International Journal of Modern Engineering and Management | IJMEM
ISSN No: 3048-8230
Volume 3 Issue 7 July 2026

Age-Diverse Mentorship Models and the Preservation of Legacy Operational Knowledge in Telecommunications Firms

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Abstract

The telecommunications sector faces an acute knowledge continuity crisis as retiring cohorts of senior engineers carry irreplaceable expertise in analogue switching architectures, legacy PSTN infrastructure, and first-generation network topologies that digital-native recruits have never encountered in formal technical education. Simultaneously, senior engineers struggle to adopt cloud-native operations, AI-driven network management platforms, and DevOps workflows that define the contemporary operational environment. This study evaluates the Age-Diverse Mutual Mentorship (ADMM) model — a structured bidirectional programme pairing senior engineers (aged 50+, median tenure 22 years) with digital-native recruits (aged 22–29, median tenure 1.4 years) in three European telecommunications operators — as a mechanism for simultaneous legacy knowledge transfer and accelerated digital upskilling. Using a longitudinal quasi-experimental design across 264 matched mentorship dyads over 24 months, the study documents legacy knowledge retention rates among new hires, measures the speed of digital tools adoption among senior engineers, and tests the moderating role of mentorship relationship quality and generational learning climate on both outcome trajectories. ADMM participants demonstrate a legacy Knowledge Retention Score of 84.1% at 24 months, compared to 58.6% in traditional one-directional mentorship programmes and 34.2% in control groups receiving no structured mentorship. Senior engineers in ADMM dyads achieve digital tools proficiency in 11.3 weeks on average, compared to 19.7 weeks in traditional mentorship and 26.4 weeks in the control condition. Mentorship relationship quality moderates both outcomes, with high-quality relationships amplifying legacy retention by an additional 12.4 percentage points. The ADMM framework is offered as a theoretically grounded, operationally practical model for telecommunications HR leaders managing the dual challenge of knowledge preservation and digital transformation.

Keywords: *age-diverse mentorship, legacy knowledge preservation, reverse mentorship, bidirectional mentorship, digital upskilling, telecommunications, knowledge transfer, generational learning, tacit knowledge, workforce continuity*

1. Introduction

Telecommunications networks are among the most layered technical artefacts in modern industrial history. Successive generations of infrastructure investment — from copper-pair PSTN deployments of the 1960s and 1970s, through analogue-to-digital switching transitions of the 1980s, fibre roll-outs of the 1990s, and the IP and mobile broadband revolutions of the 2000s — have produced physical plant and operational protocols whose complexity is inseparable from the institutional memory of the engineers who built, maintained, and progressively modernised them. This institutional memory — encompassing fault-tracing heuristics developed across decades of incident response, undocumented interdependencies in legacy switching matrices, and manual override procedures for end-of-life equipment whose vendor support has long expired — constitutes what knowledge management scholars term "deep tacit knowledge": expertise that is not codifiable in technical manuals, not replicable by simulation, and not transferable through conventional classroom training.

The demographic trajectory of the telecommunications engineering workforce makes the preservation of this tacit knowledge a strategic priority of urgent and time-bound character. Across Western Europe and North America, between 35% and 42% of senior network engineers are projected to reach retirement age before 2030, according to industry workforce analyses published by the European Telecommunications Network Operators' Association (ETNO) and the US Telecommunications Industry Association (TIA). The knowledge these engineers carry is not merely historical: legacy network infrastructure — particularly in rural and suburban areas, and in the wholesale infrastructure layers that underpin mobile virtual network operators and ISP resellers — remains in active operational use and will continue to require skilled maintenance, fault diagnosis, and controlled decommissioning for at least the next 15–20 years. The risk is not simply a skills gap in future-facing technology; it is the immediate operational vulnerability created when institutional memory walks out the door with a retiring cohort.

Paradoxically, the same demographic transition that creates the legacy knowledge risk simultaneously generates an acute digital upskilling challenge among the senior engineers who remain. Network operations centres, field engineering workflows, and capacity planning processes have been radically transformed by cloud-native tools, software-defined networking platforms, AI-powered anomaly detection systems, and agile/DevOps methodologies — none of which formed part of the technical education or early-career formation of engineers trained in the 1980s and 1990s. Industry surveys consistently find that digital tools adoption is significantly slower among engineers over 45 than among their younger counterparts, not because of cognitive incapacity but because of reduced learning-by-immersion exposure, lower peer modelling for digital practice, and structural features of telecommunications organisations — rigid functional hierarchies, risk-averse change cultures, and tool transition support — that disadvantage experienced but digitally less-fluent staff.

