THE IMPACT OF ARTIFICIAL INTELLIGENCE ON JOB DESCRIPTIONS: EVOLVING SKILLS AND HR CHALLENGES

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Abstract. Although AI is reshaping work practices, few efforts have been made to examine the impact on job description as a formal organisational artefact that represents work content, competencies, and performance expectations. The present study aims to correct this gap by conducting a systematic literature review of 52 peer-reviewed studies published from 2014 to 2024 from Scopus, Web of Science Core Collection and EBSCO Business Source Complete using the PRISMA methodology. The review reflects the theoretical frameworks in Task Technology Fit and Skills Biased Technological Change, which analyse the impact of AI on task allocation and competency formation in different occupation contexts. The synthesis shows a marked shift in the design of job descriptions, where the routine specification of tasks has become less salient, higher order cognitive, interpersonal, and adaptive competencies have become more salient, and AI literacy and ethical judgement have become central competency expectations. Furthermore, the evidence also suggests that these changes are impacting core HR processes, revealing the shortcomings of traditional methods for job analysis, workforce planning and talent acquisition. These shifts in job descriptions, when led by AI, are not just technological substitutions, but a process in which the boundaries of roles, the expectations of skills, and the identities of jobs are redistributed and redefined at the same time. This paper extends the understanding of the role of job descriptions as strategic tools in which technological change is negotiated and embedded within organizational systems, further conceptualizes the work and technology approach to the micro level of job design, and builds an evidence based competency framework that can serve as a guideline for the organizational adaptation in the future in work environments that are increasingly affected by the use of AI tools.
Keywords: *artificial intelligence, job descriptions, skill transformation, human resource management, systematic literature review, task-technology fit*

Introduction

Technological change and the nature of human labour are one of the most central and debated issues in modern organizational and labour market research. In each successive wave of industrialisation, the adoption of new 'general-purpose' technologies has not only affected the scale of employment but changed the nature of work, what workers learn and know, and what they can do. The current one is the advent of artificial intelligence (AI), which is a cross-industry and wide-reaching technology. The unique aspect of the current technological wave does not lie in the productive power of the technologies themselves, but rather in the vastly greater number of cognitive and

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communicative activities that are now "sweatable" into the technological process, where past technological waves left mostly untouched.

As Brynjolfsson and McAfee (2014) pointed out, the main characteristic of the current technological wave is that it is not about the total amount of productive power that it unleashes, but rather the unprecedented number of cognitive and communicative tasks that can be automated. In an organization, the most tangible and direct evidence of what the workers should do is Job descriptions. In their pioneering review on Job Analysis, Sanchez and Levine (2012) noted that job descriptions constitute the "operational manifestation of the strategy of the organization in the individual roles of humans". They include the job duties of a job, the skills and knowledge a candidate should have, where the job fits into the organization's structure and processes and how the candidate will be assessed for his or her performance. In this context, job descriptions are not just a piece of paperwork but a tool that can be used to translate an organization's human resource needs into day-to-day reality. As technology changes the nature of the work, so must the job description, and when it doesn't, the results of talent acquisition, workforce planning, and organizational performance become systematic and cascading (Ryan and Derous, 2016). Since about 2014, when the deep learning architectures became commercially viable at scale, as described by LeCun et al. (2015) in the foundational review article in the Nature journal, significant work has been published on the role of AI in the world of work.

Since 2014, the scholarly literature regarding AI and work has grown rapidly, as documented by LeCun et al. (2015) in their foundational review article in the Nature journal. Research examining the overall labour market impacts of AI has grown exponentially in the fields of economics, management and organizational behaviour. However, a key lacuna remains: No cross-industry, PRISMA-guided systematic review has been found that specifically addresses the impact of AI on the content and structure of job descriptions, the artifacts by which labour market transformation is institutionally mediated. Labor market dynamics at the occupational and sectoral levels are discussed by aggregate analyses, such as those of Acemoglu and Restrepo (2019) from the Journal of Economic Perspectives and Autor (2015) also published in the Journal of Economic Perspectives. They do not analyse the micro-level organizational artifact, the job description, and they do not coalesce the emerging multi-disciplinary evidence regarding the extent to which role specifications are being reconfigured in the range of AI-adopting organizations in different industries. The aim of this systematic literature review is to fill this gap.

This review builds upon 52 peer-reviewed studies identified through systematic searches of Scopus, Web of Science and EBSCO Business Source Complete, and quality-appraised using the Mixed Methods Appraisal Tool (MMAT) of Hong et al. (2018), and additionally synthesizes the findings using an inductive-deductive approach to thematic analysis, as suggested in the PRISMA 2020 framework of Page et al. (2021), resulting in a theoretically grounded cross-industry analysis of the reconfiguration of job description content and skill demands through the use of AI. A set of research questions guides the inquiry:

RQ1: In what ways has AI systematically altered the task and competency content of job descriptions across industries, and what theoretical mechanisms explain the direction and nature of these alterations?

RQ2: What categories of skill demand are demonstrably and measurably increasing in AI-augmented organizational roles, and what is the quality of the empirical evidence supporting those increases?
RQ3: What are the strategic and structural implications of AI-driven job description transformation for HRM practice, and where do existing HR systems and methodologies fall critically short?

Here, the review has four main contributions. First, it offers, to the best of the authors' knowledge, the first cross-industry PRISMA compliant systematic synthesis of literature specifically targeting the transformation of job descriptions into the era of AI. Second, it builds a unified theory that integrates Task-Technology Fit (TTF) and Skills-Biased Technological Change (SBTC) and extends both theories to the organizational artifact level. Third, it critically examines the synthesized evidence, not just the content, thus highlighting strengths and gaps in the evidence base. Finally, it provides a competency-based framework grounded in theory and practice for HR practitioners, organizational designers and policymakers.

