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Review

Generative AI and Language Ceilings: Career Capital and Mobility in Multilingual Workplaces

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Abstract

Workplace language proficiency functions as career capital because it shapes whose expertise is heard, trusted, and converted into developmental assignments, networks, promotion, and mobility. Generative artificial intelligence (GenAI) disrupts the assumed correspondence between employee-held language competence and observable communicative performance by enabling linguistic capability to be technologically accessed. This critical integrative review synthesises 41 substantive sources across language and careers, AI-mediated communication, multilingual model performance, workplace productivity, identity, attribution and signalling, sociotechnical work, and AI literacy. Sources were classified by evidentiary proximity to career outcomes, from model benchmarks and simulated tasks to workplace processes and direct mobility evidence. Evidence indicates task-level and workplace-process benefits alongside uneven cross-language performance and unresolved attribution and legitimacy concerns, but no study in the reviewed set directly links GenAI-supported multilingual communication with promotion, pay growth, lateral mobility, or access to strategic assignments. Integrating career-capital theory, attribution and signalling processes, and sociotechnical perspectives, the article distinguishes employee-owned competence, technologically accessed capability, AI-mediated communicative performance, organisationally recognised performance, and career-convertible capital. LANA provides the multilevel organising framework for a conversion model explaining how mediated performance may, or may not, become career value. Two conditional pathways theorise how GenAI may flatten language ceilings through improved performance, participation, learning, and visibility, or re-stratify work through unequal access, verification burdens, cross-language error, and legitimacy penalties. Five testable propositions are advanced. GenAI therefore changes not only communicative performance but the mechanisms through which capability is attributed, recognised, and converted into career advantage.

Keywords: AI-mediated communication; career capital; career mobility; generative artificial intelligence; language barriers; language ceilings; multilingual workplaces; workplace inclusion

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Academic Editor: Elena-Mădălina Vătămănescu

Received: 27 July 2026
Revised: 4 September 2026
Accepted: 9 September 2026
Published: 15 September 2026

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1. Introduction

Language proficiency is often treated as a communication skill, but in multilingual organisations it also functions as a mechanism of valuation. Employees who can communicate in the corporate language are more likely to participate visibly, build relationships across organisational boundaries, and be considered ready for roles with broader scope. Those who cannot may encounter barriers that are only partly related to their technical

competence. Bhar and Chua [1] describe these barriers as language ceilings and language walls. A ceiling restricts vertical advancement when the linguistic demands of a higher role exceed those recognised or supported in a lower role. A wall restricts horizontal movement by limiting access to teams, functions, locations, or networks. Through these mechanisms, language becomes career capital: a resource whose value depends on the organisational settings in which it can be mobilised and recognised.

Generative artificial intelligence (GenAI) challenges a basic assumption embedded in this literature. Before GenAI, the production of polished workplace language was usually attributed to the worker or to visible human assistance. Large language models can now draft emails, translate documents, summarise meetings, revise tone, suggest replies, and support rehearsal in near real time. AI-mediated communication therefore separates at least three elements that were previously bundled together: the worker's underlying language proficiency, the quality of the message received by others, and the organisational attribution of that quality. A worker may produce a highly effective message without independently possessing every linguistic capability manifested in the output. Conversely, a fluent worker may be evaluated negatively if AI assistance is suspected or disclosed.

Organisational adoption is no longer hypothetical. In a late-2024 survey of more than 5000 small- and medium-sized enterprises across seven countries, 31% reported using GenAI and 65% of users reported improved employee performance [2]. These figures establish organisational reach and perceived value, not causal effects or career returns. The report concerns selected economies and small- and medium-sized enterprises and should not be generalised to all workplaces.

The gap is therefore not only empirical. Existing research on workplace language and career capital generally assumes a relatively close relationship between communicative competence possessed by the employee and the communicative performance observed by others. GenAI weakens this correspondence because workplace communication can now be jointly produced by an employee and a technological system. An employee may therefore display communicative performance that exceeds their unaided language competence, while evaluators may be uncertain about how much of that performance should be attributed to the employee. Existing language-career models do not adequately explain how technologically mediated capability becomes recognised employee performance or how such performance is subsequently converted into career capital.

The assumption that observable communicative performance can serve as a reasonably direct indicator of employee-held language capability is therefore increasingly insufficient in AI-mediated work. Once linguistic performance can be technologically generated, enhanced, translated, or reformulated, competence, performance, attribution, and career value must be analytically separated.

The distinction matters because the strongest evidence concerns tasks and proximal workplace processes rather than careers. Experiments show that GenAI can reduce the time required for professional writing and improve evaluated output quality [3]. Field evidence from customer support shows productivity gains, especially among less experienced and lower-performing workers [4]. A survey of 366 employees also associated cognitive and social GenAI use with innovative job performance through knowledge transfer, resource acquisition, and job satisfaction [5]. These studies make barrier reduction plausible but they do not establish that multilingual employees subsequently receive stronger ratings, better assignments, larger wage increases, or more promotions.

Multilingual performance is also uneven. Language technologies perform systematically better for some languages than others [6,7], while experimental evidence across English, Arabic, and Chinese indicates that the work value of AI-generated content can differ by language and task domain [8]. This evidence supports concern about unequal

assistance, but not a conclusion that career inequality has already resulted. AI assistance can also alter social judgement. People may communicate more positively with AI support while being judged less favourably when AI use is suspected [9], and automated detectors can disproportionately misclassify writing by non-native English speakers [10].

This article makes three theoretical contributions. First, it distinguishes employee-owned language competence from technologically accessed communicative capability and explains why AI-mediated performance cannot automatically be treated as evidence of employee-held competence. Second, it specifies the mechanisms through which AI-mediated performance is attributed, recognised, and converted into organisational opportunity and career capital. Third, it extends LANA from a multilevel diagnostic framework into GenAI-LANA by introducing technological mediation, conditional flattening and re-stratification pathways, and testable propositions concerning performance, learning, opportunity conversion, resource asymmetry, and attribution.

Against this theoretical problem, the absence of direct career-outcome evidence represents an additional empirical discontinuity. Within the reviewed evidence, no study directly linked GenAI-supported multilingual communication with promotion, pay growth, lateral mobility, or access to strategic assignments. This absence does not constitute the primary theoretical justification for the framework. Rather, it highlights the need to test the mechanisms through which technologically mediated communicative performance may, or may not, become recognised and career-convertible.

The argument is deliberately conditional. GenAI is neither inherently inclusive nor inherently stratifying. Its career consequences depend on practical access, language and task fit, verification capability, legitimacy, and whether improved communication changes opportunity allocation. The article therefore avoids treating productivity, confidence, or message quality as substitutes for observed career outcomes.

2. Review Design and Evidentiary Boundaries

This article uses a critical integrative review as the foundation for theory development. Integrative reviews are appropriate when evidence is dispersed across fields and the purpose is to connect empirical findings, examine conceptual assumptions, and generate a framework rather than estimate a pooled effect [11,12]. The design is appropriate because research directly combining GenAI, multilingual workplace communication, and career mobility remains immature. The objective is transparent analytic integration and mechanism development, not an exhaustive census or pooled estimate.

