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ARTIFICIAL INTELLIGENCE DIFFUSION THROUGH THE UK'S KNOWLEDGE TRANSFER PARTNERSHIPS PROGRAMME

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ABSTRACT

This study examines how artificial intelligence (AI) diffused through the UK Knowledge Transfer Partnership (KTP) programme, using an archive of 3,158 projects awarded between 2007 and 2021, covering the initial period of AI growth in industry. Coding of project narratives distinguishes explicit AI and adjacent computational activity (data and computationally intensive projects not specifically related to AI), technical sophistication, first-of-kind claims, institutional participation, and output orientation. Explicit-AI projects rose from 5.5% of awards in the AI precursor period (pre-2012) to 29.1% in 2018-2021, but broader computational engagement rose much more modestly, indicating a compositional shift within an already computationally intensive programme rather than the emergence of new computational interest. As explicit-AI activity expanded, technical sophistication increased and first-of-kind claims showed no clear decline, suggesting AI diffusion without routinisation. The institutional base broadened rapidly after the precursor period and then consolidated, while participation remained broad across regions, knowledge-bases and firm sizes. Entry into explicit-AI collaboration was predicted by prior explicit-AI KTP experience, not by general KTP experience or mission-group status, supporting a domain-specific view of absorptive capacity. The findings indicate that open, demand-led programmes, such as KTP, can function as low-cost early-warning observatories of emerging technology demand within industry, especially within the diverse and dispersed SME community, and can identify major innovation trends while there is still time for policymakers and programme designers to respond. Evaluation should therefore track technical ambition, institutional entry, accessibility, and follow-on learning as well as project volume. Capability-building aligned to industry demand should seed domain-specific experience across a wider range of knowledge bases, preserve frontier-oriented support where technical ambition remains high, and add complementary mechanisms for routine adoption, re-use, and capability retention after the initial knowledge-transfer intervention.

Keywords: Artificial Intelligence, AI, innovation, technology transfer, Knowledge Transfer Partnerships (KTP), SME.

1. Introduction

Artificial intelligence is widely described as a general-purpose technology with the capacity to alter decision making, production, customer engagement, and innovation in small and medium-sized enterprises (SMEs). Research on SME adoption has grown quickly in response. Reviews organise the field around compatibility, infrastructure, knowledge, resources, culture, competition, regulation, and ecosystem conditions (Schwaeke et al., 2025), and bibliometric evidence shows publication output accelerating after 2019 alongside explicit calls for longitudinal work (Chotisarn & Phuthong, 2025). This body of research is informative about present organisational states. It is also concentrated in a narrow window of time.

The consequence of that concentration is easy to overlook. Large contemporary studies commonly measure AI through a specific adoption item or a readiness construct (Dowell et al., 2026; Polisetty et al., 2024), and syntheses of implementation address challenges as they are currently encountered (Oldemeyer et al., 2024). Designs of this kind cannot establish whether the increased prevalence of AI represents a new computational capability in firms, a re-labelling of analytical work already under way, or a change in the balance between the two. Topics such as expert systems, optimisation, decision support and predictive analytics preceded the applications now identified as AI. Whether the transition took the form that diffusion theory predicts, with expanding volume accompanied by increasingly routine technological content and a widening base of participating organisations, remains largely undetermined. Contemporary typologies of adoption resemble diffusion stages (Boonmee et al., 2025; Damjanovic et al., 2025), but they describe positions at one point rather than movement through a sequence.

The interaction between academia and business has been the subject of extensive study, however Rantala et al. (2025) identify SME engagement with academic research as being particularly under-explored. Adoption research generally treats firms as users of technology, whereas the university-industry literature examines engagement, commercialisation and knowledge transfer without tracing the changing technological content of what knowledge is transferred (D'Este & Patel, 2007; Perkmann et al., 2013). The nature of SME collaboration with academia as a disruptive technology, especially one with relevance to many industry sectors such as AI, moves from precursor experimentation towards wider application therefore falls between two literatures and leads to a gap in the research.