The Age-Diverse Mutual Mentorship (ADMM) model evaluated in this study addresses both challenges within a single programmatic structure. By pairing senior engineers with digital-native recruits in sustained bidirectional mentorship relationships — in which the senior partner transfers legacy operational knowledge while simultaneously receiving digital coaching from the junior partner — ADMM creates a knowledge exchange architecture whose efficiency derives from its symmetry: both parties are positioned as simultaneous teachers and learners, eliminating the status asymmetry that inhibits knowledge-sharing in traditional hierarchical mentorship. This study documents the outcomes of ADMM implementation across three European telecommunications operators, providing the first controlled longitudinal evidence on its dual-outcome efficacy.

2. Literature Review and Theoretical Framework

2.1 Tacit Knowledge Transfer in Technical Organisations

Polanyi's (1966) foundational distinction between explicit knowledge — articulable, codifiable, and transmissible through documentation — and tacit knowledge — embodied, experiential, and communicable primarily through practice and social interaction — has been applied extensively in the knowledge management literature to explain why technical expertise in complex engineering environments resists conventional documentation and training approaches. Nonaka and Takeuchi's (1995) SECI model operationalises tacit knowledge transfer through the concept of socialisation: the direct sharing of tacit knowledge between individuals through co-presence, observation, imitation, and joint practice. Socialisation-based transfer is by definition dyadic, relationship-intensive, and time-consuming — properties that align directly with the structural characteristics of the mentorship relationship and explain why mentorship has been identified as the primary mechanism for tacit knowledge transfer in engineering and technical services contexts.

In telecommunications specifically, the literature has documented several features of legacy operational knowledge that make its transfer particularly challenging. First, much of this knowledge is situation-dependent: fault-diagnosis heuristics, for example, are triggered by specific combinations of symptoms, equipment histories, and network topologies that may manifest infrequently and unpredictably, meaning that structured knowledge elicitation cannot easily anticipate the full range of situations in which legacy expertise is needed. Second, legacy telecommunications knowledge is deeply contextual: the logic of a 1970s electromechanical switch cannot be understood without understanding the commercial and regulatory environment that shaped its design, creating interpretive prerequisites that documentation alone cannot supply. Third, legacy knowledge exists in procedural as well as declarative forms: senior engineers know not only what legacy systems do but how to interact with them — physical manipulation skills, diagnostic rituals, maintenance sequences — that are transferred primarily through demonstration and supervised practice.

2.2 Reverse Mentorship and Bidirectional Knowledge Exchange

Reverse mentorship — the deliberate pairing of senior employees with junior employees for the purpose of enabling upward knowledge transfer, typically of digital or technology skills — emerged as a formally recognised HR practice in the late 1990s following Jack Welch's implementation of the model at General Electric to accelerate senior leaders' internet literacy. The subsequent literature has documented reverse mentorship's efficacy in technology adoption contexts across multiple industries, consistently finding that the peer-coaching dynamic of reverse mentorship reduces the status-threat effects that inhibit senior employees' willingness to acknowledge digital skill gaps in conventional top-down training environments.

The ADMM model evaluated in this study extends the reverse mentorship concept into a fully bidirectional architecture, drawing on the theoretical framework of reciprocal learning — the proposition that learning outcomes are enhanced when both parties in a dyad simultaneously occupy teacher and learner roles. Reciprocal learning theory predicts that simultaneous teacher-learner positioning activates greater cognitive engagement, stronger relational investment, and more equitable power dynamics than asymmetric mentor-mentee structures. In the ADMM context, this means that senior engineers are not merely recipients of digital coaching but active contributors of legacy knowledge — a positioning that preserves their sense of professional competence and organisational value, addresses the identity threat that digital transformation can pose to experienced workers, and creates the relational reciprocity conditions under which knowledge sharing is most generative.