Source discovery was iterative and was last updated on 20 July 2026. Targeted searches of scholarly discovery interfaces were combined with publisher and DOI records, the manuscript's existing reference set, backward reference checks, and forward citation trails visible from core sources. Search concepts combined ("generative AI" OR "large language model" OR ChatGPT) with terms from four domains: (a) workplace and organisation; (b) multilingual, non-native speaker, language barrier, translation, or communication; (c) trust, authenticity, identity, or AI literacy; and (d) career, promotion, mobility, pay, appraisal, assignment, or employability. A final direct-outcome check required at least one GenAI term, one multilingual or language-barrier term, and one career-outcome term.

Sources were eligible when they were peer-reviewed empirical, conceptual, or review publications that informed at least one link from technological capability to assisted communication, workplace recognition, opportunity allocation, or career outcome. The OECD report was retained only as adoption context. Sources were excluded when they addressed AI without a communication, language, work, identity, capability, or career mechanism; discussed traditional machine translation without relevance to GenAI-mediated work; duplicated an included publication; or provided claims that could not be checked against a

primary publisher or DOI record. Academic writing, creativity, and detector studies were retained only when they clarified identity, attribution, or standardisation mechanisms and are explicitly treated as adjacent rather than workplace-career evidence.

The final reference set contains 43 works: 41 substantive sources and two review-method guides. The substantive sources were coded into seven roles (see Appendix A): pre-GenAI language, career, and theoretical foundations (n = 22), multilingual model or benchmark evidence (n = 3), simulated work-task evidence (n = 2), direct workplace-process evidence (n = 4), adjacent recognition or identity evidence (n = 5), enabling-condition evidence on AI-mediated communication, literacy, or digital inequality (n = 4), and adoption context (n = 1). The author screened and coded the sources and checked bibliographic details against primary publisher or DOI records. Because the process did not begin with a reproducible database export and was not independently double-screened, the article is not presented as a systematic review. Table 1 summarises the review audit trail and the decision rules applied during source identification, screening, coding, and synthesis.

Table 1. Review audit trail and decision rules.

Review Element	Recorded Decision
Purpose	Integrate dispersed evidence and develop mechanisms linking GenAI-mediated multilingual communication to career capital and mobility.
Search update	Iterative discovery completed through 20 July 2026, followed by publisher/DOI verification and citation chaining.
Core concept blocks	GenAI; workplace/organisation; multilingual communication; recognition/identity/AI literacy; career and opportunity outcomes.
Eligibility	Peer-reviewed empirical, conceptual, or review work informing at least one conversion-chain link; one OECD report used only for adoption context.
Exclusion	No relevant mechanism; traditional translation without GenAI-work relevance; duplicate publication; or bibliographic/claim details not verifiable from a primary record.
Evidence coding	Each source coded by evidence role and proximity to career outcomes. Adjacent evidence was not treated as direct workplace-career evidence.
Synthesis set	The final reference set contains 43 works: 41 substantive sources and two review-method guides. Screening and coding were completed by the author.
Inference boundary	No universal absence claim. The identified gap is restricted to the reviewed set and the search date.

The bounded conclusion, therefore, is as follows: no direct study was identified within this reviewed set that linked GenAI-supported multilingual communication to promotion, pay growth, lateral mobility, or access to strategic assignments. This is an evidentiary discontinuity, not proof that no such study exists. Table 2 maps the resulting evidence chain and distinguishes what each body of evidence can establish from what remains unsupported.

Table 2. Evidence-chain map for GenAI, multilingual communication, and career mobility.

Evidence Link	Representative Evidence	What the Evidence Can Establish	What It Cannot Establish
1. Model capability	Multilingual benchmarks and language-technology evaluations (Ahuja et al., 2023; Blasi et al., 2022; Joshi et al., 2020) [6,7,13]	Relative performance across languages and tasks	Effective use in a particular workplace or any career benefit

Table 2. *Cont.*

Evidence Link	Representative Evidence	What the Evidence Can Establish	What It Cannot Establish
2. Simulated work tasks	Professional writing and multilingual email experiments (Koo, 2025; Noy & Zhang, 2023) [3,8]	Changes in speed, evaluated quality, actionability, or creativity	Durable learning, opportunity allocation, promotion, or pay
3. Workplace processes	Customer support, employee-performance, organisational-relationship, and professional-boundary studies (Brynjolfsson et al., 2025; Nguyen et al., 2026; Yinglei & Nik Hasan, 2026; Zhang et al., 2026) [4,5,14,15]	Productivity, job performance, communication satisfaction, relationships, or boundary control	Multilingual career effects across occupations or organisations
4. Recognition and identity	Attribution, authenticity, identity, detection, and output-diversity studies (Doshi & Hauser, 2024; Hohenstein et al., 2023; Hu et al., 2025; Jago, 2019; Liang et al., 2023) [9,10,16–18]	Possible mechanisms affecting trust, authorship, legitimacy, and evaluation	Net effects on formal employment or mobility outcomes
5. Multilingual career outcomes	No direct study identified within the reviewed evidence	Promotion, pay growth, lateral movement, strategic assignments, or mobility intentions, if directly studied	This missing link is the focal evidence gap

Additional references used for theoretical positioning and contextual interpretation were not treated as part of the coded synthesis set and are therefore not included in these counts.

3. Language Ceilings and Walls Before GenAI

Evidence-status convention. Throughout Sections 3–8, claims are interpreted at four levels: direct evidence (observed career or opportunity outcomes), workplace-process evidence (observed workplace behaviour or employee reports), adjacent evidence (benchmarks, simulations, academic or social settings), and theoretical proposition (a relationship advanced for future testing). No direct GenAI-multilingual career evidence was identified in the reviewed set. Accordingly, the five propositions are predictions, not findings.

3.1. Language as Career Capital

Career capital refers to resources that individuals accumulate and convert across roles and organisations. Its value is not purely intrinsic. A competence becomes capital when it is legible, valued, and usable within a field of opportunity [19–21]. Language illustrates this relational quality. Fluency can increase access to information and networks, but its career return depends on the language regime of the organisation, the role under consideration, and the people authorised to evaluate readiness.

Empirical research supports a link between language competence and mobility. Itani et al. [22] show that language skills shape both psychological and physical dimensions of career mobility. Peltokorpi [23], using two time-lagged studies of local employees in foreign subsidiaries in Japan, links English-language competence to objective and subjective career outcomes through managerial encouragement and social capital. Latukha et al. [24] similarly show that corporate language can influence career mobility in multinational corporations. These studies do more than associate language with task efficiency. They identify relational mechanisms through which competence is noticed and converted into opportunity.

For the present argument, the crucial issue is therefore not possession alone but conversion. A communicative resource becomes career capital when it is made visible, recognised as valuable, and connected to opportunities that improve the employee's position. This distinction becomes important under GenAI because technologically assisted performance may increase an employee's immediate productive capability without necessarily becoming a durable resource attributed to that employee. Improved communicative performance and accumulated career capital therefore cannot be treated as equivalent outcomes.

Language competence also structures power. In multinational corporations, language can influence formal structure, informal networks, knowledge flows, and employees' access to headquarters [25,26]. The adoption of a common corporate language may improve coordination while redistributing status toward those already fluent in that language [27,28]. In global teams, language barriers affect trust formation, emotion regulation, subgroup dynamics, and power contests [29,30]. Employees are therefore evaluated not only on what they know but also on the ease, confidence, and culturally recognisable form with which they make that knowledge available.

The language-sensitive turn in international management further shows that language is not a neutral channel layered over organisational processes. It helps constitute hierarchy, identity, coordination, and control, which makes its effects relevant to both theory and managerial practice [31,32].