This study addresses both gaps using the archive of the Innovate UK's Knowledge Transfer Partnership (KTP) programme. A KTP links a company partner, a Knowledge-Base (KB) partner and a graduate embedded in the company partner, and case research shows that transfer in this setting proceeds through participation, training, process redesign and codification rather than through the delivery of a finished technology (Arayici et al., 2011a; Wynn et al., 2009). The KB partner is located within the UK and is typically a Higher Education (HE) institutions but can also include Further Education (FE) institutions and other Research and Technology Organisations (RTOs). KTP is a knowledge and technology agnostic 'open'

funding programme, available throughout the UK, and hence the subject of each project, and the consequent knowledge transferred, is agile and primarily reflects the strategic needs of the company partner rather than being influenced by external policy drivers. The company partner funds a proportion of the cost of participating in a KTP and hence company participation is directly correlated with an investment decision by the company to invest to gain knowledge and skills in a topic of importance to their future development. KTP has been an active UK funding programme for more than 50 years and, although regularly adopting and adapting its application and delivery processes, its basic operational ethos and practices have largely remained unchanged during this period.

The archive analysed here contains the description of 3,158 KTP projects, awarded between 2007 and 2021, recorded within a broadly consistent policy instrument across an extended period which encompasses the transition of AI technology from largely academic interest (pre-2012) through to growing industry adoption (post-2017). Specifically, the study uses the Final Report produced by the Partnership, and mandated by the funding programme, soon after completion of the project which provides a summary of the project activity, its outputs, and anticipated outcomes, within a common reporting structure. Structured coding of project narratives, enabled by the Final Report dataset, yields the technological content of each project, including whether it involved 'explicit AI' (activity specifically identified as AI-related by the KTP team in the narrative), adjacent computational activity (numerically intensive but not specifically AI related), or neither, its technical sophistication, its novelty and its output orientation. The archive consequently permits volume, technological character and institutional participation in a common technology area to be observed separately over time, which a cross-section cannot do.

Rogers (2003) predicts that technology adoption broadens as technical uncertainty falls, technological compatibility improves and complementary infrastructure develops. The measurement of adoption can be achieved by coding of technological content within a consistent longitudinal dataset can separate features of such changes in adoption: the share of activity involving the technology, the character of the work undertaken, and the breadth of the adopting population. The three need not move together, because a technological frontier that continues to advance may allow technically ambitious work to persist while adoption spreads. Cohen and Levinthal (1990) define absorptive capacity as the ability to recognise, assimilate and apply external knowledge, and locate that ability in prior related knowledge. Related accumulation and general collaborative throughput are therefore distinct aspects, and the KTP archive allows both to be measured at university level as counts of earlier projects.

Two research questions follow. The first asks how the technological composition of AI-related KTP activity changed across the archive, and whether volume, technological character and the institutional base moved in the manner diffusion theory predicts. The second asks what kind of institutional experience predicted entry into explicit-AI collaboration.

The findings qualify the diffusion account in one respect and support the absorptive capacity account in another. Explicit-AI projects with the KTP archive rose from 5.5 per cent of the archive in the precursor period to 13.4 per cent and then 29.1 per cent in subsequent periods, while total computational engagement in the project portfolio rose much more modestly, from 61.0 per cent to 72.8 per cent. The expansion of explicit AI was therefore compositional, occurring within a programme that was already computationally intensive. The technological characteristics of AI related projects did not become more routine as the volume of activity grew, indicating that companies participating in the KTPs continued to seek to acquire the latest AI developments. Instead, the share of explicit-AI projects in the highest technical-sophistication category rose from 26.2 per cent to 45.1 per cent, and claims of first-of-kind work remained uncommon throughout without declining. Institutional concentration fell substantially between the precursor and growth periods, with the top-ten share of explicit-AI projects falling from 61.3 per cent to 36.4 per cent, after which the pattern is better described as consolidation than as continued broadening. Entry into explicit-AI collaboration was predicted by related prior activity rather than by collaborative volume or institutional status. A one-standard-deviation increase in a KB's prior explicit-AI KTP experience was associated with higher odds of an explicit-AI project (OR = 1.368, 95% CI [1.165, 1.605]), whereas prior experience of other KTPs was associated with lower odds (OR = 0.765, 95% CI [0.630, 0.927]), and mission group added nothing once related history was observed.