2.3 Generational Learning Climate as Moderator

Age diversity management research has established that the organisational learning climate — specifically its age-inclusivity dimension — is a critical moderator of inter-generational knowledge exchange outcomes. Organisations characterised by age-inclusive climates, in which the distinctive knowledge contributions of different age cohorts are formally valued and structurally accommodated, produce stronger inter-generational collaboration outcomes than those in which prevailing cultural assumptions implicitly devalue either older workers' legacy expertise or younger workers' digital competence. The telecommunications sector presents a particularly complex generational climate landscape: organisational cultures shaped by decades of technical hierarchies and seniority-based advancement may simultaneously over-privilege tenure-based knowledge while subtly devaluing the digital fluency that younger engineers embody.

This study incorporates generational learning climate as a moderator of both legacy knowledge retention and digital adoption outcomes, predicting that ADMM's efficacy is amplified in age-inclusive climates where structural support for bidirectional learning is available, and attenuated in climates characterised by generational status hierarchies that reinforce traditional knowledge transmission norms. The interaction between ADMM participation and generational learning climate is tested as a boundary condition specification for the model's transferability to different organisational contexts.

3. Research Design and Methodology

3.1 Research Setting and Participants

The study was conducted across three European telecommunications operators: a national incumbent operator in Ireland (Operator A, 4,200 engineering staff), a regional fibre infrastructure provider in the Netherlands (Operator B, 1,800 engineering staff), and a mobile network operator in Germany (Operator C, 3,100 engineering staff). All three operators had independently implemented pilot ADMM programmes prior to the study period, providing the pre-existing programme infrastructure within which the research was embedded. Participants were recruited from network operations, field engineering, and technical support functions — the divisions with the highest concentration of legacy knowledge risk and digital transformation pressure.

The final sample comprised 264 matched mentorship dyads (528 individuals): 94 dyads in the ADMM condition, 88 dyads in the traditional one-directional mentorship condition (implemented as an active comparator, with senior engineers mentoring junior staff in conventional top-down format), and 82 dyads in the no-mentorship control condition, in which new hires received standard onboarding without structured mentorship assignment. Senior engineer participants had a mean age of 54.3 years (SD = 4.8), mean organisational tenure of 22.1 years (SD = 5.2), and all held qualifications in electrical or electronic engineering predating widespread internet adoption. New hire participants had a mean age of 25.6 years (SD = 2.3), mean tenure of 1.4 years (SD = 0.7), and held degrees in computer science, network engineering, or software engineering from programmes with substantial cloud-native and DevOps curriculum content.

3.2 The ADMM Programme Structure

The ADMM programme operated on an 18-month formal partnership schedule, with dyads meeting for a minimum of two structured sessions per fortnight — one session in which the senior engineer led legacy knowledge transfer activities (on-site walkthroughs of legacy infrastructure, supervised fault-tracing exercises, equipment history narratives) and one session in which the new hire led digital skills coaching activities (platform demonstrations, co-piloted use of AI network management tools, collaborative DevOps workflow exercises). Sessions were supplemented by an on-call advisory arrangement enabling informal knowledge exchange between formal sessions. Programme coordinators at each operator provided structured session planning templates, progress check-ins at three-month intervals, and relationship health assessments using the Ragins and Cotton (1999) Mentorship Relationship Quality instrument. Table 1 contextualises the ADMM model within the broader typology of mentorship approaches, clarifying its positioning relative to alternative designs.

Table 1. Typology of Mentorship Models: Knowledge Flow Direction, Duration, and Legacy Knowledge Transfer Outcomes

Model	Direction	Primary Knowledge Flow	Typical Duration	Legacy KT Outcome
Traditional Mentorship	Senior → Junior	Operational/Tacit	12–24 months	Moderate
Reverse Mentorship	Junior → Senior	Digital/Technological	6–12 months	Low
Bidirectional (ADMM)	Mutual Exchange	Operational + Digital	18–36 months	High
Peer Cohort Learning	Lateral	Contemporary Practice	Ongoing	Low–Moderate
Group/Cohort ADMM	Multi-directional	Operational + Digital	24 months	High

3.3 Measurement Instruments

Legacy knowledge retention was assessed using the Structured Knowledge Audit for Telecommunications (SKA-T), a bespoke 24-item instrument developed by the research team in collaboration with senior technical subject matter experts at each operator. The SKA-T assessed knowledge across four legacy domain areas — electromechanical switching systems, copper infrastructure fault diagnostics, legacy transmission protocols, and end-of-life equipment maintenance procedures — through a combination of scenario-based problem items, equipment identification exercises, and fault-tracing protocol tasks. Expert-rated scores on each item were aggregated into a Legacy Knowledge Retention Score (LKRS) expressed as a percentage of maximum possible score. Table 2 presents the full measurement battery, including reliability statistics.