3.2. Ceilings, Walls, and Discontinuous Requirements

The concepts of language ceilings and walls consolidate these observations into a career framework [1]. A language ceiling arises when employees can perform successfully at one level but are treated as unready for roles requiring different communication repertoires. A language wall blocks movement across functions, projects, or geographies. Neither barrier needs to appear in a formal job description. It can be reproduced through staffing conversations, client-facing criteria, informal sponsorship, or assumptions about executive presence.

These barriers are reinforced by discontinuity. Suzuki et al. [33] show that the oral and literacy demands associated with job roles do not necessarily rise in a simple linear sequence. Skills that are adequate for a current role may not prepare an employee for the communication ecology of a managerial role. A technically strong employee may therefore receive little opportunity to practise the persuasive, relational, or representational communication that is later used to deny advancement. This is one reason why generic language training can miss the problem. The relevant need is not merely a higher test score but access to the communicative practices of the next role.

Evaluation is also ideological. Non-native English-speaking staff can be judged through assumptions that conflate accent, style, confidence, and competence [34]. Barner-Rasmussen et al. [35] show how language ideologies shape participation by prescribing whether employees should pursue perfection, rely on hybrid practices, or remain silent. Such norms define which forms of multilingual communication count as professional. Language barriers are therefore produced jointly by individual repertoires and organisational expectations.

These findings establish an important pre-GenAI relationship: communicative performance not only enables task accomplishment but can also function as an observable signal from which organisational actors infer less directly observable qualities such as competence and readiness [36]. GenAI complicates this relationship because the communicative performance observed by evaluators may no longer correspond closely to language capability independently possessed by the employee.

This concern is also visible at the transition into employment. Malaysian students' accounts of workplace English identify not only language-skill demands but also psychological barriers and perceived gaps in employability-oriented language preparation [37]. Although such perceptions do not demonstrate actual career barriers, they indicate that communicative readiness for work is experienced as involving both linguistic capability and confidence before employees enter organisational mobility systems.

3.3. The Original LANA Contribution

Bhar and Chua [1] developed LANA to reconnect language development with career progression. LANA examines needs at three levels. The individual level concerns an employee's current repertoire, confidence, aspirations, and developmental gaps. The organisational level concerns language policies, access to learning, managerial support, and the ways that language is embedded in talent systems. The operational level concerns the actual linguistic demands of tasks, roles, and interactions. This multilevel structure avoids locating responsibility solely in the employee.

LANA is treated in this article as a multilevel diagnostic and organising framework rather than as the principal explanatory theory. It identifies the individual, organisational, and operational locations at which language-related capability and barriers arise. Career-capital theory explains how valued resources can be converted into career advantage, while signalling and attribution perspectives explain how communicative performance is interpreted and credited [36,38], and sociotechnical theory explains how workplace performance is shaped through the interaction of social and technological elements [39,40].

GenAI-LANA is therefore not simply the original LANA framework applied to a new technological context. Bhar and Chua [1] identified the individual, organisational, and operational locations at which language needs and career barriers arise. The present extension addresses a different explanatory problem: how communicative capability that is partly supplied by technology becomes, or fails to become, capability attributed to the employee and subsequently converted into career value. It therefore distinguishes constructs that were not explicitly separated in the original framework: employee-owned competence, technologically accessed capability, AI-mediated communicative performance, organisationally recognised performance, and career-convertible capital.

This distinction becomes necessary because GenAI changes the production of workplace communication. The pre-GenAI framework understandably assumes that communicative capability resides primarily in the worker and develops through education, experience, and interaction. In AI-mediated work, however, a message may be jointly produced by an employee, a model, organisational data, and an interface. The employee still contributes intent, contextual knowledge, judgement, verification, and accountability, but may not independently possess every linguistic capability manifested in the final output. Successful communicative performance can therefore exceed unaided employee language proficiency.

The theoretical question consequently shifts from whether an employee possesses the linguistic resources required for a task to how technologically mediated capability is produced, attributed, recognised, and converted into career value. GenAI-LANA extends the original framework by introducing this conversion problem and by specifying mechanisms through which technological mediation may either reduce language-related career barriers or reproduce them in new forms. Table 3 summarises the principal distinctions between the original LANA framework and the proposed GenAI-LANA extension.

Table 3. Distinguishing LANA from GenAI-LANA.

Dimension	LANA, Bhar and Chua [1]	GenAI-LANA
Primary purpose	Diagnose language needs and career barriers	Explain how AI-mediated capability is produced, recognised, and converted
Levels	Individual, organisational, operational	Same three levels retained
Location of capability	Primarily employee repertoire supported by organisational conditions	Distributed across employee, GenAI, organisational resources, and task
Role of technology	Not a central explanatory mechanism	Transversal mediation layer
Performance distinction	Primarily employee language performance	Assisted and unaided performance explicitly separated
Core mechanisms	Needs, support, role demands, career barriers	Substitution, augmentation, scaffolding, verification, attribution, legitimacy, conversion
Outcome process	Language needs and mobility barriers	Access → mediated performance → recognition → opportunity → career outcome
Boundary conditions	Individual, organisational, and operational conditions	Language-resource position, task stakes, governance, legitimacy, verification
Predictions	Diagnostic relationships	Five explicitly testable propositions

3.4. Attribution and Signalling of AI-Mediated Performance

Organisational decision-makers cannot observe employee competence directly and therefore infer less visible qualities such as expertise, reliability, confidence, and role readiness from observable performance. Signalling theory explains how observable characteristics or behaviours can convey information about less directly observable qualities under conditions of information asymmetry [36]. Communicative performance can therefore function as a signal of underlying capability. In multilingual workplaces, linguistic fluency, responsiveness, pragmatic appropriateness, and communicative confidence may influence whether an employee is perceived as ready for more visible or demanding responsibilities.

GenAI complicates this signalling relationship because the observed performance may be partly technologically produced. A high-quality message can therefore generate different evaluations depending on how its production is attributed. Attribution theory is concerned with how observers infer the causes of outcomes and behaviour [38]. Applied to AI-mediated communication, evaluators may attribute successful performance primarily to the employee's judgement and expertise, primarily to the technological system, or to some combination of the two.

This distinction matters for career conversion. AI-supported communication may be interpreted as evidence of effective judgement, resourcefulness, and technological competence. Alternatively, it may be discounted if evaluators believe that the technology substituted for capability the employee does not independently possess. Attribution therefore becomes a critical mechanism between AI-mediated performance and career value.

Legitimacy further conditions this process. Where AI assistance is accepted as part of competent professional practice, technologically mediated performance may retain its signalling value. Where legitimate-use norms are ambiguous, disclosure or suspicion of AI assistance may weaken perceived authorship, authenticity, or role readiness. GenAI-LANA therefore treats output quality and evaluator attribution as analytically distinct. Improved communicative performance does not necessarily produce an equivalent improvement in perceived employee competence, organisational recognition, or career opportunity.

3.5. Sociotechnical Production of Communicative Performance

Sociotechnical theory provides a complementary explanation for why AI-mediated communicative capability cannot be located solely within either the employee or the technology. The sociotechnical tradition emphasises the interdependence of the social and technological components of work systems rather than treating technical systems as independent determinants of workplace outcomes [40]. Orlikowski [39] subsequently challenged deterministic accounts of organisational technology by conceptualising technology and human action as recursively related within organisational structures. Together, these perspectives support treating GenAI-mediated communication as an outcome of interacting human, technological, organisational, and task conditions rather than as a capability supplied by the model alone.