The study contributes in three connected ways. It provides a longitudinal, portfolio-level account of AI-related university-SME collaboration in which precursor computational activity (such as Bayesian Statistics, Genetic Algorithms (GAs), Natural Language Processing (NLP) which later became holistically termed 'AI'), and explicit AI reference are observed together, which addresses the temporal concentration of the existing evidence directly. It separates the volume, character and base components of diffusion empirically, and finds that they moved independently, so that expansion in one did not entail routinisation in another. It shows that absorptive capacity operated in a domain-specific rather than a generic form at institutional level, which distinguishes specialisation from breadth as the relevant contrast. A secondary methodological contribution concerns what structured coding of archival project narratives recovers reliably, since validation against manual review shows reliability varying systematically with the abstraction of the construct being coded.

The study also has direct policy relevance. Because KTP is open, demand-led and technology-agnostic, its project archive can reveal emerging innovation trends before they are visible in contemporary adoption surveys or reflected in targeted policy programmes. In the case of AI, the archive captures early industrial demand, the broadening of knowledge-base participation, continued technical ambition and SME access within a single stable instrument. This suggests that open innovation programmes can operate as low-cost early-warning observatories, enabling policymakers and programme designers to identify major technological shifts while there is still time to respond through capability-building, eligibility design, follow-on support and complementary adoption mechanisms.

The paper proceeds as follows. Section 2 reviews the temporal concentration of SME AI research, the university-industry and KTP literatures, and develops five hypotheses from diffusion theory and absorptive capacity. Section 3 describes the archive, the coding framework, the validation exercise and the construction of institutional experience measures from the wider Gateway to Research history. Section 4 reports the results. Section 5 discusses their implications for diffusion and absorptive capacity, and sets out theoretical contributions, practical and policy implications, limitations and conclusions.

2. Literature review and hypothesis development

2.1 The temporal concentration of SME AI research

Artificial intelligence has become a general-purpose technology capable of achieving disruptive change in business. Yet the growing SME AI literature is heavily concentrated on current readiness, experimentation and implementation. Schwaewe et al. (2025) organise the field around compatibility, infrastructure, knowledge, resources, culture, competition, regulation and ecosystem conditions. Chotisarn and Phuthong (2025) show that publication output accelerated after 2019 and explicitly call for longitudinal work, while Oldemeyer et al. (2024) synthesise the present implementation challenges. Large contemporary studies similarly operationalise AI through a recent adoption item or a readiness construct rather than through observed historical technological activity (Dowell et al., 2026; Polisetty et al., 2024).

The breadth of recent work reinforces this temporal concentration. Studies examine strategic transformation, adoption barriers, international decision-making, tourism investment, ERP-enabled co-intelligence, ethical implementation, generative-AI capabilities, green innovation and intellectual-capital effects (Damnjanovic et al., 2025; Boonmee et al., 2025; Demir & Demir, 2025; Aiudi et al., 2026; Chu, 2026; Kittipanya-ngam et al., 2025; Wang & Zhang, 2025; Crocco et al., 2025; Aziz et al., 2026). Damnjanovic et al. (2025), for example, distinguish traditionalists, experimenters and strategic adopters. Boonmee et al. (2025) describe movement from awareness and capacity building towards implementation and innovation leadership. These accounts illuminate current organisational states, but contemporary cross-sections cannot observe how expert systems, optimisation, decision support, predictive analytics and early machine learning preceded increasingly explicit, embedded and accessible AI applications.

The problem is not that recent studies are uninformative. Their concentration is evidence that the field has become visible only after the technology, its recognized importance, and its description and composition has matured. What remains difficult to establish is whether the rise of explicit-AI activity represents a genuinely new computational footprint, a re-labelling of pre-existing analytical work, or a change in the balance between adjacent computation and explicitly identified AI. A longitudinal project archive can separate these possibilities by observing explicit-AI projects and the wider computational category at the same time.

The gap is also relational. Rantala et al. (2025) identify SME engagement with academic research as under-explored. AI-adoption research generally studies firms as technology users, whereas university-industry research examines engagement, commercialisation and knowledge transfer without tracing the changing technological content of collaboration. The intersection - how SMEs mobilise academic collaboration as an emerging technology class moves from precursor experimentation towards wider application - therefore remains weakly explained.