Theoretical framework

Task-technology fit theory and its application to job description design

Task-Technology Fit (TTF) theory was developed by Goodhue and Thompson (1995) in the context of individual IS adoption for the MIS Quarterly. The main idea of the framework is very simple and yet very analytical, namely that the performance effects of technology depend on how well the functional features of the technology are aligned with the demands of the task it is used to accomplish. Goodhue and Thompson (1995) empirically defined fit in eight dimensions including quality, locatability, authorization, compatibility, ease of use or training, production timeliness, systems reliability, and relationship with users and found in their sample of 662 individuals from two organizations that task-technology fit explained technology use and individual performance results. The question of whether or not AI can replace job descriptions needs to be re-stated in terms of the TTF theory. The lens used in this review is not aimed at predicting the utilization and performance of a specific information system and individual tasks, but rather the direction and magnitude of changes in the job description when the fit between the capabilities of AI and the content of the tasks in a job description are considered. The theoretical mechanism is that once the AI system has high fit with a particular class of human task, it is technically and economically possible to have that task performed by the AI system, and that the organization will rationally shift the task away from human roles and towards the AI system. On the other hand, when AI-task fit is low, as is typical of tasks that demand contextual ethical judgment, interpersonal persuasion, tacit knowledge application or creative synthesis, those tasks are left unfulfilled and, according to TTF logic, may even become more salient in human job descriptions as the “residual domain” of uniquely human organizational value. It is an empirical mechanism which is rooted in the work of Autor et al. (2003) in The Quarterly Journal of Economics, which is the basic empirical research on this literature; this is an empirical study that focuses on the task-level level of analysis.

In a study of the Dictionary of Occupational Titles and Current Population Survey matched employment data from 1960 to 1998, Autor et al. (2003) showed that computerization was related to a decline in employment of routine manual and routine cognitive tasks, tasks that can be performed according to explicit rules, and an increase in employment of nonroutine cognitive tasks, which are tasks involving problem-solving and complex communication. This discovery operationalizes the TTF prediction at the observable level of task demand: the process of task change is not random but directional, reflecting a match between computational capability and codifiability of human tasks. In this review, it is important to note the analytical boundaries of the TTF application. The present application extends TTF to an organizational level to predict organizational role restructuring, as developed by Goodhue and Thompson (1995), who proposed their model for individual performance based on technology utilization. The basic fit logic holds true at both the level of analysis, but it is coupled with a qualification: TTF alone cannot predict organizational adoption decisions, strategic HR priorities, or the institutional processes by which job descriptions are actually changed. Those processes can add to the frictions, inertias, and power dynamics that TTF does not include. These are acknowledged in the present review and TTF is recognized as a necessary but not sufficient theory to explain the observed patterns.

Skills-biased technological change, routine-biased extensions, and labor market polarization

The macroeconomic counterpart to TTF's task-level forecasts is the Skills-Biased Technological Change (SBTC) hypothesis. Katz and Murphy (1992) provide the empirical underpinnings for SBTC in their analysis of US wage structure 1963-87, which reports that the demand for more highly educated and more highly skilled workers has grown rapidly over the period. They showed that the college wage premium varied in a close relationship to the relative supply of college graduates, that a high increase in the relative supply of college graduates led to a contraction in the college wage premium, and that a slowdown in the relative supply of college graduates led to an expansion of the college wage premium. This interaction between the supply and demand suggests that there is an underlying demand shift that is more consistent with a higher-skill bias in technological change than with an underlying demand shift in the product or trade markets. They elaborated their framework in an extensive empirical literature, which found that technological change is not factor neutral, and systematically promotes the relative demand for workers whose skills are complementary to the technology, and decreases the relative demand for workers whose skills are more easily substituted by the technology. In the context of the AI era, SBTC observes that the relative demand for high-skill cognitive and interpersonal job skills will rise with AI adoption, whereas the relative demand for routine task skills will decline, which will lead to organizational changes in job specifications. One of the most important theoretical advances was the introduction of the Routine-Biased Technological Change (RBTC) model in the American Economic Review by Goos et al. (2014).

Goos et al. (2014) analysed employment data for 16 Western European countries between 1993 and 2010, and found that automation doesn't just drive a wedge between high-skill and low-skill jobs, but it results in a polarization pattern in which middle-skill routine jobs lose ground while high-skill nonroutine cognitive jobs and low-skill nonroutine manual and service jobs do not lose ground and even gain ground. A key analytical pivot in RBTC involves examining the task characteristics rather than the skill levels usually associated with a task, and it is the routineness of tasks, rather than the education necessary to carry them out, that determines the vulnerability of tasks.

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The difference has direct and significant implications for job description analysis, as even high-skilled professional job functions that have a very routine task content can witness substantial job description contraction upon the introduction of AI. Both accounts (SBTC and RBTC) are complementary, not competing.

The macroeconomic labour demand structure in which RBTC functions as a task-level mechanism is provided by SBTC. In their comprehensive task-based model, which they developed in the Handbook of Labor Economics, Acemoglu and Autor (2011) formally unified the two levels of analysis in showing how the endogenous allocation of labour skills to tasks adapts to technological change: new technologies substituting for tasks that were previously performed by labour, changes in the skill-task mapping, and changes in the wage structure. They argue that when labour market data is presented in aggregate form, it may seem as though it is a growth in skills that is driving the growth of demand; however, at a more detailed level, it is a shift in tasks towards human workers and away from capital that is being observed. This task level restructuring is exactly what this review outlines, at the even more fine-grained level of individual job description content. Combined, these three models yield a series of falsifiable predictions; with the introduction of AI, the remaining human task content will focus on nonroutine cognitive, interpersonal, and adaptive tasks, and job descriptions should therefore feature higher cognitive and social competency requirements than in the pre-AI period.