Applied to GenAI-mediated communication, this perspective suggests that performance emerges through interactions among human capability, technological resources, organisational arrangements, and task conditions. The quality and usability of an AI-mediated output may depend simultaneously on the employee's language repertoire, domain knowledge, and verification judgement; the capabilities of the model and interface; organisational access, data, governance, and legitimate-use rules; and the linguistic, pragmatic, and interactional demands of the task.

The relevant unit of analysis therefore changes. Rather than treating GenAI as an independent source of capability or the employee as the sole producer of workplace communication, GenAI-LANA conceptualises communicative performance as sociotechnically produced. Technological assistance can alter what an employee is able to accomplish without eliminating the continuing importance of human judgement, contextual knowledge, verification, and accountability.

This perspective also explains why GenAI is represented as a transversal mediation layer rather than a fourth LANA level. Technology operates through the individual, organisational, and operational dimensions: employees differ in their ability to use and verify it; organisations determine access, governance, data availability, and legitimate use; and tasks differ in language, modality, complexity, audience, and consequences of error. The effects of GenAI therefore depend on interactions across the existing LANA levels rather than on technological availability alone.

Together, these theoretical perspectives specify different parts of the conversion problem. Sociotechnical theory explains how AI-mediated communicative performance is jointly produced [39,40]. Signalling and attribution perspectives explain how that performance is interpreted and credited [36,38]. Career-capital theory explains whether recognised performance changes access to valued opportunities and becomes a durable career resource [20,21]. LANA provides the multilevel organising framework within which these mechanisms operate.

GenAI-LANA therefore theorises a sequence of production → attribution → recognition → opportunity → career conversion.

4. GenAI as a Communication-Barrier Technology

4.1. From Language Tool to Mediated Agency

AI-mediated communication occurs when an intelligent agent modifies, augments, or generates messages on behalf of a communicator [41]. GenAI expands the scope and visibility of that mediation. Spell-checking corrects bounded errors; a large language model can reorganise an argument, adjust politeness, translate a document, propose a response, or simulate a difficult conversation. Technology therefore acts as a communicative mediator, but the employee remains responsible for intent, context, verification, and consequences.

For multilingual employees, the affordances are substantial. Drafting support can reduce the cognitive load of encoding ideas in a second or additional language. Translation can widen access to documents and interactions. Tone revision can help workers navigate unfamiliar pragmatic conventions. Summarisation can support comprehension when meetings or documents contain dense, fast, or idiomatic language. Rehearsal tools can create low-risk opportunities to practise. These affordances plausibly reduce the immediate cost of crossing a language wall.

Voice-based translation, live captions, and meeting interpretation extend mediation into synchronous work. In principle, they can help employees follow rapid exchanges and contribute without waiting for a human translation cycle. In practice, the value of these tools depends on speech recognition across accents, speaker identification, latency, turn-taking, privacy, and the accurate rendering of specialised meaning. The review found no workplace study that connects use of these functions to multilingual career mobility. They are therefore treated as emerging affordances within AI-mediated communication [41], not as evidence that synchronous language barriers have already been removed.

Experimental evidence provides an initial basis for barrier-reduction claims. Noy and Zhang [3] found improved productivity and evaluated quality on mid-level professional writing tasks. Brynjolfsson et al. [4] reported productivity gains in customer support, with larger gains among less experienced and lower-performing workers and improved communication fluency among international agents. At a broader organisational level, Zhang et al. [5] associated cognitive and social GenAI use with knowledge transfer, resource acquisition, job satisfaction, and innovative job performance. These findings support plausible communication and resource mechanisms, but only the customer-support study directly observed work behaviour, and none tested multilingual career mobility.

The evidence is therefore useful but bounded. Customer support involves recurring, text-rich tasks with observable resolution outcomes and extensive historical data. Survey associations with innovative performance are not causal evidence. Leadership communication, negotiation, conflict, sponsorship, and client trust rely more heavily on contextual knowledge, embodied presence, spontaneity, and accountability. Results from bounded writing and service tasks should not be assumed to transfer to these higher-stakes interactions.

4.2. Uneven Multilingual Capability

The label multilingual GenAI can create a misleading impression of equivalent capability across languages. Reviews of natural language processing document systematic inequalities in data availability, research attention, and performance [6,7]. Ahuja et al. [13] likewise show that generative models vary across multilingual evaluation tasks. These benchmark studies identify capability asymmetry; they do not show how employees use the systems, how organisations evaluate outputs, or whether any career consequence follows.

Koo [8] offers the most directly relevant experimental work-task evidence currently used in this review. In a preregistered experiment with 480 participants across English, Arabic, and Chinese, the value of AI assistance varied by language and task domain. Arabic- and Chinese-language participants received smaller gains on some dimensions of actionability and creativity, particularly in specialised tasks. The study demonstrates cross-language variation in one model, three languages, and simulated email tasks. It does not establish stable language rankings, effects in natural organisations, or career inequality.

These findings motivate, rather than confirm, the possibility of a second-order ceiling. If employees using less well-supported languages must spend more time detecting errors, reconstructing context, or translating through English, the cost of apparently equivalent

assistance may be unevenly distributed. Whether that burden affects participation, assignment allocation, or mobility remains an empirical question. The manuscript therefore treats the second-order ceiling as a conditional theoretical mechanism, not an observed career outcome.

4.3. Identity, Trust, and Attribution

Communication transmits information while also signalling effort, identity, expertise, warmth, and membership. Hohenstein et al. [9] found that AI assistance can improve the positivity and efficiency of communication while changing how recipients judge a communicator when assistance is suspected. This work supports an attribution mechanism, but it does not concern promotion or multilingual organisational careers.

Jago's [16] research on algorithms and authenticity predates the current GenAI wave but helps explain why technologically improved performance may not receive full social credit. Workplace evidence also shows that professional groups actively negotiate the boundaries of acceptable AI use. Yinglei and Nik Hasan [14], based on interviews with 16 journalists in Malaysia and China, reported selective AI incorporation alongside continued professional boundary control, particularly where accuracy and stakeholder obligations were salient. This supports legitimacy as an organisational mechanism, not a claim about career outcomes.

Identity tensions are also evident in adjacent professional settings. Hu et al. [17] found that non-native English-speaking researchers used ChatGPT for linguistic support while negotiating authorship, legitimacy, confidence, dependence, and disclosure. In an organisational study in Vietnam, Nguyen et al. [15] examined relationships among AI-mediated communication, social presence, communication satisfaction, and professional relationships. These studies show that assistance can affect voice, satisfaction, and relationships, but neither establishes multilingual promotion or mobility effects.

Detection technologies may intensify attribution problems. Liang et al. [10] demonstrated that several GPT detectors disproportionately classified writing by non-native English speakers as AI-generated. This was not an employment study, so the manuscript does not infer that such penalties are already occurring in recruitment or appraisal. It identifies a governance risk: if unreliable detection scores are used as decisive employment evidence, linguistic bias may be reproduced.

Assistance may also narrow expression. In an adjacent creative-writing context, Doshi and Hauser [18] found that GenAI increased individual creativity while reducing the collective diversity of outputs. The workplace implication remains hypothetical: standardisation may improve processing ease while weakening local rhetorical resources or distinctive professional voice. This possibility requires direct testing in multilingual organisations.

