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WHEN AI SPREADS ACROSS THE ORG CHART: CROSS-FUNCTIONAL AI DIFFUSION AND PROJECT MANAGERS' PERCEIVED NEED FOR CROSS-TEAM COMMUNICATION

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Abstract

Artificial intelligence no longer enters organisations through a single door. While project managers experiment with it in their own work, the functions they depend upon are adopting it in parallel and largely on their own initiative. This paper asks what such cross-functional diffusion is associated with in the project manager's perceived need to communicate across teams. Coordination theory yields two opposing expectations, substitution and new dependencies, and I develop a mechanism that reconciles them: AI alters the mix of pre-answered and provisional information crossing a functional interface rather than the volume of traffic across it. Survey data from 213 project professionals, gathered through the International Project Management Association network between August 2025 and April 2026, show that most respondents perceive no change (53.4%), against 29.1% reporting an increase and 8.3% a decrease. Exposure to a greater number of AI-using functions is associated, weakly and marginally, with departure from this status quo in either direction rather than with a uniform shift (OR = 1.19 per additional adopting function, p = .061), and the association does not vary with the project manager's own AI adoption. Grouping functions as hypothesised, the count of externally facing functions is associated with increased perceived need while the back-office count is not, though the formal contrast is not established. The evidence is cross-sectional, perceptual and marginal throughout, and is offered as a pattern worth pursuing rather than as a demonstrated relationship.

Keywords: *artificial intelligence; cross-functional diffusion; coordination; project communication; boundary spanning; project management*

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1 INTRODUCTION

This paper began as an irritation rather than as a gap in the literature. Over the past two years, in IPMA working groups and in ordinary conversations with project managers in several countries, I kept meeting the same puzzled report. Very little had changed in how these people ran their own projects. Yet the traffic around them had shifted somehow. Some found themselves in more meetings than before, a few in fewer, and most could not say. What the accounts had in common was the location of the change: AI had arrived somewhere else in the organisation, not primarily in their own hands.

That observation is worth taking seriously, and not only by people who study projects. Digital transformation rarely arrives as a single coordinated programme; it accumulates function by function, at different speeds, with different tools and different levels of ambition (Vial, 2019). Whenever it does, somebody has to hold the lateral interfaces together while the units on either side of them change

at their own pace. In organisations this work falls to boundary spanners: account managers between sales and delivery, product owners between engineering and marketing, plant managers between operations and planning, business partners in finance and human resources. All of them coordinate laterally across units they do not control, and all of them absorb whatever their counterparts decide to do with new technology. The question this paper asks is therefore a general one about managerial work under uneven digital transformation, and project managers are studied here because they are an unusually clear case of it rather than because the phenomenon is confined to them.

Projects make the case clear because they are coordination-intensive almost by definition. A project manager rarely controls the resources that decide a project's fate. They negotiate them across functional borders, with marketing and sales, IT operations, finance, legal, human resources, and other units whose priorities overlap with the project's own only in part (Ancona & Caldwell, 1992; Hoegl & Gemuenden, 2001). Where the pattern of communication across those borders shifts, the daily texture of managerial work shifts with it.

Artificial intelligence is altering that pattern now, though not in the manner of earlier enterprise technologies. Resource planning systems and collaboration platforms arrived top-down, function by function, on a schedule somebody had drawn up in advance. Generative AI tools spread differently: bottom-up, unevenly, and in several functions at once (Brynjolfsson, Li, & Raymond, 2025; Project Management Institute [PMI], 2024). The project manager consequently faces an organisation in which several counterpart functions may be redesigning how they produce information at the same moment, some visibly and some quietly, with no coordinated plan behind any of it.

Research on AI in project management has so far looked mostly at what AI does inside the project manager's own tasks: planning and scheduling, risk analysis, reporting, and the appropriation of generative chatbots by project managers themselves (Felicetti, Cimino, Mazzoleni, & Ammirato, 2024; Müller, Locatelli, Holzmann, Nilsson, & Sagay, 2024). Team-level experiments have started to show that generative AI can substitute for part of what human collaboration provides, and that it reshapes decision processes (Dell'Acqua et al., 2025; Zercher, Jussupow, & Heinzl, 2025). The mirror question has not been asked, as far as I can establish: how the project manager's perceived communication load covaries with AI adoption in the functions around the project. I call this condition cross-functional AI diffusion, meaning the breadth of non-project functions perceived to use AI-based tools regularly.

Theory gives two answers here, and they contradict each other. Take coordination costs first (Malone & Crowston, 1994). On that reading, information moving through machines ought to stand in for information that would otherwise have moved through people. Status reports write themselves, analytics go self-service, summaries arrive before anyone requests them, and the need to chase and remind and reconcile falls away. Now read the same theory from its other side. Each new AI system in a counterpart function comes with fresh dependencies. Outputs must be verified, assumptions aligned, errors escalated. Managing dependencies is precisely what communication is for (Faraj, Pachidi, & Sayegh, 2018; Raisch & Krakowski, 2021). My data illustrate the tension rather neatly. Asked whether AI had changed their need for cross-team communication, 53.4% of the project professionals surveyed said that nothing had changed, 29.1% reported an increase, and only 8.3% a decrease. The interesting question, then, is not which average tendency wins. It is under which organisational conditions the status quo breaks, and in which direction it breaks.

Three research questions follow. RQ1: is the breadth of cross-functional AI diffusion associated with changes in project managers' need for cross-team communication? RQ2: does the project manager's own AI adoption moderate that association? RQ3: which functions' AI use is most strongly associated with increased communication needs? I answer them with survey data from 213 project professionals working in six world regions, collected through the IPMA Special Interest Group on Artificial Intelligence between August 2025 and April 2026, using ordinal, binary and multinomial logistic models.

