sector-specific and general AI competency development in the reviewed literature, providing a comprehensive foundation for understanding both specialized and transferable AI skills in the contemporary educational and professional landscape. Readers are directed to Appendix A for detailed documentation of the framework's source materials.

Extraction of competencies

The research team conducted a systematic analysis to develop a comprehensive competency list. The methodology incorporated three pillars: knowledge, skills, and values, as discussed (see Figure 1). Each document underwent rigorous assessment, with competencies categorized across these pillars, yielding structured datasets that maintained source traceability while presenting findings hierarchically. The analysis identified 188 competency items: 75 knowledge-based, 68 skill-based, and 45 value-based components (see Figure 2). The team divided the analysis into subtasks and assigned roles based on expertise to create a concise, non-repetitive list of unique competencies. They conducted a thorough review to identify recurring themes and overlaps, ensuring that similarities among items were substantive rather than superficial. The categorization process grouped competencies based on meaning and context, with careful attention to avoiding overgeneralization or loss of specificity. For each group of similar items, the team developed detailed merger suggestions, including merger rationales and proposed consolidated competencies. Collaborative review resolved discrepancies through consensus and iterative refinement, ensuring consistency and accuracy. This consolidation process reduced the original list to 97 items: 46 knowledge-based, 40 skill-based, and 11 value-based components. The research team conducted a systematic categorization of AI competency indicators across three distinct progression levels: understand, apply, and create. These levels were operationally defined prior to classification, with "understand" representing foundational knowledge and comprehension, "apply" encompassing responsible utilization and adaptation of AI concepts, and "create" focusing on advanced implementation and ethical co-creation of AI solutions.

The categorization process employed a qualitative content analysis approach, wherein each competency indicator was methodically evaluated against predetermined level definitions. Two key constraints governed the classification process: indicators were assigned to exactly one category to maintain mutual exclusivity, and the original text of each indicator was preserved to ensure content validity. The researchers systematically analyzed each indicator's cognitive demands, complexity level, and alignment with the established progression framework. The categorization results were structured using a standardized format that clearly delineated indicators within their respective progression levels.

The competency framework

The components of the competency framework, within nine blocks, as illustrated in Figure 1 are discussed below under the three pillars of competency: knowledge, skills and values. The details of items are included in Appendix B, where all items are included with full phrases with full details and components.

Knowledge

The research study findings under the knowledge pillar indicate that construction students require a comprehensive understanding of AI knowledge encompassing various aspects and progression levels, aligning with UNESCO's work (UNESCO, 2024). At the "Understand" level, foundational knowledge includes AI capabilities and limitations, applications across related fields, machine learning and deep learning fundamentals, risk management and regulatory frameworks, smart building principles, data fundamentals, AI's impact on engineering, bias in AI systems, and social implications. Progressing to the "Apply" level, students need to demonstrate an understanding of various AI use cases like real-time tracking, AI-assisted decision-making, computational design, predictive analytics, data science principles, machine learning in structural optimization, data collection and validation, algorithmic decision-making, AI-based cost analysis, statistical aggregation and visualization, neural networks, time-series analysis, risk reduction techniques, AI integration in projects, energy auditing, structural health monitoring, predictive resource optimization, digital fabrication, and intelligent building design. This level emphasizes the application of knowledge in practical scenarios. Finally, at the "Create" level, students are expected to showcase comprehensive knowledge of AI ethics and governance, trustworthy AI, sustainability in construction and urban development, programming techniques, robotics and automation, physics-informed neural networks, and AI-driven construction management systems. This level emphasizes the integration of human-centered and ethical considerations into AI system creation, design and developments.

Skills

Findings emphasize that construction students need to cultivate a range of skills across three progression levels, a summary of which is illustrated in Figure 3. At the "Understand" level, students should acquire skills in communication, risk assessment, data analysis, tool evaluation and AI-enhanced engineering analysis, fostering a foundational understanding of AI's implications in the construction industry. As they progress to the "Apply" level, the focus shifts towards practical application, requiring skills in problem-solving using AI, project planning enhancement with AI tools, application of AI and machine learning in energy efficiency, urban analytics, structural optimization and real-world AI implementation tailored to specific needs. Finally, the "Create" level challenges students to become proficient in developing artificial intelligence/machine learning (AI/ML) solutions, encompassing dataset design, data engineering, AI integration, explainable AI techniques, robotics programming, ensuring safe deployment, fostering collaboration and leading AI-driven initiatives. These findings underscore the importance of a progressive skill development approach, enabling construction students to effectively leverage AI and contribute to the advancement of the built environment.