The UK Knowledge Transfer Partnership (KTP) archive provides a response because it records project-level university-organisational collaboration across an unusually extended period within one policy instrument. It permits comparison of precursor computational activity, explicit AI, technical sophistication, institutional participation and output orientation. The archive nevertheless has a clear boundary. Individual academic publication and citation profiles are unavailable, so institutional identity, mission group and prior project participation are aggregate substitutes rather than measures of the specific academic. Establishing this boundary early prevents institutional variables from being interpreted as individual scholarly capability.

2.2 University-industry engagement and Knowledge Transfer Partnerships

University-industry engagement is distinct from intellectual-property commercialisation. Perkmann et al. (2013) emphasise joint research, contract work and problem-oriented interaction, while D'Este and Patel (2007) show that university-industry linkages vary across individuals and institutions. KTPs formalise engagement through a business or organisational partner, a knowledge-base organisation and an associate embedded in the partner. This combination of academic supervision, public funding and support for implementation capacity is particularly relevant to SMEs that have strategic intent but lack specialist staff and skills to deliver on their ambition. 80% of all KTP projects involve an SME.

KTP case research presents transfer as a socio-technical implementation process rather than the delivery of a finished technology. Wynn et al. (2009) show how embedded associates, supervision, governance and training supported information-systems implementation and capability retention. Arayici et al. (2011a, 2011b) describe adoption as participation, experimentation, process redesign, training and codification. White et al. (2014) similarly shows how expert guidance and employee participation translated environmental standards into routines, certification and measurable change. Brown and Proudlove (2011) and Jones and Coates (2020) reinforce the importance of co-creation and changes in organisational practice.

Cowdean et al. (2019) find that KTP associates create experiential learning opportunities, but leadership, routines and willingness to unlearn condition acceptance. White et al. (2019) show that process mapping and socialisation can convert distributed knowledge into improvement, while resistance can prevent application. Manville et al. (2019) demonstrate reciprocal transfer but also expose the vulnerability of tacit knowledge when staff leave. These studies establish that KTPs are constitutionally oriented towards organisational application. They therefore

frame project coding as evidence of applied collaboration rather than academic research activity alone, and they motivate the expectation that market-facing output will be common throughout the programme.

Relational and proximity conditions remain important backgrounds even though they are no longer separate hypotheses. Boschma (2005) distinguishes geographical, cognitive, organisational, institutional and social proximity and warns against treating them as interchangeable. Granovetter (1973) and Gulati (1995) show how prior relationships structure information flows and reduce coordination costs. KTP and university-SME evidence similarly highlights trust, boundary spanning, committed leadership, social capital and prior contact (Darabi & Clark, 2012; Rosli et al., 2018; Yusup et al., 2026). In the present archive, firm-side validation is too restrictive to identify these mechanisms separately at dyadic level. Retaining this literature and acknowledging the measurement constraint is more informative than removing established conditions merely because the linkage cannot test them.

2.3 Research questions

RQ1. *How did the technological composition of AI-related KTP activity change across the archive, and did volume, technological character and the institutional base move in the manner predicted by diffusion theory?*

RQ2. *What kind of institutional experience predicted entry into explicit-AI collaboration?*

2.4 Diffusion: separating volume, character and base

Rogers' (2003) diffusion framework predicts that adoption broadens as uncertainty falls, compatibility improves, observable benefits grow and complementary infrastructure develops. For an archive that codes technological content, however, diffusion should be separated into three observable dimensions. The volume or share of adoption may rise. The character of adopted work may shift from first-of-kind development towards adaptation, integration and routine use. The population of adopting institutions may broaden beyond an initial specialist base. Cross-sectional studies cannot distinguish these movements because they observe only one point in the process.

The three dimensions need not move together. When a technological frontier continues to advance, adoption can spread while technically sophisticated or novel work persists. The frontier may move with the adopting population rather than remain fixed. This possibility is central to H2: an unsupported decline hypothesis can still be substantively informative if explicit-AI volume rises while novelty and sophistication remain stable or increase. Such a pattern would indicate diffusion without technological routinisation.