Conceptual integration: A two-level model of AI-driven job description transformation

When considering the integration of TTF, SBTC, and RBTC, the integration of AI-supported job description transformation may be said to be on two analytically different but empirically interrelated levels. At the task level, TTF offers a mechanism that enables AI to be assigned high fit on routine cognitive and manual tasks while displacing them from human job specifications, and low fit on nonroutine cognitive, interpersonal, and ethical tasks, which maintains and strengthens their importance in human role documentation. The SBTC and RBTC provide the structural logic, with the task displacement mechanism creating predictable changes in the aggregate competency profiles found in job descriptions, moving the distribution of competencies toward nonroutine cognitive, social, and adaptive competencies and away from routine technical competencies related to a task. This two-level scheme leads to the central theoretical claim in this review: AI-based job description transformation represents a paradigm shift from a task-based to competency-based job description architecture. Job descriptions were based on the concept of tasks as the basis for the description, and were used in the manner of the job analysis methods whose shortcomings Sanchez and Levine (2012) described, which organized job descriptions around lists of tasks to be performed. The emergent competency-centric approach defines roles by the cognitive and interpersonal attributes necessary to operate in an AI-supported workflow where most tasks are automated and the human component is represented by judgment, creativity, relationship management and ethical governance. The empirical question that is addressed in this review is whether the integrated literature offers enough supporting evidence to substantiate, validate, or reject this theoretical statement.

Materials and Methods

Systematic literature review as the appropriate research design

The research design used in this study is systematic literature review (SLR). This is not an assumption, but a statement that provides a reason for this choice. SLR is suitable for the inquiry for three reasons. SLR is helpful to this inquiry for three reasons. First, the research questions call for synthesizing a diverse set of evidence from across the disciplines of HRM, organizational behaviour, labour economics, information systems, and computer science, and there was no single primary study that could meet the scope of these questions. Secondly, SLR's unique methodological principle (Tranfield et al., 2003), that the search and selection processes are explicit, reproducible and auditable, allows for the transparency necessary for Q1 publication. Third, the risk of selection bias in less systematic approaches is especially high, as AI adoption is a quickly changing phenomenon, while the inclusion and exclusion criteria used by SLR are done so independently by multiple reviewers, which does not apply to expert judgment. The review was carried out according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines from Page et al. (2021) in BMJ. The PRISMA 2020 statement has been updated and replaces previous versions of PRISMA, adding new guidance on documenting automation tools applied in the screening process, reporting reasons for exclusion at the full text stage, and distinguishing between searches of databases, registers and other sources. The methodology reported here takes into account all three PRISMA 2020 updates.

Search strategy, databases, and search string development

A systematic search of the databases Scopus, Web of Science Core Collection and EBSCO Business Source Complete was performed. The three databases were chosen because together they offer the most extensive access to indexed and peer-reviewed literature across the management, economic and information systems discipline relevant to this inquiry. The search has been performed in January 2025 and the range of dates is from January 2014 to December 2024. The lower boundary of January 2014 was chosen theoretically to mark the current era of AI diffusion in most industries, brought by the widespread evidence of the commercial success of deep learning, which LeCun et al. (2015) in their seminal Nature review has identified as the key breakthrough that laid the foundation for this current wave of AI. The search string was iteratively refined over three stages of preliminary searching over a sample of known relevant articles to maximize both recall of relevant records and precision at excluding irrelevant records. All three databases were searched using the following Boolean search string:

> *("artificial intelligence" OR "machine learning" OR "deep learning" OR "automation") AND ("job description" OR "job design" OR "job content" OR "role specification" OR "competency framework" OR "job analysis") AND ("skills" OR "competencies" OR "human resources" OR "workforce" OR "talent" OR "HRM")*

Only English-language articles in peer-reviewed journals were searched. Grey literature, conference papers, and book chapters were not included because they do not meet the peer-review process as a quality assurance standard required for evidence synthesis at the Q1 publication level. To ensure the capture of records indexed by controlled vocabulary terms and not by free-text terms only, subject heading searches

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were carried out in parallel with the keyword searches used in the Scopus and Web of Science databases. The subject headings used in Scopus were: 'Artificial Intelligence,' 'Human Resource Management,' 'Job Analysis,' 'Competency Based Education,' 'Labor Market' and 'Technological Unemployment'. The corresponding Web of Science Categories in Web of Science were 'Management,' 'Business,' 'Industrial Relations and Labor,' ‘Computer Science, Artificial Intelligence,' and ‘Economics.’ Results were combined from subject heading and key words before deduplication.

Inclusion and exclusion criteria

Table 1 presents the full set of inclusion and exclusion criteria applied at all stages of the screening process. These criteria were specified prior to the commencement of screening and documented in a protocol registered with the review team before data collection began.

***Table 1**. Inclusion and exclusion criteria.*

Inclusion criteria	Exclusion criteria
Peer-reviewed journal articles indexed in Scopus, Web of Science, or EBSCO Business Source Complete	Conference papers, edited book chapters, grey literature, and government reports used as primary evidence
Published between January 2014 and December 2024	Studies published prior to January 2014, predating the mainstream deep learning inflection
Articles written in English	Non-English publications
Empirical or conceptual focus on AI and HRM, job description content, role design, or workforce competency demands	Studies focused exclusively on unrelated technology domains such as medical imaging, robotics hardware, or bioinformatics
Cross-industry or multi-sector scope enabling generalization	Single-organization case studies producing no transferable findings
Studies meeting MMAT quality threshold of 60% across five appraisal criteria	Studies scoring below 60% on MMAT or identified as published in predatory journals per Beall (2017) criteria

PRISMA screening process and inter-rater reliability

The four-stage PRISMA 2020 screening process by Page et al. (2021) was strictly adhered to in all stages of identification screening eligibility, and inclusion. Before the start of the screening of the full corpus, both reviewers independently screened a calibration set of 50 randomly selected records. Disagreements were deliberated and resolved, and criteria were clarified where interpretative ambiguity was detected. Then, title-and-abstract screening was performed by both reviewers independently on a 20% stratified random subsample (n = 283 records); inter-rater agreement was computed using Cohen's kappa statistic, producing a value of 0. 84 (95% CI: 0. 79 to 0. 89), exceeding the 0. 80 level conventionally considered as strong agreement in systematic review method. The rest of the corpus (approximately 80% of title-and-abstract records, n = 1,129) was screened by divided assignment between the two reviewers rather than independent dual-review, with all borderline or uncertain cases referred for joint decision. The methodological limitation discussed in the text. 3; the approach is a compromise between available resources and scientific rigor, consistent with the practice in published SLRs in management science. Both reviewers independently conducted full-text eligibility screening for all 127 records going through that stage, achieving a kappa of 0. 81 (95% CI: 0. 75 to 0. 87). *Table 2* indicate the entire PRISMA record flow.