The study contributes on three fronts. First, it extends diffusion of innovations research (Rogers, 2003) from the adoption decision itself to the position of a boundary-spanning role exposed to others' adoption, a position that adoption models in the TOE or UTAUT tradition are not built to capture (Tornatzky & Fleischer, 1990; Venkatesh, Morris, Davis, & Davis, 2003). Second, it offers coordination theory a mechanism, set out in Section 2.3, in which AI alters the composition of information crossing a lateral interface rather than the volume of traffic across it. Third, it gives function-level evidence about where such interfaces are most likely to be disturbed. For research on digital transformation and organisational change, the wider implication is that the consequences of adopting a technology are not confined to the unit that adopts it, and that the lateral interfaces between units may be where uneven adoption is first felt. For practice, the corresponding suggestion is that coordination arrangements should not be assumed to survive a transformation that proceeds one function at a time.

2 THEORETICAL BACKGROUND AND HYPOTHESES

2.1 AI in project-based work

Empirical work on AI in project management is young, and Müller et al. (2024) note in reviewing it that much remains conceptual. What exists sits mostly at the individual level: Felicetti et al. (2024) show that project managers' appropriation of generative chatbots depends on innovation attitude, peer influence and task–technology fit, while practitioner surveys record fast-rising adoption for planning and risk work (PMI, 2024). One level up, experiments indicate that generative AI reproduces part of the performance benefit of a human teammate (Dell'Acqua et al., 2025) and alters decision processes in team–AI collaboration (Zercher et al., 2025). At organisational level, field data from customer support document sizeable productivity gains (Brynjolfsson et al., 2025).

Interdependence between adopting units is the piece missing from this picture. Projects sit inside a lattice of functions, and a project manager's communication needs depend not only on their own tools but on how every counterpart unit produces and shares information. Organisation theorists studying AI have warned that learning algorithms change how work is organised around them, not merely how a task gets executed (Faraj et al., 2018; Raisch & Krakowski, 2021). If that is right, then adoption by surrounding functions ought to be visible from the project manager's chair, and visible specifically as a changed need to talk.

2.2 Cross-functional AI diffusion as an organisational condition

For Rogers (2003), adoption happens inside a social system rather than inside a head, and turns on what would-be adopters make of the innovation: whether it beats what they have, fits how they work, and can be seen working for somebody else. At organisational level the same tradition ties innovativeness to structure, while the technology–organisation–environment line puts the adoption decision back into its organisational surroundings (Tornatzky & Fleischer, 1990). Both traditions model the adopter. The neighbour who has already adopted, or who never will, appears only implicitly, as a node in the network through which the innovation travels.

I want to move the lens onto that neighbour. Where a counterpart function adopts AI, the interface across which the project manager works tends to look different: reports arrive machine-generated, service levels shift, new artefacts enter the conversation, and the counterpart's internal tempo changes with them. Breadth of cross-functional AI diffusion, as I define it here, is the number of distinct non-project functions that the respondent believes regularly use AI-based tools, and I treat it as an organisational condition as the project manager perceives it. Boundary spanners (Ancona & Caldwell, 1992) are well placed to perceive such diffusion and unavoidably placed to absorb whatever follows from it.

2.3 Coordination costs: substitution against new dependencies

In coordination theory, coordinating means managing the dependencies between activities, and the mechanisms available for doing so carry costs

that technology can shift (Malone & Crowston, 1994). Applied to the present question, the theory does not produce one prediction. It produces two, pointing in opposite directions.

The substitution logic goes like this. Much of what passes between teams on a project builds no relationship at all: somebody asking where a deliverable stands, requesting a figure, chasing an answer, reconciling two versions of the same number. Where counterpart functions adopt AI, part of that traffic is automated, because the dashboard answers before anyone thinks to ask, and perceived need should then be lower. The new-dependencies logic runs the other way. Each new AI system comes with outputs whose quality, assumptions and failure modes cannot simply be taken on trust (Raisch & Krakowski, 2021), and verifying them, handling exceptions and aligning generated artefacts are themselves dependencies that tend to bring coordination with them (Faraj et al., 2018). Perceived need should then be higher where diffusion is broader.

Stated at this level, neither logic is specific enough to be useful, and "something changes in one direction or the other" would be a weak theoretical claim. What is needed is an account of what exactly is being rearranged. My proposal concerns the composition of the information crossing a functional interface rather than its volume. When a counterpart function adopts AI, some of what it sends across the interface arrives already answered, in the form of generated reports, dashboards and summaries that pre-empt questions the project manager would otherwise have asked. Other output arrives provisional, carrying assumptions, confidence levels and failure modes that have to be checked before the project can rely on them. The first kind displaces communication; the second kind creates it. Diffusion therefore alters the mix of pre-answered and provisional information at the interface, and the net direction observed by any given project manager depends on which kind predominates locally.

Two implications follow, and they differ in evidential weight. First, because the local mix varies, exposure to more adopting functions should be associated with departure from the communication status quo in either direction rather than with a uniform shift. This requires a word of justification, because an increase and a decrease are plainly not the same experience, and pooling them is only defensible if they are outcomes of one process rather than two. The claim is that they are: in both cases what has changed is the composition of what arrives at the interface, and the sign of the observed movement records which component happened to dominate in that particular organisation. On this reading the theoretically meaningful contrast is between interfaces that were disturbed and interfaces that were not, which is what the pooled indicator captures. I regard this as an argument to be judged rather than a settled matter, and Section 4.2 reports the empirical check that bears on it. Even granted the argument, a bidirectional association is weak evidence, and I treat it as a symptom of the mechanism rather than as the theoretical claim itself.

Second, and more diagnostically, the mechanism should register only where the interface actually carries operational traffic. Where a project touches a function daily, a change in what that function produces has to be absorbed and renegotiated. Where the interface is thin, standardised and periodic, the same internal change can pass unnoticed from the project side. This second implication, developed as H3 below, is the sharper test, because it implies a pattern of presence and absence rather than merely some movement.