Contemporary adoption typologies resemble diffusion stages but do not observe movement historically. Damnjanovic et al. (2025) distinguish traditionalists, experimenters and strategic adopters; Boonmee et al. (2025) move from awareness to implementation and leadership.

Work on ERP integration, operational embedding, generative-AI innovation and business-model use provides evidence on the mature end of the trajectory (Chu, 2026; Kittipanya-ngam et al., 2025; Wang & Zhang, 2025; Crocco et al., 2025). Persistent barriers in finance, skills, infrastructure, data quality, employee resistance and regulation imply that diffusion broadens feasible and legitimate use without requiring uniform progression by every firm.

This separation also clarifies the institutional prediction. A fall in the top-ten institutional share of activity in a specific field, such as AI, indicates that engagement is no longer dominated by a small set of KBs, whereas a rising number of participating institutions indicates a larger base. The share of first-time entrants adds a dynamic view: high entry during an expansion phase followed by decline may indicate consolidation rather than reversal. No single indicator is sufficient, so H3 is evaluated through concentration, participation and first-entry measures together.

H1. *The share of explicit-AI projects increases across the period, while total computational engagement - explicit and adjacent combined - increases more modestly.*

H2. *As the explicit-AI share increases, the technological character of AI projects becomes less novel, indicated by a declining share of first-of-kind claims and a downward shift in technical sophistication.*

H3. *As the explicit-AI share increases, the institutional base broadens, indicated by falling concentration of AI-relevant projects across KBs and a rising share of first-time institutional entrants.*

2.5 Absorptive capacity and its domain specificity

Cohen and Levinthal (1990) define absorptive capacity as the ability to recognise the value of external knowledge, assimilate it and apply it commercially. Crucially, the capacity is path-dependent and grounded in prior related knowledge. Generic organisational capability and domain-specific accumulation are therefore distinct claims. Repeated participation in KTP, may build routines for managing associates and translating academic knowledge, but only related prior knowledge should position an institution to recognise and develop AI opportunities.

The archive permits both dimensions to be observed at KB level. Prior KTP activity captures general collaborative throughput, while prior explicit-AI KTP activity captures domain-specific accumulation. Once both terms are entered together, the companion general term is interpreted as other prior KTP activity rather than as a nested total. A negative coefficient would indicate specialisation: KBs accumulating conventional KTP volume are not automatically positioned for AI collaboration when AI-specific history is held constant.

This interpretation resolves the paradox created by the earlier undifferentiated measure. A negative coefficient on general experience does not imply that collaboration causes lower capability. It indicates that, conditional on equivalent AI-specific histories, portfolios weighted

towards other domains are less likely to produce an explicit-AI focal project. The relevant contrast is specialisation versus breadth, not experience versus inexperience.

Mission group is a third and distinct claim. Research-intensive status indicates broad institutional research capacity, not accumulated collaborative experience in AI. It should add little once related project history is observed. Current studies support capability-dependent adoption through learning, governance, resource orchestration and dynamic capabilities (Cimino et al., 2025; Peretz-Andersson et al., 2024; Polisetty et al., 2024). Because individual academic profiles are unavailable, institutional project history remains an aggregate substitute, consistent with evidence that engagement varies across academics and universities (D'Este & Patel, 2007; Perkmann et al., 2013).

H4. *Prior explicit-AI KTP experience at the KB is associated with higher odds of entering an explicit-AI KTP.*

H5. *Prior other KTP experience is negatively associated, and KB mission group is not associated, with entry once domain-specific experience is held constant.*

3. Data and methods

3.1 Setting, unit of analysis and population

The empirical setting is the UK Knowledge Transfer Partnership programme. Each KTP links a business or other organisation, a knowledge-base partner and a graduate associate embedded in the partner organisation. Each KTP project records the translation of external knowledge into organisational practice and permits observation of precursor computational activity and later explicit-AI application within a broadly consistent collaboration instrument.

The unit of analysis is the individual project, identified by a unique partnership identifier. The population studied contains 3,158 projects. The full cohort is preserved, and variable-specific denominators are used: each descriptive table or model includes records with the variables required for that analysis. Unavailable linkage or classification is never re-coded as a substantive category.

