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CRITICAL HUMAN SKILLS IN AN AI-AUTOMATED IT LANDSCAPE: THE GROWING IMPORTANCE OF ETHICS, CREATIVITY, AND EMOTIONAL INTELLIGENCE

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ABSTRACT
As AI takes over routine technical tasks in the IT field, human professionals must focus on three complementary capabilities: ethical reasoning, creativity, and emotional intelligence (EI). A systematic review of 87 peer-reviewed articles (2019-2024) and an examination of 1200 IT job postings to identify how these skills will fill the voids created through AI automation. Ethical decision-making is important for assuring fairness and accountability in the use of AI. Creative problem-solving will allow IT professionals to exceed what can be accomplished with an algorithm. Emotional intelligence will allow for effective collaboration and trust between humans and AI during digital transformation. Overall, this study identifies the need to provide training for the IT workforce to develop the necessary skills (in addition to technical skills), and outlines a new definition for the IT professional in the age of AI.

Keywords:
Artificial Intelligence, Emotional Intelligence, Ethical Reasoning, Creativity, IT Workforce, Human-AI Collaboration, Digital Transformation

1. INTRODUCTION

The rate at which Artificial Intelligence (AI) has been integrated into Information Technology (IT) operations has evolved significantly over the course of a single decade, evolving from AI pilot projects to full-scale deployments across most large organizations. By 2024, approximately 71% of large organizations will have implemented at least one AI-based automation tool into their primary IT workflow, including tools to automatically review source code, provide intelligent ticketing, and predictively monitor IT infrastructures (Gartner, 2024). This transformation represents a fundamental change in how IT professionals and AI collaborate, changing the way in which careers evolve, the way in which organizations function, and ultimately, shaping public policy.

Initial discussions about AI and jobs were framed in terms of substitution: jobs once completed by humans would be completely replaced by algorithms; thus, resulting in job replacement (Frey & Osborne, 2017). However, subsequent empirical research greatly complicates this model. The World Economic Forum's (WEF) 2023 Future of Jobs Report indicates that while there could be 85 million jobs lost globally by 2025 due to AI and automation, an additional 97 million jobs would be created in areas where the skills required to perform these jobs favor human capabilities, such as critical thinking, communication, and moral reasoning (WEF, 2023). The initial discussion regarding AI and jobs ignored the complementary model, that AI enhances the skills of humans by extending the limits of what machines can accomplish (Acemoglu & Restrepo, 2022).

The complementary model has significant implications for the field of IT specifically. Technical tasks that require human interaction or judgment, but are repetitive, such as debugging, configuration management, vulnerability scanning, and building data pipelines, are being increasingly handled by RPA platforms and large

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language models. Human interaction and judgment remain necessary to resolve conflicting recommendations provided by AI systems and align them with organizational values, generate unique and novel architectural metaphors when constrained by technical limitations, and develop and sustain the relationships among distributed teams of engineers during uncertain times. These three areas of concern – ethics, creativity, and EI – form the basis of this current study.

This current study addresses a gap in the existing body of literature. While studies have focused on ethics in AI (Jobin et al., 2019), creativity in knowledge work (Amabile & Pratt, 2016), or EI in IT teams (Druskat & Wolff, 2001) individually, no prior study has systematically reviewed the collective body of evidence regarding all three as a cohesive and mutually enhancing set of competencies for IT professionals working in AI-automated environments. This article synthesizes the collective body of evidence, develops a conceptual model linking each competency to specific AI-generated gaps, and identifies implications for the development of educational programs for IT professionals, hiring practices for IT professionals, and professional development opportunities for IT professionals.