With that in place I state a directional hypothesis alongside a status-quo-departure hypothesis, and let the data adjudicate between them:

H1a. The breadth of cross-functional AI diffusion is positively associated with an increased need for cross-team communication.

H1b. The breadth of cross-functional AI diffusion is positively associated with the probability of any change, increase or decrease, in the need for cross-team communication, relative to no change.

2.4 Contingencies: own adoption, function type, organisation size

How others' adoption is experienced plausibly depends on what one has adopted oneself. A project manager already augmenting several competence areas with AI has routines that fit AI-mediated infor-

mation flows, so machine-generated input lands in a workflow prepared for it; one with little personal adoption meets the same interfaces without that compatibility, in Rogers' (2003) sense, and should register the disturbance more sharply. Hence:

H2. The association between cross-functional AI diffusion and communication change is stronger for project managers with lower personal AI adoption breadth.

Functions also differ in how tightly their workflows interlock with project work. Externally facing and delivery-adjacent functions, such as marketing and sales, IT operations, R&D and customer support, exchange operational information with projects continuously, so their AI adoption changes artefacts that the project manager handles weekly. Back-office functions such as finance and accounting, legal and compliance, or supply chain meet projects through fewer and more standardised interfaces, budget cycles and contract reviews above all, which should buffer whatever tooling they use internally. Hence:

H3. The number of externally facing, project-adjacent functions using AI is more strongly associated with an increased perceived need for cross-team communication than the number of back-office functions using AI.

Organisation size, finally, implies functional differentiation: in a large organisation the same breadth is distributed across more formalised interfaces and more specialised counterpart roles, multiplying the points at which AI-related changes must be re-coordinated. Hence:

H4. The association between cross-functional AI diffusion and communication change is stronger in larger organisations.

Trust in AI enters as a control. Social capital theory suggests that relational resources can substitute for formal coordination (Adler & Kwon, 2002); by analogy, a project manager who trusts AI output (Glikson & Woolley, 2020; Lee & See, 2004) may verify less and therefore talk about it less, independently of how far diffusion has gone. I measure trust rather than hypothesise about it, because this design cannot separate the several roles it might be playing.

3 Method

3.1 Data and sample

The data come from the "Human–AI Competence Shift & Trust Survey", designed and put into the field by the IPMA Special Interest Group on Artificial Intelligence. The questionnaire ran in English for nine months, from August 2025 to April 2026, reaching respondents through IPMA member associations, SIG channels and the professional networks around them. Nobody was obliged to answer and nobody was asked to identify themselves; respondents knew from the opening screen that whatever they wrote would be reported in aggregate only, and only for research. The effective sample is 213 project professionals: a senior group, 62.6% reporting more than fifteen years of experience, and predominantly European, in that 62.9% deliver their projects mainly in Europe, the remainder across the Middle East and Africa (11.0%), North America (8.6%), Latin America (8.1%), Asia-Pacific (6.2%) and Australia (3.3%). Table 1 sets out the profile.

A word about my own position is in order. I belong to the IPMA SIG that designed and circulated this questionnaire, so I am not a neutral observer standing outside the data. The cost of that is distance; the benefit is that the instrument was built with practitioners rather than merely for them, and reached a population that rarely troubles to answer academic surveys. Readers should weigh both.

3.2 Measures

Communication change (dependent variable). A single item carries the outcome: "Has AI changed your need for cross-team communication?", offering four answers, which were Decreased, No change, Increased and Not sure. The ordinal specification codes the first three as 1, 2 and 3, in that order. Not sure is a different kind of answer altogether, and nineteen respondents (9.2% of valid answers) gave it; I set those aside as missing in the main models and return to them in Section 4.6. For the status-quo-departure specification behind H1b, a binary indicator called Change takes the value 1 whenever a respondent reported movement in either direction, and 0 for No change.

Table 1: Sample profile (N = 213)

Characteristic	Category	n (%)
Experience in PM	> 15 years	132 (62.6%)
	11–15 years	25 (11.8%)
	6–10 years	24 (11.4%)
	1–5 years	18 (8.5%)
	< 1 year	12 (5.7%)
Current role	Project manager / senior project manager	69 (32.7%)
	Project director / portfolio / programme manager	63 (29.9%)
	Coordinator, analyst, technical PM	27 (12.8%)
	Other (executive, engineering, education)	52 (24.6%)
IPMA certification	Level A / B / C / D	29 / 26 / 38 / 31
	Other or none reported	89 (41.8%)
Industry	IT / software	48 (22.5%)
	Public sector	26 (12.2%)
	Manufacturing / construction / energy	64 (30.0%)
	Finance, healthcare, other	74 (34.7%)
Organisation size	< 100 employees	78 (36.8%)
	100–499	32 (15.1%)
	500–4,999	45 (21.2%)
	5,000–19,999	23 (10.8%)
	≥ 20,000	34 (16.0%)

Note. Percentages computed on valid responses per item; role and certification categories grouped for presentation. Source: Author's analysis of IPMA AI SIG survey data (N = 213).

It is important to be exact about what this item does and does not capture. It records a project manager's retrospective judgement about their own need for cross-team communication. It is not a measure of communication frequency, of hours spent in meetings, of message volume, of coordination quality, or of communication behaviour of any observable kind. Perceived need and enacted communication may diverge, and nothing in this design allows me to say by how much. Every result below should be read as a statement about perceptions reported on a single occasion, and the wording throughout the paper is chosen to keep that restriction visible.

Perceived cross-functional AI diffusion breadth. A tick-list asked which other functions in the respondent's organisation regularly use AI-based tools today. Breadth is simply the count of ticked functions, running from 0 to 8 (M = 2.26, SD = 2.07), and the individual dummies carry H3. Table A2 in the technical appendix gives the marginals.