3.2 Sources and linkage

The master combines KTP administrative and final-report narratives, structured project coding, manually reviewed validation records, GtR+ project and participant data, and KB classification information. Of 3,158 projects, 2,233 contained a source-provided GtR reference. Conservative deterministic matching recovered 30 additional references by exact equality between a normalised constructed KTP title and a uniquely mapped GtR+ title, yielding 2,263 linked projects. No fuzzy threshold was used for reference recovery.

Participant selection considered all GtR+ organisations rather than assuming that the first participant was the KTP partner. Names were normalised and Jaro-Winkler similarity ranked KB and firm candidates. Low-confidence cases were reviewed, and 'replace' or 'no-valid-match' decisions were stored in versioned override files outside the master. This separation preserves a reproducible distinction between source information, deterministic links, candidate ranking and human judgement.

KB-side linkage was substantially more complete than company-side linkage. This asymmetry is consequential: firm identity is required for distance, same-region and repeated KB-firm tie measures. Those analyses would use a small and selected subset and, in the explicit-AI sample, lacked the variation required for stable inference. The study design therefore focuses on institutional KB history while retaining proximity and repeated-tie scholarship as background and limitations.

3.3 Coding of AI and technological character

AI relevance was coded into three mutually exclusive categories: explicit AI, adjacent computational activity and no AI evidence. Explicit AI required direct evidence of AI techniques or objectives. Adjacent computational activity captured data-intensive, analytical, automation or advanced computational work relevant to AI's historical development but lacking sufficient evidence for explicit classification. The three-category measure describes composition; binary selection models contrast explicit AI with adjacent-computational and no-AI-evidence projects.

After reliability screening, the retained constructs were AI relevance, AI subdomain, application domain, technical sophistication, explicit first-of-kind status and output orientation. First-of-kind status was coded from project content rather than project year, so period and technological character remain analytically independent. Technical sophistication was treated as ordered. Strategic intent, scaling, commercial uncertainty and infrastructure building were excluded from principal inference because validation did not reach the prespecified threshold.

3.4 Coding reliability and analytical restriction

Automated coding was validated against 50 manually reviewed projects. Exact agreement and Cohen's kappa were reported with bootstrap confidence intervals based on 2,000 resamples. Table 1 summarises the comparison between the automated and manual coded records. A threshold of kappa of at least .40, interpreted alongside exact agreement and prevalence, admitted the six retained constructs. Strategic-intent disagreement largely reflected a taxonomy mismatch, but the variable remained excluded because automated and manual labels were not directly comparable.

Table 1. Manual validation of retained automated coding.

Variable	n	Exact agreement [95% CI]	Kappa [95% CI]
AI relevance	50	88.0% [80.0, 96.0]	.733 [.539, .909]
AI subdomain	50	70.0% [58.0, 82.0]	.620 [.455, .770]
Application domain	50	56.0% [42.0, 70.0]	.485 [.331, .637]
Technical sophistication	50	68.0% [54.0, 80.0]	.451 [.251, .652]
Explicit first-of-kind	50	92.0% [84.0, 98.0]	.459 [-.050, .854]
Output orientation	50	80.0% [68.0, 92.0]	.450 [.215, .694]

Note. Confidence intervals are bootstrap intervals. Kappa is interpreted alongside exact agreement because some positive categories are uncommon.

3.5 Measures

The primary outcome for H1, H4 and H5 was explicit-AI classification. H2 used ordered technical sophistication and binary first-of-kind status among explicit-AI projects. H3 used institutional concentration, participation and first-entry measures. Output orientation distinguished market-facing products or services from internal, mixed and enabling outputs.

Prior KTP experience was reconstructed from the full GtR+ organisational history rather than only from the 3,158-project analytical archive. Candidate projects were identified from programme, grant-category and title fields. The final administrative rule retained projects when the programme was 'Knowledge Transfer Partnerships' or the grant category was 'Knowledge Transfer Partnership'. This produced 3,975 confirmed projects, 3,941 KB-project pairs and 281 KB organisations. The small number of projects involving two KBs (infrequently occurring in the records, typically where a PI transfers between KBs during project delivery) were retained as two legitimate KB-project pairs.