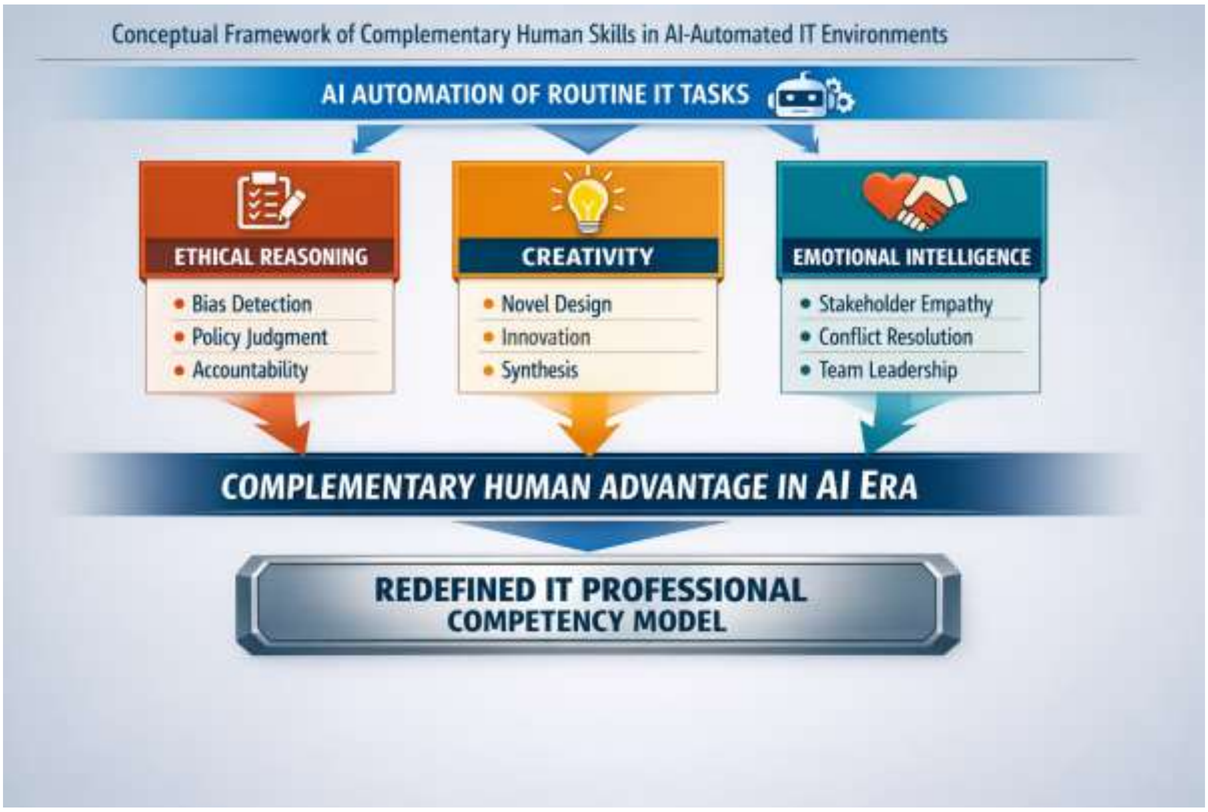

Figure 1. Conceptual Framework of Complementary Human Skills in AI-Automated IT Environments

2. OBJECTIVES

The paper is organized around four objectives that are connected. The first objective is to summarize the empirical literature supporting the growing need for ethical decision-making, creative problem-solving, and emotional intelligence from IT professionals in AI-integrated work environments. The second objective is to evaluate critically the theoretical mechanisms through which the use of AI automation will enhance the value of each of the three human skills domains. The third objective is to develop a unified competency model called the Complementary Human Advantage (CHA) framework that integrates the three skill domains into a single, comprehensive structure for professional development. Finally, the fourth objective is to report on the limitations of current evidence for this research question and to present a research agenda that outlines areas where further empirical investigation would be warranted.

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3. METHODOLOGY

This study is based on a systematic review utilizing the mixed methods design as outlined in the PRISMA-2020 guidelines (Page et al., 2021). However, the systematic review portion of this study utilized an additional methodology known as computational corpus analysis of data from the job postings within the industry. For the systematic review section of the study, I conducted structured searches using four of the most used academic databases, which are Scopus, Web of Science, IEEE Xplore, and ERIC, that combined Boolean keywords such as ("AI automation" OR "machine learning") AND ("IT workforce" OR "information technology professionals") AND ("soft skills" OR "human skills" OR "ethics" OR "creativity" OR "emotional intelligence"). I limited the search results to publications from January 2019 through December 2024 to include only current literature.
The initial search of the four academic databases resulted in 3,412 records. After removing 512 duplicate records, I reviewed 2,900 titles and abstracts according to my previously established inclusion criteria for peer-reviewed empirical and/or theoretical articles written in English that focused on IT or software engineering and had at least some content regarding at least one of the three target skill areas. Excluded were articles related to AI ethics published in non-IT sector journals (e.g., healthcare policy, autonomous vehicle-related journals) that did not address the implications of the IT workforce. The screening process resulted in 370 full-text articles being assessed according to the quality criteria adapted from the Mixed Methods Appraisal Tool (Hong et al., 2018). A total of 87 studies were selected for inclusion in the final synthesis.