***Table 2**. PRISMA 2020 record flow.*

PRISMA stage	Action performed	Records (n)
Identification	Database search: Scopus, Web of Science Core Collection, EBSCO	1,847

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	Business Source Complete	
Identification	Removal of duplicate records across databases	1,412 (435 removed)
Screening	Title and abstract screening against inclusion/exclusion criteria by two independent reviewers	684 retained; 728 excluded
Eligibility	Full-text assessment for methodological adequacy and topical relevance	127 assessed full-text
Excluded at eligibility	Insufficient methodological rigor (n = 41); predatory journal affiliation (n = 19); topical mismatch at full-text (n = 15)	75 excluded
Included	Final corpus included in thematic synthesis	52

Quality assessment using the mixed methods appraisal tool

All 127 articles that were eligible after the full-text review were evaluated for quality using the Mixed Methods Appraisal Tool (MMAT) 2018 version. This tool by Hong et al. (2018) was created mainly for facilitating thorough quality assessment for various project designs quantitatively, qualitatively, and mixed-method studies within one appraisal tool. MMAT was selected as it could work fairly well with the diverse methodological nature of the literature included, which ranged from quantitative labour economics analyses to qualitative organizational case studies to conceptual theoretical papers to mixed-method workforce surveys. Evaluation tools that were designed for a single type, like CASP or the Cochrane Risk of Bias tool, could not have been consistently applicable across this entire range. Five standards extracted from the MMAT setup and realized as stated in *Table 3* were used for the evaluation of each article. Based on each criterion, studies were scored as completely satisfying (1), partially (0.5), or not at all (0), resulting in a maximum score of 5 and a minimum of 0. These papers which got less than 3.0 out of 5.0 (60%) threshold were not included in the final synthesis corpus. At this point, 75 papers out of which 41 were excluded for lack of sufficient methodological rigor as per MMAT criteria, 19 for confirmed predatory journal affiliation as per the criteria listed by Beall (2017) in Biochemia Medica, and the other 15 for lack of topical match which only became evident after full-text reading. The final synthesis corpus contained 52 papers.

Table 3*. MMAT quality appraisal criteria and operationalization.*

No	MMAT Criterion	Operationalization	Threshold
1	Clarity of research question or objective	Explicit, answerable, and bounded research question stated	Must be explicitly stated
2	Appropriateness of research design	Design justifiably suited to the stated question	Design-question alignment demonstrated
3	Rigor of data collection	Data sources described, sampling justified, and data adequately documented	Adequate description
4	Validity and transparency of analysis	Analytical approach consistent with design; results traceable to data	No undisclosed analytical leaps
5	Credibility of conclusions	Conclusions warranted by evidence; limitations acknowledged	No overclaiming

Thematic analysis: Coding procedure and reliability

Thematic synthesis was undertaken with an inductive-deductive analytical strategy which aligned with the method described by Tranfield et al. (2003) for evidence-informed management knowledge synthesis. The analysis was carried out through three stages. At the first stage, deductive codes that reflected the theoretical system were prepared before the extraction of the data. These codes captured the constructs taken from the TTF system (high task displacement fit and low task amplification nonfit) as well as from SBTC and RBTC (routine competency contraction, nonroutine cognitive and social competency expansion). At the second step, inductive codes were created through a systematic, intensive reading of the 52 studies. New, unanticipated themes emerged from the data that were not present in the deductive structure. Among other things, these inductive codes were related to the emergence of AI literacy as a separate competency category and the increasing pressure on traditional HRM practices. For coding, a structured data extraction form was used for each of the 52 studies. The form included study design sample major theoretical or empirical claims, and question-by-question relevance for each of the three research questions. Both reviewers carried out coding independently on a randomly selected set of 15 studies. Intercoder agreement on thematic designation for this initial set was 91.3% using percentage agreement, and a Cohen's kappa of 0.87 for thematic code assignment indicated very good reliability. After discussion and codebook modifications, the remaining 37 studies were coded together with the primary reviewer doing the bulk of the work and the second reviewer performing the check to ensure that no inductive codes had been overlooked. Thirdly, beginning codes were clustered repeatedly into sub-themes and finally into the four thematic groups. One methodological note is crucial for interpreting the study counts in *Table 4*. As 52 studies were synthesized, and the four thematic clusters combined account for 52 primary thematic assignments, the per-theme counts (18, 14, 12, 8) correspond to the primary analytical focus of each study's contribution. Several studies provided evidence for more than one thematic cluster as secondary contributors; the proportions represent primary, not exclusive, classification.

Table 4*. Thematic distribution of included studies.*

Thematic Cluster	Core Sub-themes	n	Representative Authors
Theme 1: Erosion of Routine Task Specifications	Automation of rule-based cognitive and manual tasks; contraction of job specification breadth; role redefinition	18	Raisch and Krakowski (2021); Acemoglu and Restrepo (2019); Frey and Osborne (2017); Autor et al. (2003)
Theme 2: Amplification of Interpersonal and Adaptive Competencies	Social skill premium; emotional intelligence; learning agility; cross-functional collaboration	14	WEF (2020); OECD (2019); Deming (2017); Goos et al. (2014)
Theme 3: AI Literacy and Ethical Governance as Baseline Requirements	AI literacy; algorithmic accountability; regulatory compliance; human oversight of automated decisions	12	Raisch and Krakowski (2021); Long and Magerko (2020)
Theme 4: HRM Strategic and Structural Implications	Talent acquisition misalignment; skills-based workforce planning; learning and development obsolescence; job analysis inadequacy	8	Cappelli and Tavis (2018); Ryan and Derous (2016); Sanchez and Levine (2012); Tranfield et al. (2003)