For each focal project, earlier projects at the same validated KB were counted only when they preceded the focal project. An audit identified material disagreement between some linked GtR start dates and KTP archive years: 80 records differed by more than one year and 10 by more than five years. Temporal ordering therefore used the KTP archive start year consistently, assigning 1 January of that year to the focal project. This conservative rule excludes projects beginning in the same calendar year from being included as prior experience.

The principal look-back period was five years. Continuous GtR+ KTP coverage was treated as beginning on 1 January 2010, so complete five-year windows were available for focal projects from 2015. Prior explicit-AI experience counted confirmed explicit-AI projects within that common history. Prior other KTP experience comprised all remaining earlier KTPs in the window, including projects without sufficient narrative coding to confirm explicit AI. The term 'other', rather than 'non-AI', is deliberate. Ten-year counts were retained descriptively, but only

ten focal projects had complete ten-year windows, and the measure was not suitable for the principal model.

Institutional entry was a KBs first observed explicit-AI KTP project. The annual entry series begins after a burn-in period through 2012, allowing earlier projects to establish prior participation. Concentration was measured as the top-ten share and a Gini coefficient using two denominators: KBs active in explicit-AI work and all KBs active in KTPs in the period. KB Mission group membership and project calendar year were included in the selection model. Funding, duration and region were documented where available, but a common extended model was not investigated because duration was not available in the Stage 6 master specification and forcing controls would change the model sample and comparability.

3.6 Coverage

Figure 1 summaries the data coverage available to this study. Coverage exceeded 97% for all retained content-coding variables. Validated KB identity and mission group were observed for approximately 70% of projects. Complete five-year experience measures were available for 1,056 projects (33.4%), reflecting both the validated KB requirement and the 2015 start of complete history windows. Coverage was weaker before 2011 but exceeded approximately 90% for most years from 2012 onwards. Concentration and entry are therefore interpreted as patterns among observed participating KBs rather than as a census of all historical institutional activity.

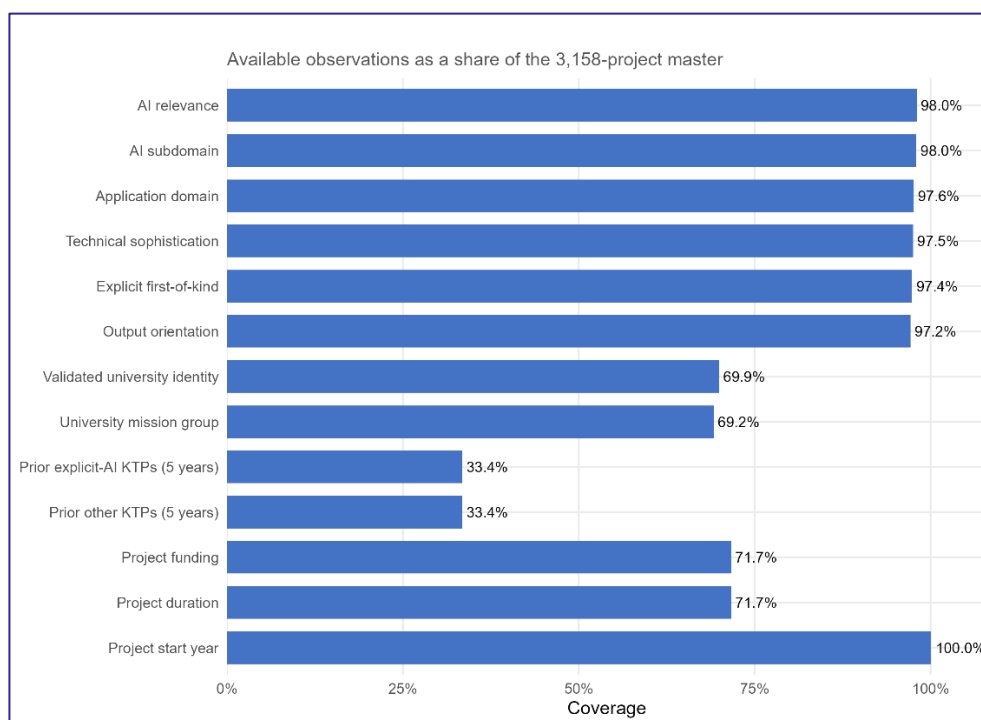


Figure 1. Project and variable coverage across the analytical pipeline.