This index deserves a word of defence, because a simple count treats every adopting function as equivalent. It does. Breadth is not intensity: the measure says nothing about how mature a function's AI use is, which use cases it covers, how deeply the tools are integrated into that function's systems, or whether any of it reaches the project interface. Two organisations scoring four may therefore differ enormously in their actual AI environments, and I make no claim otherwise. The index is formative rather than reflective, and it is deliberately coarse: it captures how many fronts a

project manager is exposed to, which is the construct the theory needs, and not how intense the exposure is on each front. Two observations support its usefulness. It behaves as one would expect against related constructs, correlating with the respondent's own AI breadth (ρ = .38), own AI depth (ρ = .22) and trust in AI (ρ = .21) while showing no relation to organisation size (ρ = .09, p = .204), which is reassuring in a measure of exposure rather than scale. And the substantive results hold their sign across several alternative codings, summarised in Section 4.7 and set out in Table A4. The absence of an intensity measure remains a genuine weakness, and Section 5.3 returns to it.

Personal AI adoption. Breadth here counts the project management competence areas that a respondent augments with AI, out of the six listed in Table A2 (M = 2.62, SD = 1.70). Depth is the self-reported share of effort in those areas now executed by AI tools, ordinal, running from 0% up to 76–100%. Anyone reporting no AI use at all was coded 0 on depth.

Trust in AI. Four items adapted from the automation-trust tradition (Jian, Bisantz, & Drury, 2000; Lee & See, 2004) asked respondents to rate the reliability, predictability, transparency and goal alignment of AI recommendations on five-point scales. Internal consistency of the mean composite was acceptable (Cronbach's α = .79, inter-item correlations between .41 and .56).

Controls. Organisation size, in five ordinal bands from under 100 to 20,000 or more employees, project management experience in five bands, and a region dummy for Europe enter every model. Multicollinearity is not an issue, with all VIF values at or below 1.30.

One instrument, one informant: common method variance is a fair worry here (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Three features of the questionnaire work against it. Responses were anonymous. The dependent item sat several unrelated blocks away from the diffusion tick-list. And the two used different response formats, a categorical choice on one side and a count of ticked boxes on the other, which limits artefactual covariance for count-based predictors. None of this makes the problem disappear, and I return to it in Section 5.3.

3.3 Analytical strategy

I estimate three complementary specifications. The first is an ordinal logistic regression, with proportional odds, of the three-level outcome, which tests the monotone prediction in H1a. Because that assumption becomes doubtful when movement runs away from a middle category in both directions (Brant, 1990; Williams, 2006), which is what H1b anticipates, the second is a binary logistic model of Change against No change, and the third a multinomial model with No change as reference. Continuous predictors are mean-centred before interaction terms are formed for H2 and H4. Listwise deletion leaves an estimation sample of N = 164, and the other 49 cases should be accounted for. Most are lost on the dependent variable itself, where 19 respondents answered Not sure and 7 skipped the item; missing personal AI breadth removes a further 15, and the rest go singly across the remaining covariates. Table A1 sets out the sequence. The attrition is not innocuous: respondents retained report higher diffusion breadth than those dropped (M = 2.46 against 1.49, p = .006) and greater personal AI depth (M = 1.38 against 0.64, p < .001), so the analytic sample is more AI-engaged than the survey as a whole and the estimates describe that more engaged group. Among respondents who did supply a valid outcome, however, those later dropped on covariates do not differ from those retained in the distribution of reported change (χ^2, p = .498), so attrition appears to shift the sample's exposure profile rather than its outcome profile. All estimation was carried out in Python 3.10 using statsmodels 0.14, and exact p-values are reported throughout. Given a modest sample and a construct that nobody has measured before, I read this evidence in an openly exploratory spirit, and I would ask the reader to do the same.

4 Results

4.1 Descriptive results

Table 2 gives the descriptive statistics and Spearman correlations. Most respondents, 53.4%, report that AI changed nothing about their perceived communication needs; 29.1% report an increase and 8.3% a decrease. The outcome correlates

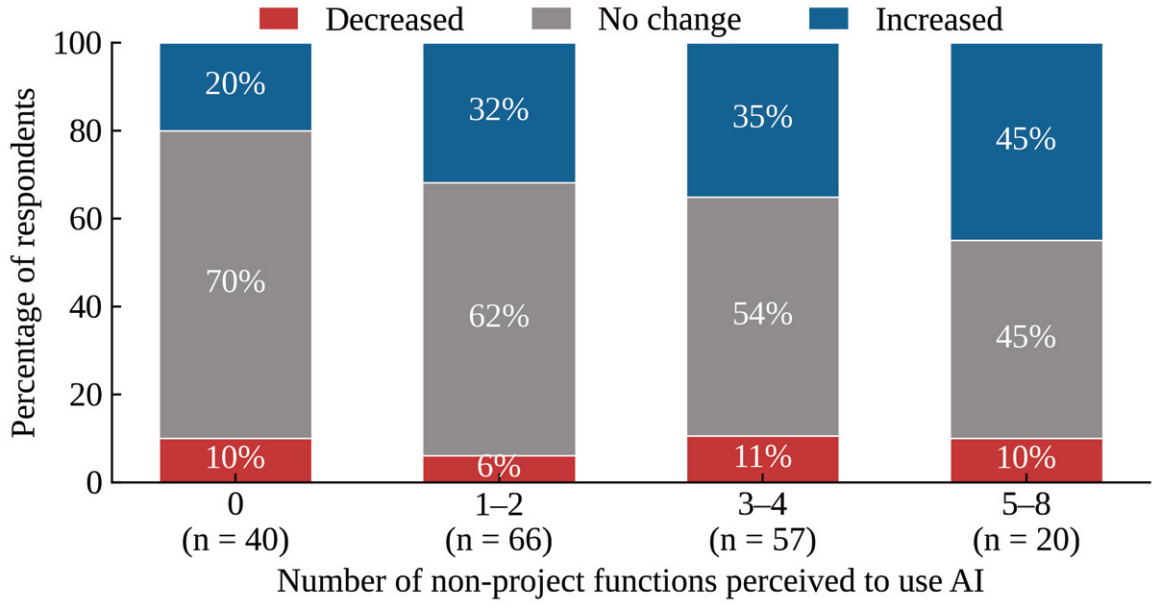
weakly and positively with perceived diffusion breadth (ρ = .12) and personal adoption breadth (ρ = .15), and essentially not at all with trust, organisation size or experience. One pattern in the group means is worth pausing on: respondents reporting no change sit lowest on diffusion breadth (M = 2.07), those reporting a decrease higher (M = 2.44), those reporting an increase highest (M = 2.79; Kruskal–Wallis H = 4.93, p = .085). That ordering is not monotone, which is the first hint of a non-uniform pattern. Figure 1 shows the same across breadth bands: the share reporting no change falls from 70% where no other function is perceived to use AI to 45% where five or more are.