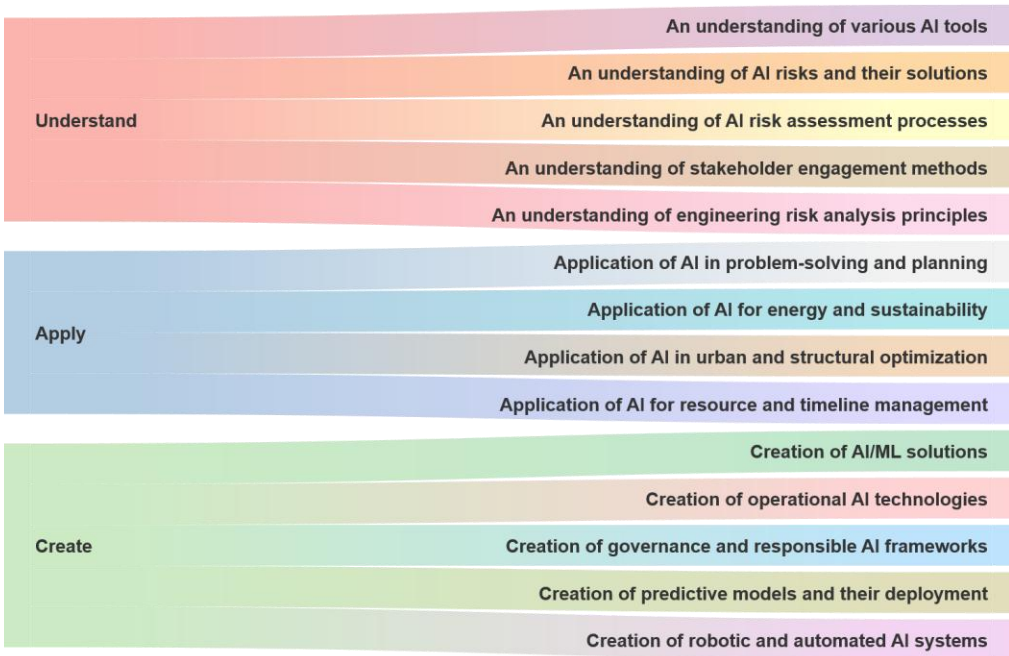

Figure 3. Broad Competency Items for the Skills Pillar

Values

The eleven items for the values pillar were classified under the three progression levels, with major ideas illustrated in Figure 4, which shows the broad category of value-based competency items. The findings highlight essential values that construction students must develop across three progression levels. At the "Understand" level, students must grasp the importance of transparency, accountability, trustworthiness, and fairness in AI systems and governance, ensuring responsible automation and decision-making. They should recognize safety and well-being as paramount in AI deployment, particularly in urban and construction applications. Ethical data handling principles and privacy are also crucial, ensuring responsible management of sensitive data. Additionally, students must value lifelong learning and adaptability in the constantly evolving field of AI. As they move to the "Apply" level, students should embrace collaboration, interdisciplinarity, and human-centered design practices that preserve human agency. This includes valuing responsible innovation, balancing technological progress with societal well-being, and integrating AI into public policy responsibly. Furthermore, a commitment to inclusivity, diversity, equity, and fairness in AI is vital, encompassing addressing underrepresentation, mitigating bias, ensuring inclusive and accessible design, and promoting equitable AI literacy for all communities. This progressive development of values ensures that construction students approach AI ethically and responsibly, contributing to a sustainable and equitable built environment.

Figure 4. Broad Competency Items for the Values Pillar

Conclusion

This study makes a significant contribution by introducing one of the first competency frameworks specifically designed for the construction context. It advances the domain through three key achievements: synthesizing major AI competency discourse sources, developing a comprehensive taxonomy of competency items, and establishing approaches for defining competency elements. The presented framework serves as a foundation for developing validated models that can inform curriculum and course development. Furthermore, this framework can be evaluated by construction industry experts through focus groups to determine the relevance of specific competencies, establish required proficiency levels, and define targeted learning outcomes. This expert validation process enables customization of the base model to address the construction industry's practical needs. Despite these contributions, the findings should be considered within certain limitations. First, the framework remains conceptual and requires validation. Future studies can use it as a foundation for validation and modification through exposure to field data. Furthermore, the categorization and theoretical lens represent one of several possible theoretical structures for defining such competency frameworks. Future research should examine various theoretical perspectives to underpin AI competency frameworks in construction, representing another research direction revealed by the present study's findings.

Appendix

Appendix A: https://doi.org/10.26188/27748143.v1
Appendix B: https://doi.org/10.26188/27748137.v1

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