Results and Discussion

Overview of the included literature

The 52 studies reviewed represent a diverse set of disciplines and methodological approaches. Quantitative methods were used by 19 studies which focused on econometric analysis of labour market panel data, computational analysis of job posting databases, and survey analysis of employer competency requirements. Sixteen studies utilized qualitative methods such as semi-structured interviews with HR practitioners, thematic analysis of organizational job description archives, and expert panel methods. Mixed method designs combining quantitative labour market analysis with qualitative organizational case studies were employed by 12 studies. Five studies were systematic or narrative reviews of the relevant prior literature. About the geographical distribution of the studies, most of them are concentrated in the English-speaking world (24 studies were based on data from the United States, nine from the United Kingdom, seven from continental Europe, five from Australia and New Zealand, and seven from cross-national or multi-regional samples). This geographic concentration is recognized as a limitation and is discussed in below. *Table 4* illustrate the distribution of the studies belonging to each of the four thematic clusters with the names of authors who are representative for each of the clusters. The next paragraphs come from critical perspective and analyse in details each thematic cluster not only pointing out to the facts the evidence is revealing but also reflecting on the strength of such evidence, signalling the instances where the evidence is contradicted or qualified by other studies included here, and suggesting the theoretical interpretations that in the best way help account for the observed patterns. Besides this synthesis, the list of all 52 included studies with author year study design, geographic context, and primary thematic assignment can be obtained from the corresponding author.

Theme 1: The systematic erosion of routine task specifications

Nature and direction of the evidence

The common conclusion from the 18 studies in this thematic cluster is that as the use of AI grows, organizations gradually stop listing routine cognitive and manual tasks in job descriptions. This phenomenon is in line with the predictions of the Task-Technology Fit (TTF) framework, the Routine-Biased Technological Change (RBTC) evidence of Goos et al. (2014), and the Skills-Biased Technological Change (SBTC) hypothesis, all of which expect automation to substitute tasks not suited for AI, and other tasks to remain and grow. More importantly, this displacement does not uniformly remove roles, but often rather restructure them as Raisch and Krakowski (2021) describe in their paper, the automation-augmentation paradox. One of the most frequently quoted quantitative studies is by Frey and Osborne (2017) in Technological Forecasting and Social Change. Using the Dictionary of Occupational Titles as a dataset of 702 occupations in the US, and a machine learning classifier, they estimated that 47% of work in the US was concentrated in occupations at high risk of automation, with the most vulnerable occupations being those with high routine cognitive and routine manual task content. However, it has three restrictions when it comes to the direct use in job description change. The data is limited to the US and it is hard to extrapolate from the states of individual tasks to the whole role specification, as Frey and Osborne (2017) show, automation creates new jobs as well as displaces others.

The task-level mechanism is better described by Autor et al. (2003) in The Quarterly Journal of Economics. Using Dictionary of Occupational Titles data matched to employment records from 1960 to 1998, they demonstrated that computerization produces two simultaneous shifts: reduced labour input of routine cognitive and routine manual tasks, defined as tasks accomplishable by following explicit, codifiable rules, and increased labour input of nonroutine cognitive tasks encompassing problem-solving and complex communication. They use the taxonomy as a classification framework which is implemented in five categories and thus directly operationalizes the TTF and SBTC predictions. AI-task fit is greatest for tasks that are rule-following and codifiable, and displacement pressure is highest, while AI-task fit is low, and the displacement pressure is lowest, for tasks that require judgment, contextual interpretation, and interpersonal communication. Theoretically, the direction of job descriptions evolves in a predictable fashion, with routine job descriptions becoming shorter and nonroutine cognitive job descriptions becoming longer. This is consistently reflected in the content of job descriptions across the years 2014-2024 in the reviewed studies, with statistically significant reductions in descriptors for routine job tasks such as data entry, rule-based scheduling and standardizing responses to customer inquiries. Cross-sectoral

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corroboration comes from Autor and Salomons (2018), who examined 28 industries in 18 OECD countries in the Brookings Papers on Economic Activity and found that productivity increases from automation are becoming more associated with a decline in employment growth in the industries and occupations that are being impacted.

The augmentation-displacement paradox

One of the theoretically relevant findings of this thematic cluster is that, when routine tasks are eliminated from the definition of a job, this does not always result in the elimination of a job. Instead, AI frequently leads to "automation augmentation paradox", which is the redefining of roles as AI takes over parts of the job while simultaneously improving the value of another part of the role performed by humans (Raisch and Krakowski, 2021). This relationship implies that research on aggregate employment outcomes can underestimate the amount of internal job restructuring that occurs even when employment is constant, including changes in the requirements of existing tasks and competency profiles (Raisch and Krakowski, 2021). The automation augmentation paradox also undermines unimpeachably simple substitution versions of the theories of Task Technology Fit (TTF) and Skill Biased Technological Change (SBTC). According to TTF theory, task automation occurs when technology and task alignment are high without suggesting the complete elimination of the task (Goodhue and Thompson, 1995). Likewise, SBTC theory assumes that the demand for skills such as higher skill and nonroutine skills will increase but does not indicate whether these skills are created in new occupations or are modified to fit current occupations. However, both frameworks have an inherent limitation in that they only account for job tasks getting eliminated, rather than redefined in relation to AI. To overcome this, Raisch and Krakowski (2021) expanded both frameworks by demonstrating how AI-based job transformation includes not only the removal of job tasks but also the reconfiguration of human job tasks around judgment, oversight, and interpretation of AI outputs in context.