Table 2: Descriptive statistics and Spearman correlations

Variable	M	SD	1	2	3	4	5	6
1. Communication change (1–3)	2.23	0.60	–					
2. Diffusion breadth (0–8)	2.26	2.07	.12	–				
3. Personal AI breadth (0–6)	2.62	1.70	.15*	.38**	–			
4. Personal AI depth (0–3)	1.22	0.75	.09	.22**	.10	–		
5. Organisation size (1–5)	2.54	1.47	.05	.09	−.06	−.01	–	
6. Experience (1–5)	4.17	1.25	−.03	.12	.07	.05	.07	–
7. Trust in AI (1–5)	3.33	0.76	.02	.21**	.15*	.31**	.04	.00

*Note. Pairwise N = 170–210. Communication change excludes "Not sure". * p < .05; ** p < .01 (two-tailed).*
Source: Author's analysis of IPMA AI SIG survey data (N = 213).

Figure 1: Reported change in cross-team communication need by breadth of cross-functional AI diffusion



Source: Author's analysis of IPMA AI SIG survey data (N = 213).

4.2 Diffusion breadth and communication change (H1a, H1b)

Table 3 reports the regressions. In the ordinal specification of Model 1, diffusion breadth shows no significant monotone association with increased perceived need (OR = 1.12, 95% CI [0.94, 1.33], p = .205), so H1a is not supported. The model as a whole is significant (LR $\chi^2(7) = 16.73$, p = .019, McFadden's R^2 = .056), but that owes most of its strength to the region control.

Things sharpen in the specifications that respect the non-monotone pattern. In the binary model of any change against no change (Model 2), perceived diffusion breadth is positively associated with departure from the status quo, though only marginally (OR = 1.19 per additional adopting function, 95% CI [0.99, 1.43], p = .061; model LR p = .009). With covariates at their means, the predicted probability of reporting some change rises from .32 where no other function is perceived to use AI to .49 at four functions and .66 at eight (Figure 2).

Model 3, the multinomial, provides the check that bears on whether pooling the two directions is defensible. If increases and decreases were driven by different processes, one would expect the breadth coefficients for the two branches to diverge. They do not: Increased RRR = 1.20 (p = .074) and Decreased RRR = 1.22 (p = .224) are almost identical in magnitude and identical in sign. That is what a single process with a locally varying balance would produce, and it is the empirical warrant for the pooled specification. It is not proof, since with 15 respondents in the decrease category the Decreased coefficient is imprecisely estimated, and a genuine difference between the branches could be hidden by that imprecision. The evidence is directionally consistent with H1b but marginal by conventional thresholds.

The direction of this association cannot be established from these data, and the point is important enough to make here rather than only among the limitations. Both variables are reported by the same person at the same moment. A project manager who already works across many functional boundaries has more opportunity to observe what those functions are doing, so broader perceived AI use may be a consequence of extensive cross-functional contact rather than a condition that produced it. The association reported above is compatible with either reading, and with a third in which some further factor, such as the organisation's general pace of change, produces both. Nothing in the design distinguishes them. Readers should treat every result that follows as a statement about covariation among perceptions recorded on one occasion, and Section 5.3 returns to what would be needed to do better.

Table 3: Logistic regression models of perceived communication change (N = 164)

Predictor	M1 Ordinal OR (p)	M2 Change OR (p)	M3 Increased RRR (p)	M3 Decreased RRR (p)
Diffusion breadth (Q19)	1.12 (.205)	1.19 (.061)	1.20 (.074)	1.22 (.224)
Personal AI breadth (Q7)	1.13 (.229)	0.98 (.828)	1.05 (.668)	0.72 (.149)
Personal AI depth (Q8)	1.21 (.455)	1.33 (.283)	1.37 (.274)	1.20 (.681)
Organisation size	1.14 (.236)	1.13 (.315)	1.16 (.238)	0.99 (.961)
Experience	1.05 (.721)	0.92 (.556)	0.97 (.832)	0.84 (.431)
Trust in AI	0.65 (.080)	0.87 (.597)	0.74 (.284)	1.57 (.325)
Region: Europe	0.36 (.003)	0.29 (.001)	0.25 (< .001)	0.50 (.267)
McFadden's R^2	.056	.084	.089	
Model LR test (p)	.019	.009	.024	

Note. OR = odds ratio; RRR = relative risk ratio (reference category: No change). Diffusion breadth, personal AI breadth and trust are mean-centred. Two-tailed p-values in parentheses.
Source: Author's analysis of IPMA AI SIG survey data (N = 213).

Figure 2 also shows why the upper part of that range should be read cautiously. The confidence band widens considerably beyond four functions, because few respondents sit there: 4, 2, 4 and 9 cases at breadth values of five, six, seven and eight respectively, against 30 to 40 cases at each of the lowest values. The rising line is estimated mostly from the dense lower range and extrapolated across a thin upper one, and the difference between a predicted probability of .66 and one of .40 at the top of the scale is not something these data can adjudicate.