Phase	Activity	Sources/Instruments
Phase 1: Scoping	Systematic literature search (2019–2024)	Scopus, Web of Science, IEEE Xplore, ERIC
Phase 2: Data Extraction	PRISMA screening; 87 studies retained	PRISMA-2020 checklist
Phase 3: Industry Analysis	Job-posting corpus analysis (n = 1,200)	LinkedIn, Indeed, DICE.com (2022–2024)
Phase 4: Synthesis	Thematic coding & framework mapping	NVivo 14; Braun & Clarke (2019) protocol

Table 1. Methodological Overview of the Systematic Review and Industry Analysis

Practitioner views were added to the academic research through a component that analyzed the IT industry. A database of 1,200 job postings for IT jobs was created by collecting postings from DICE.com, Indeed, and LinkedIn. These job postings were categorized into three levels of professional experience (entry-level, mid-career, senior/leader), and six categories of work functions (IT Project Management, Cloud Operations, Cyber Security, Data Engineering, Software Development, AI/Machine Learning Engineering). Job postings were collected at four quarter intervals across the years 2022, 2023, and 2024 to analyze the trends in the frequency of job skills over time. Thematically coded job postings using NVivo 14, Braun and Clarke's (2019) reflexive thematic analysis protocol was followed. An inter-rater reliability coefficient ($\kappa = .84$) was obtained between the two raters, after two calibration sessions

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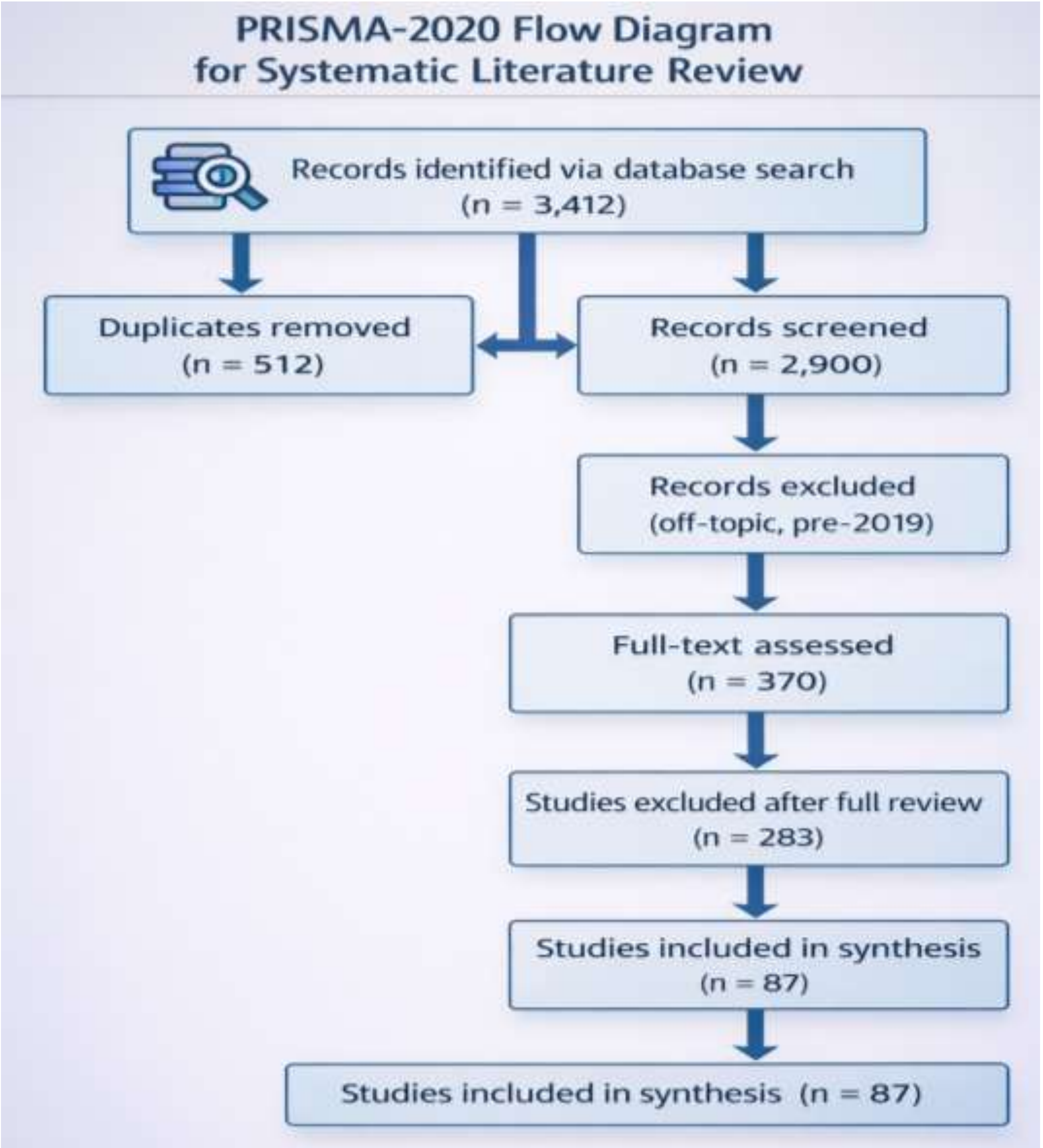