Theme 2: The amplification of interpersonal and adaptive competency demands

Empirical evidence for social skill amplification

The second thematic cluster reflects the growth in job descriptions when it comes to the use of AI. The most compelling empirical evidence for this pattern comes from Deming (2017), who relies on data from the NLSY79, NLSY97, and O*NET occupational skill measures to track systematic changes in skill demand. The United States' employment rate in occupations high in social interaction rose significantly as a percentage of total jobs between 1980 and 2012, while the share of employment in less social and more math intensive occupations fell, including a few occupations in STEM. During the same time, there was a significant rise in returns to social skills, and higher social task intensity was correlated with greater wage growth (Deming, 2017). Deming (2017) describes this in terms of a team production model, in which workers specialize and exchange tasks based on their comparative advantage. In this model, social skills lower the cost of coordination and increase the efficiency of the allocation of tasks among workers. This mechanism becomes more relevant in the context of AI-based task-fragmentation, where routine, task-executable and automated components are increasingly replaced by coordination-intensive human components. As a result, job profiles now include more and more soft skills like communication, coordination,

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interpretation and the management of relationships, which is a structural change in human value added. These findings are also confirmed by cross national evidence. According to the World Economic Forum (2020), there is a growing emphasis on critical thinking, creativity, emotional intelligence and leadership across 26 economies and 15 industrial sectors across the board. The findings are consistent with both task-trading framework proposed by Deming (2017) and the routine biased technological change hypothesis put forward by Goos et al. (2014). Furthermore, the OECD (2019) Skills Outlook shows that the need for reskilling capacity and learning agility is increasingly mentioned in formal job descriptions in professional and managerial job roles across OECD countries, indicating a heightened awareness in OECD countries of the limited durability of current competencies in AI-supported work settings.

Critical evaluation: Generalizability and causation

The evidence base needs to be methodologically and conceptually qualified with respect to two dimensions: social skill amplification. Firstly, Deming (2017) extrapolation of his results to today's artificial intelligence driven transformation of the labour market is limited in scope, due to the time and technology in which the results were obtained. The analysis relies on the analysis of the labour market until 2012, before the broad dissemination of sophisticated AI systems across sectors. The demand for social skills is observed in the task reconfiguration, which is also logically consistent with the use of artificial intelligence as a cause of the increased demand. The original research does not explicitly link the demand for social skills to artificial intelligence, but it is a logical extension. Thus, any generalization of the present findings to the current changes in job descriptions resulting from artificial intelligence is only an inference and not a direct conclusion. The literature gathered in this review is more recent, and covered the period 2014-2024, but the empirical studies cited in this article have fewer participants, more heterogeneous measures of exposure to AI, and less robust econometric identification methods than those of Deming (2017) in the large-scale design with a longitudinal sample.

Second, the evidence base is not comprehensive enough to make robust causal attributions for social skill amplification linked to AI adoption. The observed patterns can be explained by a number of alternative factors, such as globalization, occupational polarization, organizational decentralization, shift toward knowledge-intensive services, and demographic changes in the labor force. The methods used to identify appropriate studies vary widely according to the study reviewed. The most solid design is by Deming (2017), who conducted longitudinal cohort comparisons using NLSY79 and NLSY97 data, which partially controlled for the effects of cohort composition and enhanced the internal validity of the design compared to cross sectional designs. Another subset of studies uses difference in differences designs to take advantage of the different schedules and magnitudes of technology adoption across industries and regions. Other studies use instrumental variable methods, where historical technology exposure or the penetration of robots serve as exogenous variables for artificial intelligence adoption. But a significant portion of literature is based on cross sectional correlation between exposure to artificial intelligence and occupational or sectoral skill composition, which fails to establish causality. In broad terms, the evidence base aligns with the notion of AI being linked to the intensification of social skills in job requirements, but strong causal identification only applies to a subset of studies, thereby highlighting the need to take great care with attribution claims.

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Theme 3: AI literacy and ethical governance awareness as emerging baseline requirements

The emergence of a new competency domain

The third thematic cluster is the newest, and also the least empirically developed and most novel of the four identified themes. Twelve studies, primarily from 2019 onwards, record the progressive adoption of AI literacy and ethical governance awareness as expectations in job descriptions in various occupational settings, in the role of a baseline competency requirement. The most cited framework on AI literacy is defined by Long and Magerko (2020) in the Proceedings of the CHI 2020 Conference as a competency with multiple dimensions: a capacity to identify the presence of AI systems, understand how they work, to critically examine AI outputs, interact with AI systems, and to be able to interpret the social implications of AI. The reason for this CHI Conference paper being included must be explained. Conference proceedings were excluded on the quality grounds, however, after Mixed Methods Appraisal Tool assessment, Long and Magerko (2020) was included because CHI is an influential, low acceptance rate (< 25 percent) conference with double-blind review that matches the rigor of Q1 journal standards. Raisch and Krakowski (2021) continue to be theoretically followed in the emergence of AI literacy as a minimum requirement. When AI adoption creates an automation augmentation paradox, such that human workers need to monitor, interpret, and override AI outputs, then the ability to do so becomes a part of job performance in AI augmented jobs. This adds a competency element that is not adequately addressed by either the Task Technology Fit theory or the Skill Biased Technological Change theory, focusing on the management and oversight of AI-enabled processes rather than the actual tasks themselves. The studied literature indicates that this mandate is becoming more common in job postings in healthcare administration, financial auditing, legal and human resource management, and that decisions made with the help of AI are still held accountable to people.

Limitations and risks of overclaiming

Three important caveats to interpretation emerge from critical examination of this thematic cluster. The evidence base is the least in comparison to the other four clusters, with a total of twelve studies and a geographic focus on technologically advanced economies where the regulatory focus on AI governance is relatively high. Therefore, the extent to which AI literacy is required in the general description of a job position in less AI-adopted economies and industries is still not proven. Secondly, many of the studies included were conceptual or normative in nature and presented arguments for the importance of AI literacy, rather than empirically demonstrating that it is widely utilized in formal job descriptions. The difference between normatively prescriptive and empirically observed has important implications for analytical rigor in the synthesis. Third, there is not a full consensus on the definition of AI literacy in the literature. The definitions of what constitutes the operation of AI systems are very different, from a general awareness of AI systems to the capacity to audit, evaluate, or govern algorithmic outputs. The lack of a universal definition of constructs makes it difficult to compare AI literacy across studies and measure it as a work requirement.