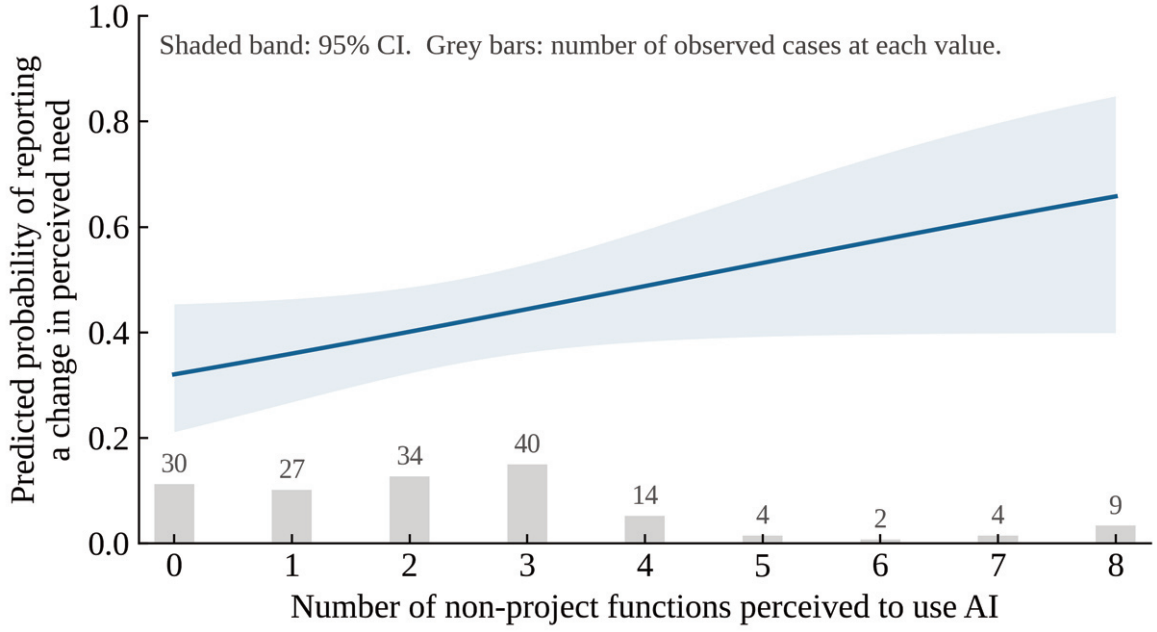
4.3 Moderation by personal adoption (H2)

Adding the interaction between diffusion breadth and personal AI breadth to Model 2 produces a coefficient near zero (b = 0.02, p = .654; likelihood-ratio test p = .653), so H2 is not supported. The null is informative in its own right: the association between organisational diffusion and perceived communication change does not vary with how much AI the project manager uses personally. Whatever is being registered is registered at the interface, whether or not the focal manager is an adopter.

4.4 Which functions matter (H3)

H3 contrasts two categories of function, so I test it first as a contrast rather than as eight separate coefficients. Following the classification set out in Section 2.4, I count the externally facing, project-adjacent functions using AI (R&D and engineering, marketing and sales, IT operations, customer support; M = 1.59, SD = 1.24) and the back-office functions using AI (finance and accounting, HR and recruiting, supply chain and logistics, legal and compliance; M = 0.87, SD = 1.13), and enter both counts together with the usual controls (N = 166). The pattern runs in the predicted direction. For any reported change, the front-office count is associated with departure from the status quo (OR = 1.40, p = .048) while the back-office count is not (OR = 1.00, p = .983); for increased perceived need the gap is similar (front OR = 1.50, p = .025; back OR = 0.89, p = .545). The formal contrast, however, is weaker than the individual coefficients suggest: a Wald test of equality between the two cannot reject the null for any change ($\chi^2 = 1.29$, p = .256) and only approaches conventional levels for increased need ($\chi^2 = 2.76$, p = .097). The two counts are themselves cor-

Figure 2: Predicted probability of reporting any change in cross-team communication need, by diffusion breadth



Note. Estimated from Model 2 with all covariates held at their means; shaded band shows the 95% confidence interval. Source: Author's analysis of IPMA AI SIG survey data (N = 213).

related (r = .53), which limits how sharply they can be separated. H3 therefore receives qualified support: the association is carried by the front-office count and is absent for the back-office count, but the difference between them is not established statistically.

Table A3 in the appendix reports the disaggregated version, and two features require caution. The eight dummies do not improve fit jointly, either for any change (LR $\chi^2(8) = 9.77$, $p = .282$) or for increased need (LR $\chi^2(8) = 11.14$, $p = .194$); and testing eight coefficients invites false positives, so the one nominally significant result does not survive adjustment. AI use in customer support carries the largest individual coefficient for increased perceived need (OR = 2.69, uncorrected $p = .024$), but this fails both Holm and Benjamini–Hochberg correction ($p = .193$ in each case). I therefore do not treat it as an established finding. It is the largest coefficient in a set jointly indistinguishable from noise, consistent with the composite contrast and with field evidence on where generative AI has gone deepest (Brynjolfsson et al., 2025), which is a reason to look again in a better-powered study rather than a reason to believe it now.

4.5 Organisation size (H4)

The interaction between diffusion breadth and a large-organisation indicator, set at 500 employees or more, is essentially zero ($b = −0.04$, $p = .841$). H4 is not supported: the diffusion–communication association is no stronger in large organisations than in small ones. Organisation size shows no main effect in any specification either.

4.6 Region

Region is the strongest association in every model I estimated, and it deserves more than a footnote. Project managers who deliver their projects mainly in Europe are considerably less likely to report an increased perceived need for cross-team communication (Model 3: RRR = 0.25, $p < .001$). Descriptively, 22.5% of European respondents report an increase against 40.0% elsewhere, while the proportions reporting a decrease are nearly identical (7.8% and 9.3%). Comparing standardised coefficients in the binary model makes the ranking explicit: a one standard deviation shift in the Europe indicator moves the log-odds by −0.59, against +0.36 for a one standard deviation shift in diffusion breadth. Whatever this variable is capturing, it is capturing more of the variance in reported change than the construct the paper is about.