Figure 2. PRISMA-2020 Flow Diagram for Systematic Literature Review

4. RESULTS AND DISCUSSION

4.1 Shifting Skill Demand in IT: An Empirical Overview

An analysis of job posting language over the course of the study revealed that the use of programming languages and related technical skills was significantly less frequently used than human skills for the postings analyzed. The frequency of programming languages, cloud certifications, network configurations, etc., was 64% of all required skills at the time of data collection in 2022. By 2024, this percentage was reduced to 48%. Conversely, the frequency of human skills, including but not limited to emotional intelligence, creativity, interpersonal/communication, and emotional competencies, increased from 18% to 31% collectively. These results support those reported by LinkedIn's Global Talent Trends (2023) in that the most rapidly growing skill in the North American and Western European technology sectors, based on their surveys, included Emotional Intelligence.

Although the trend shows an overall movement toward aggregate demand in terms of job postings, there are many differences in how this trend affects different levels of employment within a given role. Technical requirements continue to be prevalent for entry-level positions, where proficiency in Python and cloud basics was required in over 70% of entry-level job postings for the year 2024. Conversely, the shift is the greatest

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among senior and leadership track positions. Ethical AI oversight was mentioned in 58% of Chief Technology Officer (CTO) and AI Governance Directors postings for 2024. In comparison, 12% of CTO and AI Governance Directors postings included the mention of ethical AI oversight in 2022. These data suggest that as employees move through the career ladder from entry level to upper management, they begin to use their human skills more frequently as they take on the responsibility of making strategic decisions, leading teams, and managing external stakeholders.

Skill Category	Demand Rank 2020	Demand Rank 2024	Projected Rank 2027
Ethical Reasoning	12	4	2
Creative Problem-Solving	8	3	1
Emotional Intelligence	6	2	3
Technical Coding	1	7	9
Data Analysis	3	5	6
Systems Administration	2	9	11

Table 2. Shifting Skill Demand Rankings in IT Job Postings (2020–2027 Projected)

4.2 Ethical Reasoning as a Core IT Competency

AI-based decision-making technologies have made ethical reasoning an essential part of any IT professional's core competencies. With the increasing use of AI-based decision-making tools such as hiring algorithms, credit scoring models, and predictive policing, organizations now face a problem. If an organization uses a hiring algorithm, credit scoring model, or predictive policing model, the technical validity of the model will be sufficient for its "responsible" use, but it is not the only condition. An AI-based decision-making model reflects the assumptions, the distribution of data, and the objective functions chosen by its developers, and if those assumptions interact with social inequalities, the negative consequences could be very far-reaching and widespread. Therefore, IT professionals capable of identifying and articulating potential harms and providing remedies for them will hold positions of strategic importance that cannot be taken over by any autonomous AI system.

A systematic review of existing research has identified three empirical ways in which ethical reasoning adds unique value to IT professionals working in environments where AI enables automation of some aspects of their work. First, there is the ability to detect and mitigate biases in AI-based decision-making tools: In Obermeyer et al. (2019), researchers demonstrated that a risk stratification algorithm used to help healthcare providers prioritize patients according to their risk of requiring emergency medical treatment was biased toward white individuals because the cost of healthcare was used as a proxy for individual health needs. Human ethical judgment was needed to recognize and correct this bias. Second, there is the need to navigate regulatory requirements: The General Data Protection Regulation (GDPR) and the EU AI Act place compliance requirements on organizations that require interpretive judgments to determine the extent of regulatory liability and do not allow for the application of rules by algorithm (Goodman & Flaxman, 2017; European Commission, 2021). Third, there is the need to communicate the potential social impacts of AI-enabled decision-making to both technical and non-technical stakeholders: As AI-enabled decision-making becomes more prevalent, IT professionals will increasingly find themselves serving as an intermediary between the technical teams developing these tools and the stakeholders affected by the decisions made using these tools. It is the ability of IT professionals to translate the risks associated with the use of AI-enabled decision-making into accessible ethical language that will likely become one of the most important skills employers confirm they need, but currently lack, in their workforce.