5. Two Competing Pathways

The propositions operationalise different components of this theoretical architecture. Propositions 1 and 3 concern the sociotechnical production and development of AI-mediated capability, distinguishing immediate assisted performance from transferable employee competence. Proposition 2 addresses career-capital conversion by specifying the pathway through which improved communication becomes visibility, opportunity, and ultimately career value. Proposition 4 identifies sociotechnical boundary conditions that determine whether technological capability can be realised equitably across languages and tasks. Proposition 5 addresses signalling and attribution by specifying when AI-mediated performance may be discounted as evidence of employee competence or role readiness. The propositions therefore test different transitions within the broader sequence of production, attribution, recognition, opportunity, and career conversion.

5.1. Pathway A: Flattening Language Ceilings and Walls

The flattening pathway begins with compensation. Employees use GenAI to reduce the time, anxiety, or error associated with communication in a non-dominant language. Better messages then improve comprehension and interaction. If these gains enable employees to contribute more frequently, enter cross-border exchanges, and take on visible assignments, they can strengthen knowing-how, knowing-whom, and knowing-why forms of career capital. Assistance becomes consequential when it changes opportunity, not merely prose.

Three mechanisms deserve separation. First, substitution allows a model to perform part of a task that the employee could not yet perform independently. Second, augmentation allows the employee to express existing expertise more effectively. Third, scaffolding uses AI-supported feedback, comparison, instructional input, and rehearsal to support learning rather than merely produce an immediate communicative output. Evidence from AI-supported EFL speaking research identifies pedagogical design, instructional input, and affective conditions as important dimensions of AI-mediated language development [42]. Such educational evidence does not establish workplace transfer, but it supports the conceptual distinction between AI as a substitute for language production and AI as a potential scaffold for developing employee-owned competence. Substitution can remove an immediate wall but leave the underlying ceiling intact. Augmentation can correct an evaluation distortion by allowing substantive competence to be seen. Scaffolding can produce a durable gain if the employee internalises new linguistic and pragmatic knowledge.

The compensatory pattern in Brynjolfsson et al. [4] suggests that benefits may be larger among workers with less experience or lower initial performance. Translating that pattern into a language proposition requires care. Language confidence, unaided task-language proficiency, domain expertise, and verification accuracy are distinct constructs. Lower proficiency may create more room for improvement while also making fluent errors harder to detect.

Theoretical Proposition 1 (not yet directly tested). *Assisted-performance compensation. For bounded, text-based, and verifiable tasks, GenAI assistance will produce larger communication-performance gains when unaided task-language proficiency is lower, provided that domain knowledge and verification accuracy are sufficient for the task's error consequences.*

Career value emerges only if communication affects visibility and allocation. An improved email that remains peripheral to decision making may have no mobility effect. By contrast, assistance that enables an employee to speak in a cross-border meeting, lead a client exchange, or join a strategic project can alter network position and managerial expectations.

Theoretical Proposition 2 (not yet directly tested). *Opportunity conversion. The effect of GenAI-assisted communication on career outcomes will be mediated sequentially by communication quality, participation and visibility, and access to developmental assignments or influential networks.*

Substitution and scaffolding also imply different time horizons. Adjacent learner evidence has also linked interaction with AI language tools to perceived improvements in English learning [43]. However, perceived improvement cannot establish transferable competence, reinforcing the need to distinguish immediate AI-supported performance from language capability that remains available when assistance is removed.

Theoretical Proposition 3 (not yet directly tested). *Learning conversion. Over repeated use, scaffolded GenAI practice that includes comparison, explanation, feedback, and unassisted*

performance will produce greater transferable language gains than substitution-only use, even when both approaches generate similar immediate assisted performance.

5.2. Pathway B: Re-Stratifying Multilingual Work

The re-stratification pathway begins when access and effective use are uneven. Digital inequality includes not only whether a person has a device or account but also differences in skills, support, autonomy, and realised outcomes [44]. In workplaces, some employees receive secure enterprise tools, training, and permission to experiment. Others rely on restricted free versions, cannot input confidential context, or work in roles where AI use is prohibited. A nominally available technology may therefore distribute capability unevenly.

AI literacy creates another distinction. Effective use requires more than prompt formulation. Employees must understand tool limits, judge output quality, protect sensitive information, and decide when not to use the system. Measures of AI literacy increasingly distinguish technical use, critical evaluation, ethical awareness, self-efficacy, and self-management [45,46]. When language support becomes dependent on these capacities, the old language ceiling can become an AI-fluency ceiling.

Model inequality interacts with this skills gap. Employees communicating in less well-resourced languages may need greater expertise to verify outputs and may incur higher error costs. In high-stakes domains, a polished but incorrect translation can be more dangerous than visibly imperfect human language because fluency increases unwarranted trust.

Theoretical Proposition 4 (not yet directly tested). *Resource and governance asymmetry. The barrier-reducing effect of GenAI will be weaker where model performance is poorer for the relevant language and task, verification costs are higher, or secure access and training are unequally distributed; these disadvantages will intensify as the consequences of error increase.*

Re-stratification can also arise through social judgement. If evaluators interpret AI assistance as evidence that an employee lacks authentic ability, improved output may not convert into status. The penalty may be especially sharp when organisations have no shared disclosure norms. Employees are left to choose between concealing assistance and risking accusations of deception or disclosing assistance and risking competence discounting.

Theoretical Proposition 5 (not yet directly tested). *Attribution and legitimacy penalty. Disclosure or credible suspicion of GenAI assistance will reduce evaluator judgements of authorship, authenticity, and role readiness when legitimate-use norms are ambiguous, with stronger penalties in relational and leadership communication than in bounded administrative tasks.*

Institutional arrangements determine whether these risks remain isolated or become systematic. Performance systems may continue to reward unaided linguistic polish after routine work becomes AI-mediated. Managers may also allocate stretch work to employees whose spontaneous fluency appears safer while allowing other employees to use AI only for low-visibility tasks. In that case, assisted performance improves without expanding access to the communicative practices required for advancement.

Proposition 4 treats access, training, model quality, and verification burden as cross-level boundary conditions. Proposition 2, by contrast, tests whether an observed communication gain is converted into opportunity and career outcomes. This distinction separates unequal inputs from unequal returns.

The pathways are not mutually exclusive. A worker may experience immediate task-level flattening and longer-term re-stratification. The propositions also require different evidence. Propositions 1 and 4 can first be examined in multilingual task experiments;

Proposition 5 requires evaluator studies; Proposition 3 requires repeated assisted and unassisted assessment; and Proposition 2 ultimately requires longitudinal organisational data linking communication to assignments and mobility.

6. Extending LANA for GenAI-Mediated Work

6.1. GenAI as a Transversal Layer

LANA levels identify the sites at which language needs and responsibilities are located: the employee, the organisation, and the task or interaction. GenAI is different. It is not a stable diagnostic site because its operation is constituted through all three levels. Output depends simultaneously on the employee's repertoire and judgement, organisational access and governance, and the language, modality, genre, audience, and stakes of the task. Treating technology as an independent fourth level would risk obscuring these dependencies and reifying the tool as an autonomous cause. For the present explanatory purpose, GenAI is therefore modelled as a transversal mediation layer. A fourth-level formulation may still be useful for studies focused on external vendors or technological ecosystems, but it is less suitable for diagnosing how workplace communication is produced and evaluated. Table 4 operationalises this extended diagnostic logic across the individual, organisational, and operational levels, identifying potential flattening mechanisms, re-stratifying risks, and illustrative indicators at each level.

Table 4. GenAI-LANA diagnostic matrix.