What it is capturing, I cannot say. One possibility can be ruled out: European respondents are not simply less exposed, since perceived diffusion breadth does not differ significantly by region (M = 2.37 against 2.05, $p = .274$). The difference lies in reported change at similar levels of exposure. Beyond that I can only speculate, and would rather label it as speculation than dress it up. Slower or more cautious rollouts, the phased application of the EU AI Act, regional differences in how readily professionals report change in surveys, and composition effects in a sample where non-European respondents are fewer, are all candidates. Cross-national surveys do record wide variation in how people regard AI (KPMG & University of Melbourne, 2025), so a difference of this size is not anomalous. Establishing what produces it would need a design built for the purpose, and I flag it as the most substantial unexplained result in the paper rather than as an incidental control.

4.7 Robustness

Three sets of checks bear on the conclusions, and the technical appendix reports them in full. The first concerns the Not sure category: treating it as a fourth multinomial outcome leaves the results intact (diffusion breadth on Increased: $b = 0.18$, $p = .069$; N = 177), and recoding it conservatively as No change gives OR = 1.17 ($p = .077$) in the binary model. The second concerns the breadth measure. Re-estimating the binary model with the square root of the count, a dichotomy at three or more functions, a dichotomy at one or more, an inverse-prevalence weighted index and the first principal component of the eight dummies returns the same sign in every case, with odds ratios between 1.19 and 1.79. Significance, however, is not robust: only the original count and the principal component approach conventional levels, while the coarser dichotomies do not. The direction of the association is stable across reasonable operationalisations; its statistical support is not. The third check is simply the accumulation. Across every specification the es-

timate stays between 1.17 and 1.22 with p-values between .056 and .10, and no single test in this paper would survive a demanding standard of evidence on its own.

5 Discussion

5.1 Theoretical implications

The first implication concerns those who merely stand nearby while an innovation spreads. Diffusion research has traditionally asked why units adopt and when (Rogers, 2003; Tornatzky & Fleischer, 1990). These data are consistent with the idea that a boundary-spanning role registers diffusion around it as a change in its own coordination environment, and, given the null on H2, does so whether or not the focal manager has adopted anything. If that reading is right, exposure to others' adoption may be worth treating as a variable in its own right, in research on digital transformation as much as in diffusion research. I put it forward as a proposition the present design can motivate but cannot confirm.

The second implication is for coordination theory. A pure substitution reading of Malone and Crowston (1994), in which technology absorbs informational traffic and the need for communication falls, sits poorly with these data: only 8.3% report a decreased need, and diffusion breadth is associated with a decrease no more strongly than with an increase. What the data are compatible with is the interface-composition mechanism proposed in Section 2.3, in which AI changes the mix of pre-answered and provisional information crossing a functional boundary rather than reducing the traffic across it (Faraj et al., 2018; Raisch & Krakowski, 2021). Two observations point that way: the bidirectional association, which is what a locally varying mix would produce, and the contrast between front-office and back-office counts, which is what an interface-dependent mechanism would produce. Neither observation is strong on its own, and neither identifies the mechanism directly. What would identify it is evidence on the content of the communication involved, which this design does not supply.

Third, the function-level pattern is suggestive rather than probative, and I want to be careful here because it is the part of the paper most likely to be over-read. The composite contrast behaves as the mechanism would require, with the front-office count associated with increased perceived need and the back-office count flat, but the difference between the two is not statistically established. At the level of individual functions the eight dummies add nothing jointly, and customer support, the largest single coefficient, does not survive correction for multiple testing. What can fairly be said is that the direction of the pattern matches both the proposed mechanism and independent field evidence on where generative AI has gone deepest (Brynjolfsson et al., 2025). What cannot be said is that this study demonstrates a customer-support effect, or indeed any function-specific one. It identifies where a better-powered study should look.

5.2 Tentative implications for managerial practice

Evidence of this kind, cross-sectional, single-source, perceptual and marginal, cannot support prescriptions, and I offer none. What it can support is a question worth putting on the agenda. Organisations commonly treat an AI deployment in one function as a matter internal to that function, to be judged by that function's own efficiency measures. The pattern here, weak as it is, is at least consistent with the possibility that such deployments are felt at the interfaces, by people who adopted nothing themselves and are not usually consulted about the decision. If that is so, the costs and benefits of a functional deployment are being assessed in the wrong place, since part of the adjustment is borne laterally.

The people who would bear it are not only project managers. Any role that coordinates across units it does not control, whether an account manager, a product owner or a business partner in a support function, sits at the same kind of interface. A manager overseeing a transformation programme might reasonably ask, when a function introduces AI, whether anything at its interfaces has changed: whether reports arriving from it are now machine-generated and what checking they warrant, whether a standing meeting has lost or gained a purpose, whether escalation paths can handle exceptions the tools cannot. These are prompts for enquiry rather than recommendations, and the appropriate answer may often be that nothing needs to change, which

is what a majority of respondents here reported. For professional bodies such as IPMA, the more defensible implication concerns competence frameworks, which might treat awareness of what neighbouring functions are doing with AI as part of boundary-spanning competence rather than concentrating on the manager's own toolbox.

5.3 Limitations and future research

Several limitations bound these claims, and I would rather state them bluntly than bury them. The most serious is the one set out in Section 4.2: outcome and diffusion count rest on a single informant's perception at a single moment, so the direction of the association cannot be established and a reading in which cross-functional contact produces perceived diffusion is as consistent with the data as the reading the paper develops. No amount of careful modelling disposes of that; it requires multi-informant or observational data. Nothing about the design is longitudinal. The sample arrived through professional networks, which makes it senior, Europe-heavy and self-selected. The associations themselves are small, hovering between $p = .06$ and $p = .09$ depending on specification, and I would rather call them a pattern awaiting replication than call them a finding.