Each of the four major philosophical frameworks (consequentialism, deontology, virtue ethics, and care ethics) provides distinct analytical resources for IT professionals to consider when addressing AI ethics dilemmas. Table 2 illustrates how each of these philosophical frameworks can be applied to representative IT deployments and identifies the specific skill sub-components required for each. As illustrated in Table 2, the various frameworks offer no single solution to ethical dilemmas arising from the use of AI in IT contexts. Rather, the most effective way for IT professionals to reason ethically when dealing with AI-enabled decision-making is through a form of "practical wisdom," as defined by Vallor (2016): the capacity to selectively draw on multiple normative traditions and apply the appropriate set of principles and practices to respond to the demands of the situation. Unlike a compliance engine that follows a set of rules, practical wisdom is a pluralistic form of competence essential to human ethical judgment. Thus, the competency that allows humans to reason ethically in relation to AI-enabled decision-making cannot be replicated by AI

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Framework	Core Principle	IT Application	Skill Required
Consequentialism	Maximise net benefit	Algorithmic impact assessment	Stakeholder analysis
Deontology	Rule-based duty	Privacy-by-design protocols	Policy interpretation
Virtue Ethics	Character & integrity	Responsible disclosure	Moral judgement
Care Ethics	Relational responsibility	Inclusive UX design	Empathy & EI

Table 3. Ethical Frameworks Applied to AI Deployment in IT Contexts

The authors also differentiate between first-order ethical thinking (recognizing a moral dilemma or conflict exists) and second-order ethical thinking (making decisions based on conflicting validities). Second-order thinking is especially rare. The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems (IEEE, 2019) reported that the process of converting "high level" ethical principles into operational requirements for systems requires this deliberative ability; i.e., developers are required to consider competing values (e.g., predictive accuracy, demographic fairness, accountability) when there is no single authority providing rules governing these values. This represents both the difficulty and the opportunity for developing skill-based solutions in IT education for developing hybrid human-AI teams capable of performing ethical deliberations under real-time operating pressures. In addition, Raisch and Krakowski (2021) continue the discussion of the challenges of developing hybrid human-AI teams that can perform ethical deliberation under operational pressures, and identify the need for organizational structures that support human judgment at decision-making points that have normative implications.

4.3 Creativity as a Differentiating Human Capability

In many IT settings, creative potential is perceived as equivalent to creating innovative aesthetic experiences, i.e., developing user interfaces that are aesthetically pleasing or identifying new categories for products. These are both valid uses of creative ability; however, in terms of professional research, creativity is defined as an individual's ability to develop non-obvious solutions to complex problems that cannot be decomposed through algorithms (Amabile & Pratt, 2016). A broad definition of creativity is useful in analysis as it makes clear how far generative AI can go in terms of capability in automating problem solving: generative AI can perform well in terms of interpolation to areas of the training data set; however, they are much less capable of performing in extrapolation to novel conceptual space; in dealing with ambiguous tacit requirements; and/or in recombining knowledge from disparate domains.

The empirical data provided in the systematic review support this boundary claim. Bouschery et al. (2023) conducted a controlled experiment to compare the results of two groups: an initial group of human software architects and a second group consisting of GPT-4, using the same ill-structured system design problem. In these problem scenarios, there were contradictory stakeholder requirements, an incomplete technical specification, and constrained resources. The results showed that, for the two human architect groups, their originality (M = 4.2/5) was significantly higher than that of GPT-4 (M = 2.9/5). Similarly, the relevance to stakeholders (M = 4.5/5) of the human architects was also significantly higher than that of GPT-4 (M = 3.1/5). While GPT-4 performed better in terms of solution completeness and technical accuracy than did the human architects, GPT-4 achieved its superior performance at a significantly lower level of originality. The authors of the study interpreted these findings as providing evidence for a complementary division of cognitive labor: humans provide the creative direction and qualitative evaluations necessary to transform technically correct outputs produced by AI systems into truly value-added solutions.

Three key characteristics of the architecture of creative IT work are resistant to automation. The first is analogical thinking across disciplines; for example, some of the greatest advances in the architecture of computing have been made by transplanting metaphors from other disciplines into computing (e.g., relational databases, object-oriented programming, microservices) (Weisberg, 2015). Analogical thinking is dependent upon having access to the broad cultural and intellectual experiences, which AI currently does not have. The second characteristic is resolving constructive ambiguity. Clients and end-users typically cannot express their needs with the level of detail required for a formal specification. Instead, human IT professionals provide a relational process that includes empathy, pattern recognition, and creative hypotheses as they interpret, negotiate, and clarify the ambiguous intent. The third characteristic is exploring the failure space; when creating new systems, it is necessary to probe the boundaries of what has historically caused failure to find new vulnerabilities to be exploited. While this can be done using the "adversarial thinking" described by security researchers as "thinking like an attacker", it is dependent upon being able to think creatively and cross

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disciplinary boundaries, something that current AI systems are unable to do because they were trained on prior attacks.