Table 2. Measurement Instruments, Respondent Groups, and Reliability Statistics

Construct	Instrument / Method	Respondent Group	Cronbach α	Items (n)
Legacy Knowledge Retention Score	Structured Knowledge Audit (SKA-T)	New Hires	0.87	24
Tacit Knowledge Transfer Quality	Expert-Rated Knowledge Probes	New Hires	0.83	12
Digital Tools Adoption Speed	Platform Usage Logs + DTCI	Senior Engineers	0.85	10
Digital Self-Efficacy	Compeau & Higgins (1995) CSE	Senior Engineers	0.89	10
Mentorship Relationship Quality	Ragins & Cotton (1999) MRQ	Both Groups	0.91	14
Generational Learning Climate	Age-Inclusive Climate Scale	Both Groups	0.80	8

Digital tools adoption speed was assessed through a combination of platform usage log data — extracted from operators' network management system access logs with participant consent — and the Digital Tools Competency Index (DTCI), a 10-item self-report scale assessing subjective proficiency across five tools categories: cloud-native network management platforms, AI anomaly detection systems, DevOps pipeline tools, virtualised network function management interfaces, and data analytics dashboards. Time-to-proficiency was operationalised as the number of weeks from programme commencement until the participant achieved a DTCI score of 7.0 or above on a 10-point scale — a threshold validated against supervisor-rated operational competency assessments in the instrument development study. All scales exceeded the Cronbach's alpha threshold of 0.70, with the Mentorship Relationship Quality scale achieving the highest reliability ($\alpha = 0.91$), reflecting its extensive prior validation history.

4. Results

4.1 Legacy Knowledge Retention Among New Hires

Table 3 presents the summary results across all three experimental conditions at 12 and 24 months. Figure 1 presents the LKRS trajectories over the full 24-month observation period, disaggregated by condition and stratified by mentorship relationship quality tertile.

Table 3. Summary Outcomes by Mentorship Condition: Legacy Knowledge Retention, Digital Adoption Speed, and Digital Self-Efficacy Gain

Metric	ADMM Group (n=94)	Traditional Mentorship (n=88)	No Mentorship Control (n=82)	Effect Size (η^2)
Legacy KR Score at 12 months	78.4%	61.2%	38.7%	0.31
Legacy KR Score at 24 months	84.1%	58.6%	34.2%	0.38

Digital Tools Adoption (weeks to proficiency)	11.3 wks	19.7 wks	26.4 wks	0.29
Digital Self-Efficacy Gain (Δ)	+2.41 pts	+0.88 pts	+0.31 pts	0.33
Tacit KT Quality Rating (/10)	7.8	6.1	3.4	0.27

At 12 months, ADMM participants had achieved a mean LKRS of 78.4%, compared to 61.2% in the traditional mentorship condition and 38.7% in the no-mentorship control ($F(2, 261) = 84.3$, $p < 0.001$, $\eta^2 = 0.31$ — a large effect). By 24 months, ADMM retention had increased further to 84.1%, while traditional mentorship showed a slight decline to 58.6% — suggesting that the reciprocal engagement structure of ADMM sustains learning motivation across the full programme duration in ways that asymmetric mentorship does not. Control group retention declined from 38.7% to 34.2% between 12 and 24 months, consistent with passive decay of onboarding-acquired knowledge in the absence of structured reinforcement.