LANA Level	Traditional Diagnostic Focus	Potential Flattening Mechanism	Re-Stratifying Risk	Illustrative Indicators
Individual	Repertoire, confidence, aspirations, development needs	Drafting, translation, rehearsal, feedback, reduced anxiety	Weak verification, miscalibrated confidence, dependence, identity conflict, unequal AI literacy	Language proficiency and confidence; AI literacy; verification accuracy; assisted and unassisted performance; perceived voice ownership
Organisational	Policy, learning access, managerial support, talent processes	Secure access, role-specific training, legitimate-use norms, fair evaluation of substantive expertise	Tiered access, surveillance, detector misuse, ambiguous legitimacy, unchanged promotion norms	Tool access by grade; training uptake; policy clarity; manager attitudes; rating, assignment, and promotion gaps
Operational	Actual language demands of tasks and roles	Role-specific templates, live support, multilingual knowledge access	Poor task fit, cross-language error, high verification cost, over-standardisation	Task genre; modality; language pair; model error rate; verification time; interaction stakes; audience response

This choice changes the diagnostic question. Traditional needs analysis asks what language an employee needs to perform a role. GenAI-LANA also asks which parts of performance may be mediated, what the employee must still understand and verify, what organisational data and permissions are required, and how evaluators will attribute the resulting performance. The unit of analysis becomes a sociotechnical communicative performance rather than an isolated worker deficit.

6.2. The Conversion Chain

The extended framework proposes five distinct stages. First, employees obtain practical access to a secure and permitted tool that fits the relevant language and task. Second, access is converted into AI-mediated communicative performance through generation, translation, contextualisation, and verification. Third, that performance affects proxi-

mal workplace outcomes such as communication quality, participation, visibility, and trust. Fourth, those outcomes may change the allocation of developmental assignments, sponsorship, cross-unit networks, or higher-status interaction. Fifth, accumulated opportunities may affect promotion, pay growth, lateral mobility, employability, or career satisfaction. Figure 1 illustrates this five-stage career-capital conversion chain and the points at which GenAI-mediated capability may be strengthened, constrained, or fail to convert into career outcomes.

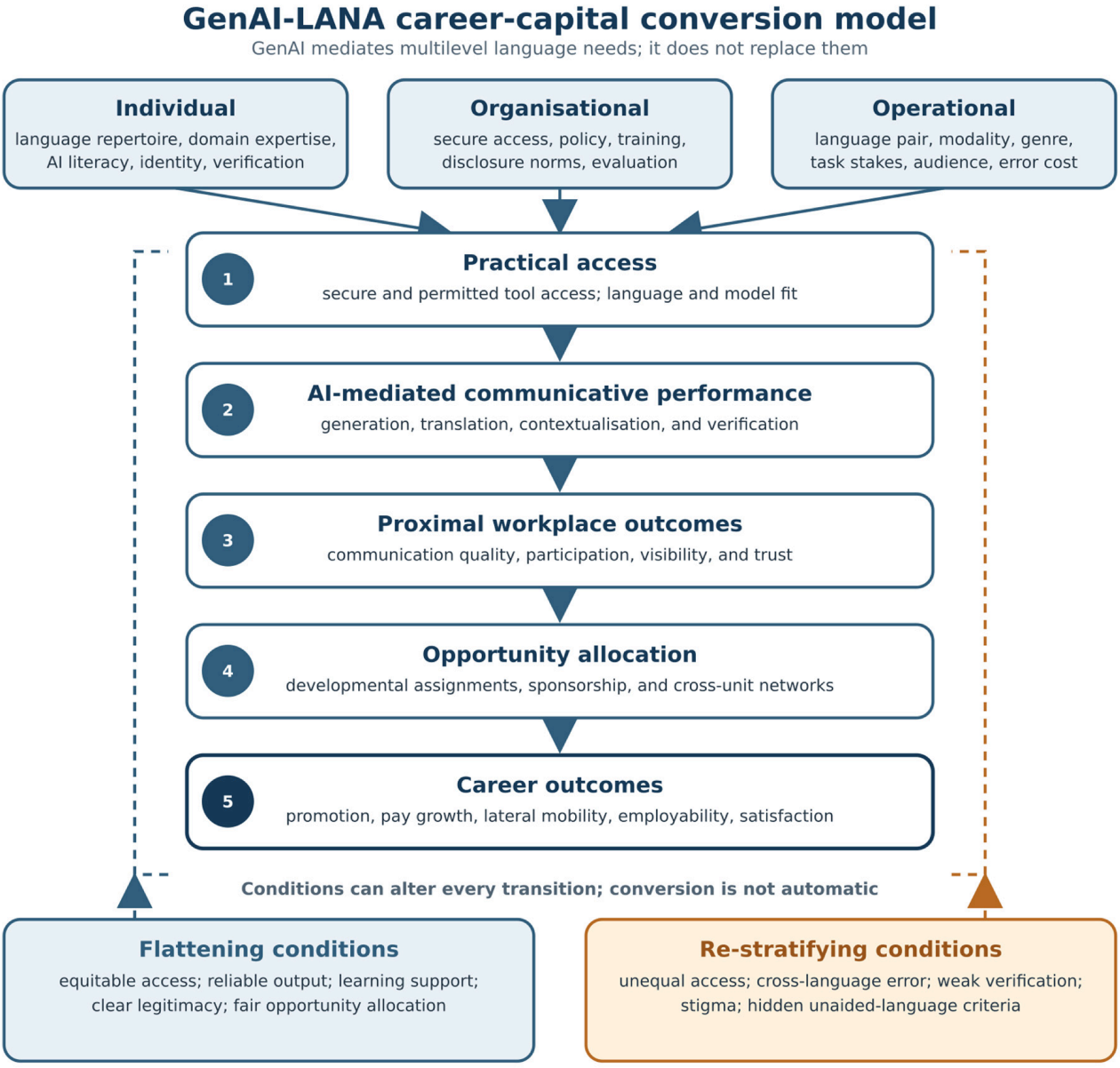

Figure 1. GenAI-LANA career-capital conversion model.

The revised chain makes the evidentiary discontinuity explicit. Failure can occur at any transition. A tool may be licenced but unusable with confidential data. Output may be fluent but inaccurate. An accurate contribution may be discounted as inauthentic. A well-received contribution may still fail to change staffing decisions, and repeated opportunity may not be rewarded if promotion criteria remain tied to unaided performance. Flattening and re-stratifying conditions therefore operate across the full chain rather than only at the final career transition.

The framework also distinguishes proximal from distributive inclusion. Proximal inclusion occurs when employees communicate more easily, participate more, or feel more confident. Distributive inclusion occurs when valued assignments, sponsorship, ratings, pay, and mobility become more equitably allocated. The first is desirable but does not guarantee the second. A credible inclusion claim must trace conversion beyond user experience.

6.3. Boundary Conditions

Four boundary conditions recur across the three LANA levels. The first is language-resource position. Performance in high-resource languages cannot be presumed for all languages or dialects. The second is task stakes. Low-stakes drafting permits experimentation; legal, clinical, safety, financial, and executive communication demands stronger verification. The third is governance maturity. Clear rules, secure systems, appeal processes, and manager training reduce uncertainty and arbitrary penalties. The fourth is legitimacy. Employees must know which uses are accepted and how their contribution will be attributed.

These conditions interact. A low-resource language used in a high-stakes task under weak governance presents a markedly different risk profile from English-language drafting in a well-supported administrative role. LANA offers a way to make that variation visible before an organisation labels a tool inclusive.