Two further limitations deserve naming rather than burying. The outcome is a perception of need, not communication of any observable kind, so a respondent who reports no change may nonetheless be communicating differently, and one who reports more may be reporting salience rather than volume. And the principal predictor counts adopting functions without weighting them, which means it cannot distinguish an organisation where four functions run mature, integrated AI systems from one where four functions have licences that a few people occasionally use. Adoption intensity, maturity, use case and system integration are all unmeasured here. Since the mechanism I propose turns on what actually crosses the project interface, this is not a peripheral gap: the study measures exposure breadth as a proxy for something it does not observe.

The most valuable next step is not a larger version of this survey but evidence of a different kind, in two stages. Qualitative work should establish what the additional communication actually consists of where managers report it: whether they are verifying AI-generated figures, renegotiating what a counterpart function now treats as a finished deliverable, or absorbing exceptions the tools cannot handle. Without that, the mechanism proposed here remains an interpretation. Behavioural and longitudinal data should then test whether perception tracks anything observable. Meeting metadata, calendar records and messaging logs already exist in most organisations, and following a set of projects through a functional AI rollout would allow perceived need and enacted communication to be compared directly while separating transition effects from any steady state. Pairing managers' reports with adoption data from the counterpart functions themselves, with measures of intensity rather than mere presence, would address the endogeneity and construct problems together. The regional difference in Section 4.6 also invites comparative work in its own right.

6 CONCLUSION

This paper asked whether the spread of AI through the functions surrounding a project is associated with how project managers perceive their need to communicate across teams. In a survey of 213 project professionals, the answer most respondents gave was that nothing had changed. Among the rest, exposure to a greater number of AI-using functions was associated, weakly and at the edge of conventional significance, with departure from that status quo in either direction rather than with a uniform shift, and this association did not vary with the respondent's own AI adoption. A composite contrast offered qualified support for the idea that the association is concentrated at interfaces with operationally coupled functions, though the difference from back-office functions could not be established statistically.

These results are consistent with the possibility that AI rearranges what crosses a lateral interface rather than simply reducing the traffic across it. They do not demonstrate it. The evidence is cross-sectional, the outcome is a perception rather than a behaviour, the principal predictor counts functions without weighting their AI use, and the associations are marginal throughout. What the study offers is a

reframing worth pursuing, that the consequences of adopting a technology may be borne by people who did not adopt it, together with an indication of where a better-designed study should look for them.

Declarations

Ethics. Participation was voluntary and the questionnaire collected no personal data. Respondents were informed at the outset that results would be reported only in aggregate, for research purposes.

Funding. The study was carried out without external funding.

Conflict of interest. I declare no conflict of interest. I serve in the IPMA Special Interest Group on Artificial Intelligence, which administered the survey; Section 3.1 discusses what that implies for the reading of these data.

Data availability. The anonymised dataset and analysis scripts can be obtained from me on request.

Declaration of generative AI use. I used generative AI tools while preparing this manuscript, for scripting parts of the statistical analysis and for language editing. I reviewed and revised all resulting text and output myself, and I take full responsibility for the content of this publication.

EXTENDED SUMMARY/IZVLEČEK

Umetna inteligenca v organizacije ne vstopa več zgolj na en sam način. Medtem ko projektni vodje eksperimentirajo z njeno uporabo pri lastnem delu, jo vzporedno in večinoma na lastno pobudo uvajajo tudi različna funkcijska področja, od katerih so pri svojem delu odvisni. Prispevek preučuje, kako je takšno širjenje umetne inteligence med različnimi funkcijskimi področji povezano z zaznano potrebo projektnih vodij po komunikaciji med timi. Teorija koordinacije ponuja dve nasprotujoči si pričakovanji: nadomeščanje obstoječe komunikacije in nastajanje novih soodvisnosti. V prispevku razvijem mehanizem, ki obe pričakovanji povezuje: umetna inteligenca spreminja razmerje med informacijami, ki so ob prehodu med funkcijskimi področji že obdelane in pripravljene za uporabo, ter informacijami, ki so še začasne oziroma zahtevajo dodatno usklajevanje, ne pa nujno celotnega obsega izmenjave informacij.

Podatki ankete, izvedene med 213 strokovnjaki s področja projektnega managementa, zbrani prek mreže International Project Management Association med avgustom 2025 in aprilom 2026, kažejo, da večina anketirancev ne zaznava sprememb v potrebi po komunikaciji (53,4 %), medtem ko jih 29,1 % poroča o povečanju, 8,3 % pa o zmanjšanju te potrebe. Izpostavljenost večjemu številu funkcijskih področij, ki uporabljajo umetno inteligenco, je šibko in zgolj mejno statistično značilno povezana z odstopanjem od nespremenjenega stanja v katero koli smer, ne pa z enotnim povečanjem ali zmanjšanjem potrebe po komunikaciji (OR = 1,19 za vsako dodatno funkcijsko področje, ki uvaja umetno inteligenco; p = 0,061). Ta povezanost se ne razlikuje glede na to, ali projektni vodja tudi sam uporablja umetno inteligenco.

Ob razvrstitvi funkcijskih področij v skladu s postavljenimi hipotezami se je pokazalo, da je število funkcijskih področij, usmerjenih v zunanje okolje organizacije, povezano s povečano zaznano potrebo po komunikaciji, medtem ko pri številu podpornih oziroma zalednih funkcijskih področij takšne povezanosti ni bilo. Vendar statistična primerjava obeh učinkov ni potrdila njune razlike. Raziskava temelji na presečnih podatkih in subjektivnih zaznavah, ugotovljene povezave pa so večinoma zgolj mejno statistično značilne. Rezultati zato predstavljajo predvsem raziskovalno zanimive prve ugotovitve, ki jih je smiselno nadalje preučiti, ne pa dokončne empirične potrditve predpostavljenih povezav.

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