Theme 4: Strategic and structural implications for HRM practice

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The inadequacy of conventional job analysis

This review's contribution to HRM theory and practice is the most direct, and is captured in the fourth thematic cluster. The key insight across the eight studies is that traditional job analysis techniques that have informed the development of job descriptions since the early 1900's are increasingly out of alignment with the changing nature of competency needs for work in AI-driven environments. The pre-AI diagnosis for this misalignment is from Sanchez and Levine (2012) in the Annual Review of Psychology. They explain that the number of articles on job analysis in the major industrial and organizational psychology journals has decreased over the past few decades, and that the use of competency modelling is becoming prevalent as a more flexible way to capture changing work needs. This methodological shift becomes even more significant and challenging in the era of AI. The literature reviewed demonstrates the existence of well-defined mechanisms that explain the inadequacy of traditional job analysis in AI augmented contexts. The existing methods like task inventories, critical incident techniques, and Position Analysis Questionnaire are fundamentally retrospective in nature and record the existing task structure and related knowledge, skills, abilities and other attributes. However, in fast-changing AI environments, job descriptions may become obsolete more quickly than task configurations change and are subject to job analysis cycles. Furthermore, these techniques are mostly descriptive, and lack the ability to reflect emerging competency needs. Requirements related to the adoption of AI, such as AI literacy, algorithmic accountability, and collaboration between AI and humans, may not be addressed by traditional tools unless they represent an anticipated redesign of the role rather than the execution of current tasks.

Talent acquisition and workforce planning misalignments

Lack of job description has a ripple effect throughout the HRM system, and there is a disconnect between job design, selection, and workforce planning. Ryan and Derous (2016) present in the International Journal of Selection and Assessment a series of tensions in the contemporary recruitment and selection processes: innovation vs efficiency; customization vs consistency; transparency vs effectiveness; wide reach vs coherence; diversity vs standardization. These tensions are exacerbated by instability in job descriptions brought on by AI, which undermines the validity foundation that underlies selection systems. If the job description does not properly reflect the competencies needed for an AI-enhanced job, those who demonstrate more AI literacy, adaptive capacity, and learning agility will experience systematic errors since these are not adequately represented in selection methods and the tools used to measure the competencies defined by the job description. The resulting problem is not restricted to recruitment, as it is an overall issue of a breakdown in workforce planning logic at the system level. In their Harvard Business Review article on the subject of agile HR, Cappelli and Tavis (2018) state that headcount planning models based on static role taxonomies are not well suited to environments where skills are rapidly recombined. In these settings, headcount is still a useful indicator of the amount of labour but becomes a less useful indicator of the quality of labour. They are unable to evaluate if their current staff has the changing competency profile necessary to match the role and are not able to support skill portfolios in the process of AI driven transformation. This means a structural mismatch between staffing models and requirements for staff capabilities. One logical methodological reaction to this mismatch is skills-based

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workforce planning that monitors and predicts individual competency journeys over time, albeit not widespread in practice.

Critical assessment: Practical feasibility and implementation barriers

The HRM implications cluster reveals a basic conflict between the theoretical prescriptions and the organizational feasibility. The literature reviewed highlights the same set of desired capabilities, such as designing jobs dynamically, continually updating competencies, skills-based workforce planning and incorporating AI into talent acquisition, but these are still mostly conceptual and not necessarily found in practice across organizations. In total, they suggest a significant change in HR infrastructure, one that demands advanced data capability, ongoing managerial commitment and reconfigured HR systems. But there is limited empirical evidence of the implementation of these capabilities. The reviewed studies are much better in terms of explaining what HRM systems should be like when implemented under AI adoption and fewer in terms of actualizing successful HRM transition in real organizational contexts. This leaves an enduring disconnect between “how it should be” and “what is happening in the organization”. In this respect the literature provides a relatively strong record of a transformation agenda that is well specified, but not as much evidence about feasibility, scalability and institutionalization.

Theoretical contributions

Before articulating the specific theoretical contributions, this review must be positioned within adjacent streams of literature. Existing work on AI and labor markets, notably Acemoglu and Restrepo (2019) and Autor (2015), operates primarily at the macro level of occupations, wages, and sectoral employment shifts. While highly influential, these studies do not examine job descriptions as micro level organizational artefacts through which labor demand is formally specified and operationalized. Similarly, HRM oriented reviews of AI and work address implications for managerial practice in broad terms but do not isolate job descriptions as the central analytical unit, nor do they employ a PRISMA guided synthesis focused on role specification as data. In contrast, this review reframes AI driven labor transformation at the level of job description content, treating it as the institutional mechanism through which macro labor market change is encoded into organizational design. Against this backdrop, the review makes three interrelated theoretical contributions. First, it extends Task Technology Fit theory from its traditional individual level focus to the organizational design of job descriptions. Goodhue and Thompson (1995) conceptualized TTF as alignment between task requirements and technology capabilities affecting individual performance. This review demonstrates that the same logic operates upstream at the level of role construction, where AI systems reshape job descriptions by absorbing high fit task components and expanding low fit human centred activities. This shifts TTF from an adoption and performance framework to a theory of organizational role reconfiguration.

Second, it reconceptualizes Skill Biased and Routine Biased Technological Change frameworks as processes that are first observable at the level of job specification before they manifest in aggregate labour market outcomes. While Goos et al. (2014) and Katz and Murphy (1992) establish SBTC and RBTC at the macroeconomic level, this review identifies job descriptions as the micro institutional site where these dynamics are

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initially translated into concrete skill demands. In this sense, job descriptions are not passive reflections of labor market structure but active mechanisms through which technological change is encoded into organizational expectations. Third, the review identifies AI governance capability as a distinct competency domain that is not fully explained by existing TTF or SBTC logics. Traditional formulations of TTF focus on task performance alignment, while SBTC focuses on shifts in skill demand distributions. In contrast, AI governance competencies involve oversight, evaluation, and contestation of algorithmic outputs, where the human role is defined not by task execution but by regulation of machine generated decisions. This introduces a reflexive human AI relationship that existing frameworks do not fully capture. Future research may develop a governance fit construct that specifies alignment between human oversight capacity and AI system transparency, interpretability, and controllability, thereby extending TTF into a governance centred theoretical domain.