7. Discussion

The first theoretical implication is that GenAI requires a sharper distinction among employee-owned competence, technologically accessed capability, organisationally recognised performance, and career-convertible capital. Employee-owned competence refers to linguistic, pragmatic, domain, and verification capabilities that remain available to the employee independently of a particular AI system. Technologically accessed capability refers to communicative capacity made available through GenAI but not necessarily internalised by the employee. Organisationally recognised performance arises when the resulting contribution is observed, judged as legitimate, and credited to the employee. Career-convertible capital represents a further stage: recognised performance must influence access to assignments, networks, sponsorship, ratings, mobility, or other resources that carry career value. These categories should not be collapsed because movement from one to the next is conditional rather than automatic.

This distinction extends conventional career-capital reasoning. Career-capital theory has primarily concerned resources accumulated by individuals and converted across career settings [20,21]. GenAI introduces the possibility that productive capability can be accessed without being fully owned. An employee may perform a communicative task successfully through technological mediation without possessing the complete linguistic repertoire manifested in the output. Such performance may remain dependent on a particular model, organisational licence, data environment, or permission structure and therefore cannot automatically be treated as portable career capital. Conversely, repeated scaffolded use may contribute to employee-owned competence when knowledge and judgement transfer to unaided performance. GenAI therefore requires career-capital theory to distinguish between capability that is possessed, capability that is technologically accessed, performance that is organisationally recognised, and resources that become durable and career-convertible.

The second theoretical implication concerns attribution and recognition. Language research shows that competence acquires career value through social capital, managerial encouragement, and access to organisational arenas [23]. In AI-mediated work, however, observable communicative performance provides a less direct signal of employee-held

capability because evaluators may attribute some of the performance to the technological system [36,38]. Recognition therefore becomes a distinct conversion mechanism rather than an assumed consequence of improved performance. The same AI-supported output may be interpreted as evidence of effective judgement and technological competence or discounted as evidence that the employee lacks independent capability. Communication parity is consequently not equivalent to recognition parity, and recognition parity does not necessarily produce mobility parity.

Third, the framework extends organisational-language theory by relocating language barriers from individual proficiency alone to the sociotechnical production and evaluation of communicative performance. Language-sensitive research has shown that organisational language practices structure participation, status, networks, and power. GenAI adds a technological component to this relationship because workplace communication can now be jointly produced through employee knowledge, model capability, interface design, organisational data, governance, and task conditions [39,40]. A language ceiling can therefore be reduced at the point of message production while remaining intact at the points of verification, attribution, recognition, or opportunity allocation. GenAI does not simply remove an existing language barrier; it can relocate the mechanism through which that barrier operates.

Fourth, inclusion should therefore be theorised as conversion rather than availability. Providing the same GenAI licence to every employee may satisfy a narrow access criterion while leaving differences in training, language support, task permission, model performance, verification cost, and managerial legitimacy untouched. Equal technological inputs do not ensure equal realised capability, organisational recognition, or career returns. This distinction also separates proximal inclusion from distributive inclusion: employees may communicate more easily or participate more frequently without gaining greater access to developmental assignments, influential networks, promotion, or mobility. Claims that GenAI democratises workplace communication should therefore be evaluated according to whether improved communicative performance is converted into more equitable opportunity and career outcomes.

Fifth, GenAI requires a distinction between compensation and development. Technological substitution may legitimately enable an employee to perform a task without increasing unaided language proficiency, whereas augmentation may allow existing expertise to become more visible and scaffolding may contribute to transferable competence. These pathways have different implications for career capital. The problem arises when organisations benefit from AI-assisted performance while continuing to use unaided communicative performance as an implicit criterion for advancement. Performance systems must therefore distinguish whether they are evaluating independent language production, effective AI-supervised communication, transferable learning, or some combination of these capabilities.

Finally, GenAI may move rather than remove the language ceiling. As routine linguistic production becomes technologically accessible, the scarce and valued capability may shift toward supervising outputs, detecting errors, preserving contextual meaning, exercising metalinguistic judgement, and using AI in ways considered legitimate by the organisation. Employees with strong domain knowledge, verification capability, secure technological access, and opportunities to develop these skills may benefit disproportionately. Those working in less well-supported languages, high-verification tasks, or restrictive organisational environments may encounter new barriers. The theoretical contribution of GenAI-LANA is therefore not the prediction that technology will uniformly flatten or reproduce language inequality. It is the proposition that GenAI changes where communica-

tive capability resides and introduces additional conversion points at which capability can acquire, lose, or fail to acquire career value.

Implications for HRM and Organisational Language Policy

Organisations can operationalise the framework through a GenAI-LANA audit. The audit begins with role and task analysis rather than a generic commitment to AI adoption. It identifies communication practices that constrain mobility, such as presenting to senior leaders, writing client proposals, joining cross-border meetings, negotiating, or managing conflict. For each practice, the organisation records the relevant language and modality, acceptable assistance, verification requirements, data restrictions, evaluator expectations, and access to developmental opportunities. This produces a repeatable diagnostic that can be compared across roles, languages, and employee groups.

Consider a multilingual engineer being prepared for a client-facing role. At the operational level, the audit may separate proposal drafting, technical explanation, and spontaneous client questioning. At the individual level, it may assess task-specific language proficiency, confidence, domain knowledge, and the ability to detect AI errors. At the organisational level, it may identify whether a secure tool is available, whether assisted drafting is legitimate, and whether managers discount AI-supported work. The audit may show that GenAI improves proposals but offers limited support during live questioning. The resulting intervention would combine secure drafting assistance, supervised rehearsal, client-meeting exposure, and explicit promotion criteria rather than treating tool access as sufficient development.

Access should include secure tools and role-specific learning. Training limited to prompt tips is insufficient. Employees need practice in checking meaning, detecting confident errors, protecting confidential information, preserving voice, and escalating uncertain outputs. Training should be differentiated by task stakes and language-resource position. Where model performance is weaker, additional human review or bilingual expertise may be necessary.

Organisations should also establish explicit legitimacy and disclosure norms. Policies need to distinguish prohibited delegation from accepted assistance. A worker should not face a hidden authenticity penalty for conduct the organisation encourages. Managers require guidance on evaluating AI-supported work, and employees need a safe route to question inconsistent judgements. Automated AI detectors should not be used as decisive evidence in employment decisions, particularly given documented bias against non-native English writing [10].

Performance management should reward substantive contribution, judgement, verification, and effective communication rather than treating unaided polish as a proxy for capability. This does not mean abandoning language development. Spontaneous interaction, listening, relationship building, and accountability remain essential in many roles. It means making the relevant standard explicit and ensuring that employees can practise the communication of the next role before being assessed against it.

Finally, organisations should measure opportunity distribution. Useful indicators include participation in multilingual meetings, speaking time, authorship of visible documents, access to client work, cross-unit assignments, sponsorship, performance ratings, lateral moves, and promotions. These should be examined by language background, language confidence, role, grade, and practical access to GenAI, with appropriate privacy safeguards. Monitoring only adoption or self-reported satisfaction will miss whether the ceiling has changed.

8. Research Agenda

The most urgent need is longitudinal evidence linking GenAI use to career outcomes. Cross-sectional perceptions of employability or confidence cannot establish whether employees actually move. Researchers should observe both proximal mechanisms and distal outcomes over sufficient time for staffing and promotion decisions to occur. Table 5 outlines a research agenda designed to address these gaps by linking GenAI use, language-related resources, workplace mechanisms, and longer-term career outcomes.