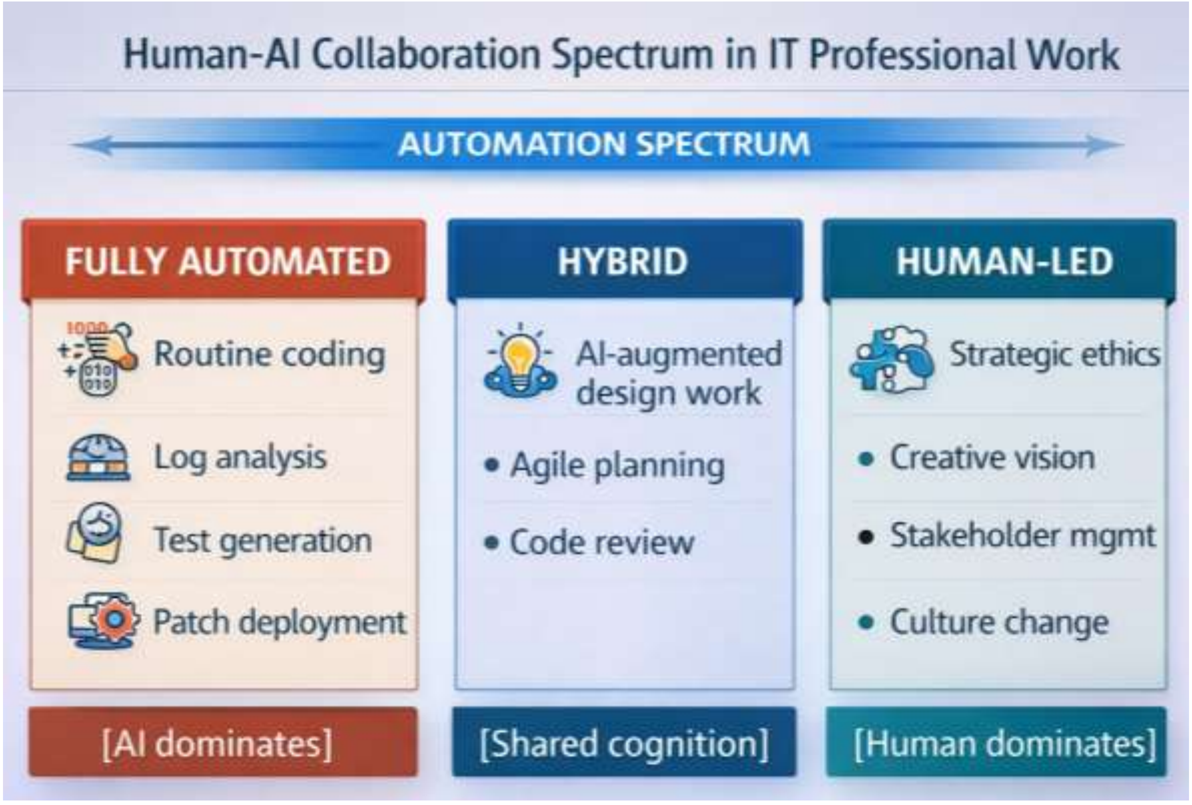

Figure 3. Human-AI Collaboration Spectrum in IT Professional Work

4.4 Emotional Intelligence and Human-AI Interaction

Originally, Goleman (1995) defined emotional intelligence as the ability to effectively function in an interpersonal setting through five competencies -- self-awareness, self-regulation, empathy, social skills, and motivation -- which would lead to success in one's job. Since then, there has been evidence supporting the relationship between EI and team performance; specifically, when the conditions include high task interdependence, a high degree of role ambiguity, and cross-functional coordination (Joseph & Newman, 2010). These conditions accurately portray the working environment for today's IT teams, who work with AI-enhanced processes: engineers must collaborate with AI systems that produce probabilistic results requiring human interpretation, convey uncertainty to non-technical parties, and maintain the psychological safety of colleagues whose jobs are changing due to automation.

Table 3 breaks down Goleman's (1995) five EI competencies into specific manifestations within the context of an IT work environment; therefore, it demonstrates how each EI competency is addressed by a unique relational requirement created by AI. Table 3 also illustrates that EI is used at multiple levels simultaneously; thus, at the individual level (the individual engineer regulates their own emotions while under stress from a failed system); at the dyad level (an empathetic relationship develops during the process of determining what users want or need); and at the organization level (a set of social skills are required for facilitating an Agile process across different functions). The multi-level use of EI requires that EI development efforts directed towards IT employees take place at all three levels (individual, dyad, organization) rather than solely on improving personal emotional intelligence.