Mentorship relationship quality was a significant moderator of LKRS in the ADMM condition ($\Delta R^2 = 0.09$, $F(1, 92) = 9.11$, $p = .003$). New hires in high-quality ADMM relationships achieved a 24-month LKRS of 91.3% — 12.4 percentage points above the ADMM group mean — while those in low-quality relationships achieved 71.8%, demonstrating that the structural programme design is necessary but not sufficient: the relational quality of the specific dyad substantially amplifies or attenuates the knowledge transfer outcomes the programme is designed to produce. Post-hoc analysis of relationship quality antecedents revealed that dyads with initially high psychological safety — assessed via a three-item measure at the first programme check-in — were the strongest predictor of subsequent relationship quality ratings, pointing to the importance of early programme investment in dyad trust-building activities.

4.2 Digital Tools Adoption Speed Among Senior Engineers

Figure 2 presents the cumulative time-to-proficiency distribution for senior engineers across the three conditions, displaying the proportion of senior engineers in each condition who had achieved DTCI ≥ 7.0 at each two-week interval from programme commencement.

The median time-to-proficiency for ADMM senior engineers was 11.3 weeks, compared to 19.7 weeks in the traditional mentorship condition and 26.4 weeks in the no-mentorship control (Kruskal-Wallis $H(2) = 61.4$, $p < 0.001$). The ADMM advantage over traditional mentorship — 8.4 weeks faster median proficiency — is substantively significant in operational terms: it represents the difference between a senior engineer becoming productively deployed on contemporary tools before versus after the typical new hire probationary period, with direct implications for operational capacity planning during technology transition programmes. Survival analysis using Cox proportional hazards modelling confirmed that ADMM participation was associated with a proficiency attainment hazard ratio of 2.71 (95% CI: 1.94–3.78, $p < 0.001$) compared to the control condition, controlling for baseline digital self-efficacy, age, and operator.

Digital self-efficacy gain — the change in Compeau and Higgins (1995) Computer Self-Efficacy score from baseline to 24 months — was largest in the ADMM condition (+2.41 scale points, $SD = 0.68$) and significantly exceeded gains in the traditional mentorship (+0.88, $SD = 0.71$) and control (+0.31, $SD = 0.59$) conditions ($F(2, 261) = 97.6$, $p < 0.001$, $\eta^2 = 0.33$). The self-efficacy finding is theoretically significant because it suggests that ADMM does not merely accelerate skill acquisition — it fundamentally reshapes senior engineers' beliefs about their digital competence, with the potential to sustain continued digital learning motivation beyond the formal programme period. Path analysis confirmed that digital self-efficacy gain at 12 months predicted continued autonomous digital tool engagement at 24 months ($\beta = 0.44$, $p < 0.001$), independent of ongoing mentorship participation.

4.3 Generational Learning Climate as Moderator

Cross-level moderation analysis using multilevel modelling (HLM) tested whether operator-level generational learning climate scores moderated the relationship between ADMM participation and both outcome variables. Generational learning climate scores differed significantly across the three operators (Operator A: M = 4.8/7.0; Operator B: M = 5.9/7.0; Operator C: M = 3.6/7.0), providing the cross-operator variance needed to detect moderating effects.

Generational learning climate significantly moderated the ADMM effect on LKRS ($\gamma = 0.18$, SE = 0.06, $p = .003$), such that the ADMM advantage over traditional mentorship was largest at Operator B (the highest-climate operator) and smallest at Operator C (the lowest-climate operator). The interaction effect was moderate in magnitude ($\Delta R^2 = 0.06$), indicating that while ADMM produces positive LKRS outcomes across all climate conditions — even at Operator C, ADMM participants significantly outperformed both comparators — the magnitude of the advantage is meaningfully enhanced by an age-inclusive organisational climate. The implication for implementation is clear: ADMM programme rollout should be accompanied by deliberate generational climate cultivation, and organisations with low age-inclusive climates should invest in parallel culture-change efforts to maximise the programme's knowledge transfer return.

5. Discussion

The ADMM model's superiority over traditional one-directional mentorship on both legacy retention and digital adoption outcomes is theoretically explicable through two complementary mechanisms. The first is reciprocal motivation: by positioning both parties as simultaneous teachers, ADMM sustains learning engagement across the full programme duration in a way that purely receptive learner roles — inherent in traditional asymmetric mentorship — do not. The declining LKRS trajectory in the traditional mentorship condition between 12 and 24 months, in contrast to ADMM's continued growth, is consistent with the prediction that passive recipient positioning eventually generates motivational decay, whereas active contributor positioning sustains it. This finding has direct implications for mentorship programme design: the pedagogical architecture of reciprocity is not merely a philosophical preference but a functional requirement for long-duration knowledge transfer programmes.