Practical contributions

The synthesized evidence supports four concrete, evidence grounded recommendations for HR practitioners and organizational designers, each derived directly from the reviewed literature rather than normative aspiration. First, job description design should be reconceptualized as a continuous strategic capability rather than a periodic administrative exercise. The evidence indicates that competency requirements in AI augmented roles evolve at a pace that renders conventional review cycles insufficient. The agile HR model advanced by Cappelli and Tavis (2018) provides an operational foundation for this shift, emphasizing iterative role redesign, continuous competency tracking, and alignment between job architecture and organizational AI deployment strategies. Within this logic, job descriptions become dynamic instruments of workforce design rather than static documentation artifacts. Second, competency frameworks underpinning job descriptions should be restructured around four empirically recurrent domains emerging across the reviewed literature. These include AI interaction and literacy competencies as defined by Long and Magerko (2020), higher order cognitive and complex problem-solving competencies consistent with Autor et al. (2003), interpersonal and social intelligence competencies supported by Deming (2017), and ethical as well as governance-oriented competencies identified in the Theme 3 evidence base. These domains collectively indicate that AI adoption is associated not only with skill upgrading but with a qualitative reconfiguration of what constitutes core occupational competence.

Third, talent acquisition systems must be systematically realigned with the evolving competency architecture of AI augmented roles. The evidence demonstrates that misalignment between job descriptions and actual role requirements propagates structural inefficiencies across recruitment, selection, training, and performance management systems. This creates compounding error in talent identification, where selection decisions are optimized against outdated competency models. Addressing this requires upstream redesign of job descriptions as the primary lever of intervention, supported by downstream refinement of assessment instruments. Ryan and Derous (2016) provide a foundational framework for diagnosing the inherent tensions in selection system design, particularly the trade-offs between standardization and adaptability that become more pronounced under AI driven change. Fourth, workforce planning must transition from headcount-oriented logic to skills inventory and capability-based architectures. The evidence indicates that the defining challenge of AI driven workforce transformation is not aggregate labour quantity but the speed, complexity, and uneven distribution of competency change within roles. Organizations that develop real time skills intelligence systems capable of mapping current competencies, identifying emerging gaps, and forecasting future capability requirements will be better positioned to manage AI induced transitions proactively. In this model, workforce planning becomes a dynamic capability management function rather than a static staffing exercise.

Limitations of this review

This review has five limitations that must be acknowledged clearly and that bound the appropriate generalization of its findings. First, the restriction to English-language publications introduces a geographic and linguistic publication bias that systematically underrepresents evidence from high-AI-adoption economies in East and Southeast Asia, where Chinese, Japanese, and Korean-language research on AI and workforce transformation is extensive but not captured in this synthesis. The reviewed evidence should be understood as reflecting predominantly Anglophone organizational contexts. Second, the 2014 lower time boundary, while theoretically justified by reference to LeCun et al. (2015), excludes the long history of research on technology and job design that predates the AI era. Job description transformation in response to technological change is not a new phenomenon; the omission of the pre-2014 literature prevents this review from situating AI-era transformation in its historical context and risks attributing to AI processes that may represent continuations of longer-term trends. Third, the cross-industry synthesis necessarily aggregates findings across sectors with highly divergent AI adoption trajectories, regulatory environments, and job description conventions. A finding of social skill amplification across the synthesized literature does not mean that social skill amplification is occurring at the same rate or in the same form in financial services, healthcare, manufacturing, and retail simultaneously. Sector-specific systematic reviews are required to generate operationally precise conclusions for individual industries.

Fourth, while the MMAT quality appraisal and inter-rater reliability procedures employed in this review are robust by SLR standards, 52 studies is a relatively modest synthesis corpus for a cross-industry, multi-decade review. The included literature's statistical power to detect systematic patterns across industries and methodological traditions is consequently limited. The four thematic clusters identified should be understood as reflecting the strongest consistent patterns in a heterogeneous literature rather than as exhaustively characterizing all facets of AI-driven job description transformation. Fifth, the five cluster studies in this review that are classified as systematic or narrative reviews create a risk of evidence recycling, in which the same primary studies contribute to this synthesis both directly and indirectly through their inclusion in those prior reviews. Where such recycling was identified during data extraction, the evidence from prior reviews was treated as supporting rather than primary evidence.

Conclusion

This systematic literature review synthesizes evidence from 52 peer reviewed studies to provide a PRISMA compliant (Page et al., 2021), cross industry account of how artificial intelligence is transforming job descriptions. The central finding is that AI

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driven change reflects a structural shift from task based to competency-based role specification. This shift is driven by two reinforcing mechanisms, task displacement through which AI automates routine cognitive and manual activities, and competency amplification through which remaining human work concentrates in nonroutine cognitive, interpersonal, adaptive, and governance related functions. Task Technology Fit theory (Goodhue and Thompson, 1995) and Skills Biased Technological Change (Katz and Murphy, 1992) jointly explain the direction of this transformation, while Deming (2017) and Autor et al. (2003) provide empirical grounding for task and skill reconfiguration. The augmentation displacement paradox proposed by Raisch and Krakowski (2021) further extends this account by showing that AI restructures rather than simply reduce human work content, introducing new requirements for human AI coordination and oversight. For HRM, the review establishes that job descriptions function as strategic workforce design instruments rather than administrative records, with direct implications for talent acquisition and workforce planning. Persisting with static, task-based job description models risk systematic misalignment with AI augmented work environments, whereas competency centric and continuously updated approaches represent a necessary structural shift rather than incremental improvement. Future research should prioritize sector specific analyses, longitudinal tracking of job description evolution, development and validation of governance fit as an extension of Task Technology Fit, comparative studies in developing and non-Anglophone contexts, and implementation focused research on how organizations operationalize dynamic job description systems in practice.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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