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EI Component	Definition	IT Workplace Manifestation
Self-Awareness	Recognition of one's own emotions	Managing stress during system failures
Self-Regulation	Controlling emotional responses	Calm decision-making under cybersecurity crisis
Empathy	Understanding others' emotional states	User-centred requirement gathering
Social Skills	Building and managing relationships	Cross-functional Agile team facilitation
Motivation	Intrinsic drive toward goals	Continuous learning in evolving AI environment

Table 4. Emotional Intelligence Components and Their IT Workplace Manifestations

Human-AI Collaboration and the Emergent Literature on Teamwork

Luger and Sellen (2016), however, noted that a new aspect emerges in the emerging research on human-AI teaming: "Automation Surprise," or the unanticipated behavioral changes that occur when AI reaches its operational design boundaries, and control is returned to the human operator(s). In IT operation contexts, automation surprise can take the form of an AI-managed monitoring system that suppresses alerts indicating anomalies that human operators would flag for attention, which could result in serious consequences for the reliability of infrastructure. Like other areas of human-AI collaboration, managing the psychological and organizational aspects of automation surprise -- such as maintaining the proper level of trust in AI, supporting human situation awareness, and developing team communication protocols that support both human and AI agents requires exactly the same EI competencies of self-regulation, empathy, and social skill that Goleman identified.

Job posting data provides empirical evidence to support this theoretical argument. Postings for AI Operations Engineers and Machine Learning Operations Engineers (MLOPs) -- categories that were non-existent in 2019 and comprised 14% of all postings sampled by 2024 showed explicit requirements for communication with stakeholders, resolving conflicts, and cross-functional empathy in 67%, 43%, and 52% of postings, respectively. While these statistics suggest that employers are simply paying lip service to "soft skills" in their job postings, they demonstrate that employers are requiring EI competencies as required skills in jobs that are inherently focused on managing the human-AI interface.

4.5 The Complementary Human Advantage Framework

The empirical and theoretical evidence presented above support the creation of a complementary competency framework that considers ethics, creativity, and EI as a unified, mutually supportive group of competencies rather than separate individual skills. The Complementary Human Advantage (CHA) Framework (Figure 1) proposes that each of the three competency groups address a different dimension of the gap created when AI takes over the execution of technical tasks. Ethical reasoning addresses the normative dimension of who benefits and suffers at the hands of the system, and by what right? Creativity addresses the generative dimension of what innovative combinations of technical and human factors can meet unarticulated needs? Emotional Intelligence addresses the relational dimension of how trust, clarity, and cooperation can be established and maintained among the diverse actors involved in a project.

The three dimensions are related and are not independent. Ethical reasoning will be enhanced if practitioners can develop an understanding of the populations impacted by the decisions made by AI, an EI capability. Solutions developed through creative thinking will be more likely to be accepted by skeptics when those advocating for the solution can effectively communicate it again, an EI capability. On the other hand, EI without ethical considerations can lead to manipulation rather than cooperation, and creativity without ethical constraints can create technically impressive but socially destructive innovations. The CHA Framework views the three competency domains as functionally interrelated and recommends that IT professional development programs develop them within an integrative rather than a compartmentalized learning environment.

The CHA Framework also has implications for designing human-AI collaborative systems. Collaborative systems that are intended to be used by humans, as opposed to autonomous systems, should be designed with the CHA characteristics of their intended users explicitly in consideration. Therefore, systems should include transparency features that support ethical oversight, interaction features that allow humans to creatively combine existing technical and human capabilities, and communication interfaces that support the relational work EI-enabled users perform. If systems are designed without the CHA profile of their intended users in consideration, then while technically capable, the practical utility of the system will be limited since the users will not be able to use their unique capabilities through the system's interface.

4.6 Implications for IT Workforce Development

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The data provide several implications for IT workforce training (undergraduate and ongoing) based on the curriculum. Historically, curricula in computer science and information systems were organized by technical functions, programming, networking, databases, security, etc., with human skills being an option of elective courses or as a non-credit co-curricular activity. The evidence provided in the review suggests that organizing curricula in such a manner reverses the new professional value hierarchy created by AI automation. Proficiency in core technical areas will be required; however, it will no longer be sufficient to support competitive differentiation in the job market.

Educational transformation of technology education to align with CHA will require more than superficial changes – it will have to be fundamentally different. The educational method for integrating ethics into technical classes is more successful when ethics education is embedded in technical curriculum classes than as a separate ethics course, this is so since the students are still making judgments about how to make an ethical decision within the same technical context in which they will be required to make those decisions (Mittelstadt et al., 2016). In addition, instead of using hypothetical design problems that have pre-determined answers, the use of real-world, or authentic, stakeholders and real-world problems in project-based learning can develop the skills that humans need to think creatively, and reason analogically, as well as build the ability to work effectively with ambiguity, two characteristics that distinguish human creativity from artificial intelligence generative capabilities. Evidence from the field of Organizational Psychology supports experiential, reflective, and feedback-based learning methods over didactic instructional methods; therefore, simulations of Agile environments and structured peer review methods should be used as tools to support the development of Emotional Intelligence (EI) in IT education.