Table 5. Research agenda for GenAI, language, and career capital.

Research Question	Suitable Design	Key Measures	Contribution
Does GenAI access alter promotion, pay growth, lateral mobility, or access to stretch work for multilingual employees?	Staggered organisational rollout with difference-in-differences or matched longitudinal comparison	Tool logs with consent; language background and confidence; assignments; ratings; pay; moves; promotions	Tests the full conversion chain rather than task performance alone
Does AI support increase participation and visibility in multilingual teams?	Field experiment across meetings, email, and collaborative documents	Speaking time; contribution uptake; response latency; network centrality; task allocation; manager ratings	Identifies proximal mechanisms linking assistance to opportunity
How do effects differ across language-resource positions and task types?	Multilingual, multi-country factorial experiment using equivalent high-stakes and low-stakes tasks	Accuracy; pragmatic fit; verification time; confidence; error severity; evaluator response	Tests resource asymmetry and limits English-centric inference
Does disclosure or suspicion of AI use change competence and authenticity judgements?	Paired-profile evaluator audit varying disclosure, language background, accent cues, and task genre	Trust; authenticity; competence; leadership potential; promotion recommendation	Estimates legitimacy penalties and their interaction with language status
Does repeated use scaffold learning or create dependence?	12- to 24-month panel with assisted and unassisted assessments	Transfer, retention, error detection, self-efficacy, spontaneous interaction, usage pattern	Separates durable capability formation from substitution
Which policies prevent AI-fluency ceilings?	Comparative case study or natural experiment across access, training, and disclosure regimes	Access equality; policy clarity; training uptake; appeals; opportunity gaps; career outcomes	Connects governance choices to distributive inclusion

Three design principles should guide this agenda. First, language should be measured as a multidimensional, situated resource rather than a native versus non-native binary. Relevant variables include proficiency by modality, confidence, language use at work, accent visibility, language pair, and the match between an employee's repertoire and a task. Second, AI exposure should not be reduced to self-reported use. Researchers should distinguish tool version, enterprise versus public access, frequency, function, task, autonomy, verification practices, and training. Third, outcomes should be traced across levels. A study that measures output quality, evaluator judgement, subsequent task allocation, and later mobility can identify where conversion succeeds or fails.

Mixed methods are especially valuable. Digital trace and HR records can identify patterns, but interviews and observation can reveal why employees conceal use, avoid high-visibility tasks, distrust translations, or perceive a loss of voice. Participatory approaches can also prevent researchers from treating English-centric performance criteria as neutral. Employees who work across languages should help define what effective and authentic communication means in their setting.

Sectoral comparison is necessary. GenAI may reduce barriers quickly in codified service work yet provide little assistance in embodied, safety-critical, or relationship-

intensive roles. Regulated sectors introduce confidentiality and accountability constraints. Small- and medium-sized enterprises may have less capacity for secure infrastructure and formal training. Public organisations may face additional obligations concerning accessibility, procedural fairness, and language rights. A robust research programme should treat these settings as theoretically meaningful boundary conditions, not merely sample variation.

9. Limitations

This review has four limitations. First, it is a critical integrative review and theory-development study rather than an exhaustive systematic review. Although the query concepts, eligibility rules, evidence categories, search date, and synthesis set are reported, discovery was iterative, screening was completed by one author, and no database export or independent duplicate screening was available. The evidence set therefore cannot support a universal claim that no relevant study exists; the conclusion is limited to the reviewed set. Second, much of the literature is English-centred or restricted to a small number of languages, occupations, and task types. Benchmark inequalities, simulated emails, academic identity, and detector bias cannot represent the full diversity of multilingual workplace regimes.

Third, models, interfaces, and organisational policies change quickly. A capability limitation observed in one model version may be reduced later, while new dependencies or governance risks emerge. The propositions therefore concern mechanisms and boundary conditions rather than fixed technology rankings. Fourth, direct multilingual career evidence was not identified. Several links in the framework connect adjacent evidence on productivity, communication, identity, professional boundaries, and digital inequality. Those links are theoretically reasoned but remain propositions until tested with assignment, appraisal, pay, and mobility data.

10. Conclusion

GenAI changes the theoretical relationship between language competence, workplace performance, and career mobility. In pre-GenAI organisational settings, communicative performance could more readily be interpreted as a signal of capability possessed by the employee. AI-mediated communication weakens that correspondence by allowing employees to access linguistic capability through technology. The relevant distinction is therefore no longer simply between stronger and weaker language proficiency but among employee-owned competence, technologically accessed capability, organisationally recognised performance, and career-convertible capital.

GenAI-LANA explains the transitions among these categories through a five-stage conversion chain from practical access to AI-mediated communicative performance, proximal workplace outcomes, opportunity allocation, and career outcomes. Career conversion is not automatic. A system may improve communication without developing unaided competence; improved performance may be discounted because of attribution or legitimacy concerns; recognised contributions may fail to change opportunity allocation; and expanded opportunities may still fail to produce mobility where advancement criteria remain tied to unaided linguistic performance.

The framework therefore extends career-capital theory by showing that productive capability may be technologically accessed without being fully employee-owned and that organisationally useful performance does not necessarily become portable career capital. It extends organisational-language theory by showing that GenAI can flatten a language barrier at one stage while reproducing it at another. Language ceilings may consequently

be reduced at the task-performance level yet persist as verification, attribution, legitimacy, opportunity, or mobility barriers.

The central implication is that GenAI does not simply remove or preserve language ceilings. It changes the mechanisms through which communicative capability acquires organisational and career value. Whether AI-mediated communication expands mobility therefore depends on how organisations distribute technological capability, attribute performance, legitimate assistance, allocate opportunity, and define the competencies that count for advancement.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The author declares no conflicts of interest.

Appendix A. Evidence-Role Inventory

Pre-GenAI language, career, and theoretical foundations (n = 22). Barner-Rasmussen et al. [35]; Bhar and Chua [1]; Bourdieu [19]; Brannen et al. [31]; DeFillippi and Arthur [20]; Harzing and Pudelko [27]; Hinds et al. [29]; Inkson and Arthur [21]; Itani et al. [22]; Karhunen et al. [32]; Kelley [38]; Latukha et al. [24]; Marschan-Piekkari et al. [25]; Neeley [28]; Orlikowski [39]; Peltokorpi [23]; Śliwa and Johansson [34]; Spence [36]; Suzuki et al. [33]; Tenzer et al. [30]; Trist and Bamforth [40]; Welch and Welch [26].

Multilingual model or benchmark evidence (n = 3). Ahuja et al. [13]; Blasi et al. [6]; Joshi et al. [7].

Simulated work-task evidence (n = 2). Koo [8]; Noy and Zhang [3].

Direct workplace-process evidence (n = 4). Brynjolfsson et al. [4]; Nguyen et al. [15]; Yinglei and Nik Hasan [14]; Zhang et al. [5].

Adjacent recognition or identity evidence (n = 5). Doshi and Hauser [18]; Hohenstein et al. [9]; Hu et al. [17]; Jago [16]; Liang et al. [10].

Enabling-condition evidence (n = 4). Carolus et al. [46]; Hancock et al. [41]; Liu et al. [45]; Lythreatis et al. [44].

Adoption context (n = 1). Organisation for Economic Co-operation and Development [2].

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