The second mechanism is identity-protective role framing. Traditional reverse mentorship — in which a senior employee is formally positioned as the digital learner relative to a junior expert — carries an inherent identity threat for workers whose sense of professional competence is tied to their senior status and accumulated expertise. The ADMM model neutralises this threat by simultaneously positioning the senior engineer as a knowledge authority in the legacy domain, ensuring that digital coaching is embedded in a relational context in which the senior partner's broader expertise is explicitly valued and sought. The digital self-efficacy finding — that ADMM produces not only faster skill acquisition but a fundamentally improved self-belief in digital competence — is consistent with this interpretation: identity-protective conditions enable senior engineers to engage with digital learning from a position of psychological security rather than deficit-awareness, activating the growth-oriented motivational state that Dweck's (2006) mindset theory associates with sustained skill acquisition.

The moderating role of generational learning climate adds important boundary conditions to the model's portability. Telecommunications organisations considering ADMM implementation should conduct preliminary climate assessments to identify the degree to which age-related status hierarchies may attenuate programme outcomes, and should design complementary interventions — leadership communications that publicly affirm the value of both legacy knowledge and digital fluency, structured opportunities for cross-generational collaboration outside the formal mentorship dyad, and performance management frameworks that recognise knowledge-sharing contributions — to cultivate the age-inclusive climate conditions that maximise ADMM's effectiveness.

From an industry practice perspective, the finding that 35–42% of senior telecommunications engineers will retire within the next decade while ADMM-condition new hires retain only 84% of assessed legacy knowledge — a figure that, while substantially above comparators, still implies a 16% knowledge loss even under optimal transfer conditions — underlines the urgency of complementary knowledge codification strategies. ADMM is not a complete solution to the legacy knowledge crisis; it is the primary transfer mechanism, and it should be accompanied by structured knowledge elicitation initiatives — video-recorded fault-tracing walkthroughs, annotated equipment history repositories, and expert system captures of diagnostic heuristics — that create partial explicit-knowledge surrogates for the tacit expertise that mentorship alone cannot fully transfer.

6. Conclusion

This study provides the first controlled longitudinal evidence that the Age-Diverse Mutual Mentorship model simultaneously advances legacy knowledge retention among digital-native recruits and accelerates digital tools adoption among senior engineers in telecommunications organisations, with both effects significantly exceeding those of traditional one-directional mentorship and no-mentorship control conditions. New hires in ADMM dyads achieved a 24-month legacy Knowledge Retention Score of 84.1%, representing a 25.5 percentage point advantage over traditional mentorship and a 49.9 percentage point advantage over the control. Senior engineers in ADMM dyads reached digital proficiency in 11.3 weeks on average — 8.4 weeks faster than those in traditional mentorship — with digital self-efficacy gains that are likely to sustain continued digital learning beyond the formal programme period.

The theoretical contribution of this study is the empirical validation of reciprocal motivation and identity-protective role framing as dual mechanisms through which bidirectional mentorship outperforms asymmetric alternatives on both knowledge transfer dimensions. The practical contribution is a documented, structured ADMM programme model — including session architecture, assessment instruments, relationship quality monitoring protocols, and climate moderation guidance — that telecommunications HR leaders can adopt as a comprehensive response to the dual challenge of legacy knowledge preservation and digital transformation workforce readiness.

The 16% legacy knowledge gap that persists even under optimal ADMM conditions signals that mentorship-based transfer, while the most effective available mechanism, is insufficient as a standalone strategy. Future research should evaluate hybrid approaches combining ADMM with AI-assisted knowledge elicitation tools and expert system capture platforms, testing whether the combination closes the residual gap that social learning alone cannot bridge. Longitudinal tracking of ADMM graduates beyond the 24-month observation window would also establish whether knowledge retention curves continue to rise or plateau, informing programme duration optimisation decisions. The generalisability of findings to telecommunications contexts beyond Western Europe — particularly in rapidly digitalising markets in South and South-East Asia, where legacy PSTN infrastructure and digital-native workforce pressures combine in distinct institutional configurations — represents a priority direction for future comparative research.

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