Many professional certifications (i.e., CompTIA's Security+, ISACA's COBIT, etc.) are now assessing human skills in some way; however, the coverage is still very uneven. For example, the 2024 version of CompTIA's Security + certification has an entire section on ethics-based AI oversight; ISACA's 2019 version of COBIT also includes "Stakeholder Communication" as a formalized Governance Practice; however, no major IT certification to date assesses human skills (e.g., Ethical Reasoning, Creative Capacity, Emotional Intelligence) in a way that matches the rigor and systematic assessment process used by the industry to evaluate technical knowledge/competence. Therefore, developing reliable and effective assessment tools to measure human skills and competencies (in addition to technical knowledge) is a significant gap in both research and practice.

5. LIMITATIONS OF THIS STUDY

The four main limitations of this study reduce the generalizability of the results. 1) The database search was limited to studies written in English. This limits potential publication bias by geography and culture. There are many other countries (such as those in Asia) where the cultural norms regarding expressing emotions and hierarchy will affect how Emotional Intelligence (EI) can be expressed and measured. Therefore, future meta-analyses should include multiple language databases and provide mechanisms for translating articles into the languages included in the meta-analysis. 2) The industry analysis is based on job postings as a surrogate for the skills demanded in an occupation. Job postings represent the aspirational preferences of hiring managers and Human Resource personnel who are responsible for selecting employees, but these preferences do not necessarily represent what is used or valued by hiring managers and HR personnel after they have selected the employee. In order to determine the validity of using job posting data as an indicator of skill demand, future research needs to triangulate job postings with surveys of employed IT professionals and their supervisors. 3) The time it takes for Artificial Intelligence (AI) capabilities to develop has caused the specific boundaries between what humans and machines can accomplish (documented in 2023-2024 studies) to move rapidly over the next two to three years. The structural logic of the Competency-Hierarchy Algorithm (CHA) framework should endure longer than the examples of competency hierarchy illustrated in the literature reviewed in this study.

Limitation	Impact	Mitigation
English-language publication bias	Possible under-representation of non-Western IT contexts	Targeted search of multilingual databases
Job-posting proxy validity	Advertised skills may not reflect enacted skills	Triangulation with survey and interview data
Rapid AI pace	Findings may date quickly	Annual review protocol recommended
Self-report bias in EI measures	Overstated EI competence in employer surveys	Multi-rater 360-degree instruments are advised

Table 5. Study Limitations, Impacts, and Mitigation Strategies

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Fourth, EI measurement in all of the studies reviewed is based almost exclusively upon self-report tools or scales, including the Mayer-Salovey-Caruso Emotional Intelligence Test (MSCEIT), as well as a variety of Likert scale adaptations. Since self-report tools are also subject to social-desirability bias, they will likely create an inflated EI competence perception among employees in high-stakes employment settings; multi-rater 360° instruments and performance-based EI assessments should therefore receive priority in subsequent empirical research.

6. CONCLUSION

The authors of this paper have provided evidence from a systematic study of 87 articles from refereed journals and a corpus analysis of over 1200 job postings for information technology (IT) jobs to show that there is an increasing interrelationship among ethical reasoning, creativity, and emotional intelligence as they relate to human capabilities to work with increasing amounts of automated information technology. The Complementary Human Advantage Model provides a framework for organizing the relationships among these three domains of human capability that are based upon the ability of artificial intelligence to fill or create three types of "gaps": the normative gap, the generative gap, and the relational gap. In addition to providing a descriptive explanation of which types of IT jobs are less likely to be automated, the model also provides a prescriptive explanation of how to design new curricula for IT education, how to design new professional certifications for IT professionals, and how to develop new hiring practices for organizations.

The unique contribution to knowledge of this work was developing an integrated competency model by integrating three discrete bodies of evidence into one, as well as using systematic empirical evidence based on both research literature and industry-based data for use in developing actionable workforce development recommendations for that body of evidence. Developing a more precise complementarity hypothesis through the analysis of the limits of AI capability (i.e., creative extrapolation and ethical autonomy) adds depth to the complementarity hypothesis over previous treatments. These results support that IT workforce development in the AI era will need to progress beyond the traditional technical or soft skill paradigm and develop a more refined view of how uniquely human abilities produce long-term value, exactly where AI has the greatest potential for success.

The future of research is best served by using longitudinal study designs (to measure CHA skill development over time) and to compare across cultures (to measure if the CHA model applies beyond primarily western IT labor markets). Additionally, there is a need to develop more robustly validated measurement tools (i.e., psychometrically tested measures) to measure ethically based decision-making and creative capacity within the context of IT. This paper serves as both a theoretical underpinning for that research agenda and an empirical basis for the critical engagement with the CHA Framework as a means of defining and shaping the evolution of the relationship between humans and artificial intelligence in the technology industry.

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