Figure 2 shows the distribution of AI relevance across the full archive with 12.5% (387 out of 3095 records) being identified as being explicitly related to AI.

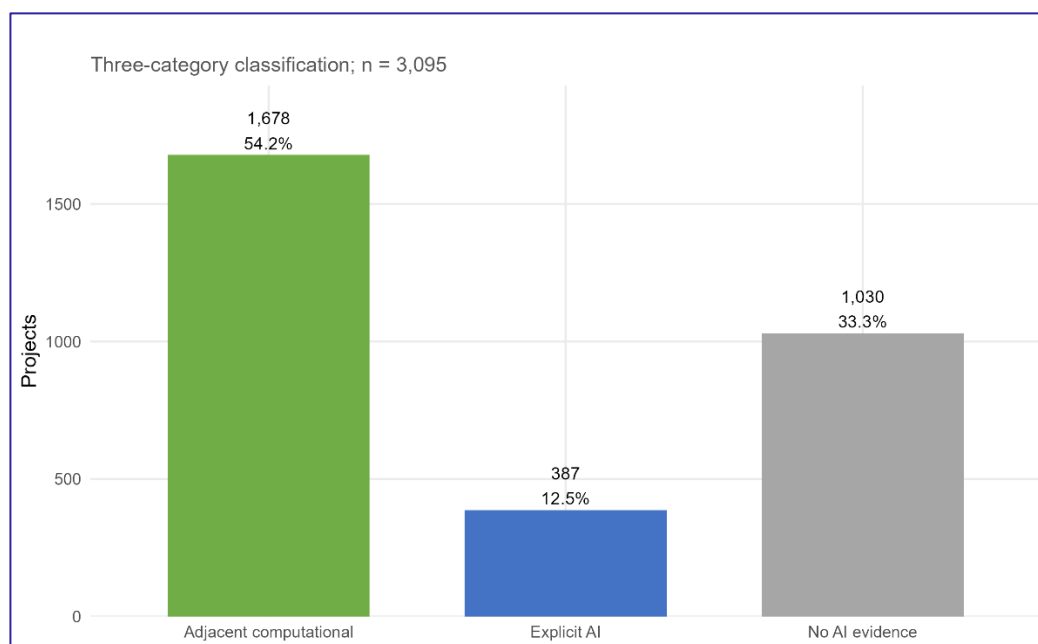


Figure 2. Distribution of AI relevance across the full archive.

3.7 Estimation and reporting

Compositional analyses report counts, denominators, proportions and confidence intervals. Pearson chi-square tests combined with Cramer's V provide categorical association. Monte Carlo Fisher tests are used only when expected counts are sparse. Ordered technical sophistication is compared across periods using Kruskal-Wallis analysis. Binary outcomes are estimated with mean bias-reduced logistic regression; continuous predictors are standardised within the complete-case model sample and coefficients are reported as odds ratios with 95% confidence intervals.

Tests accompanying descriptive tables are reported as reference statistics rather than treated uniformly as confirmatory inference. Confirmatory interpretation is concentrated on the H4-H5 selection model. All effects are described as associations. The workflow is scripted in R, original and recovered references are stored separately, manual overrides are versioned outside the master, and the full-GtR+ history construction is preserved in sequential audit outputs.

4. Results

4.1 The changing composition of computational engagement

Figure 3 shows the change in composition of AI relevance over the three time periods; pre-2012 precursor, 2012-2017 deep learning growth, 2018-21 applied AI diffusion. These periods were chosen to cluster projects in the overall study period. The sample size in each of these periods is shown in Table 2.

H1 was supported. Explicit AI increased much faster than the broader computational category. Across the three periods, explicit-AI projects accounted for 5.5% (65/1,191), 13.4% (198/1,478) and 29.1% (124/426) of projects. Explicit plus adjacent computational activity rose more modestly from 61.0% to 69.6% and 72.8%. The association between period and the three-category classification was statistically significant, $\chi^2(4) = 172.68$, $n = 3,095$, $p < .001$, Cramer's $V = .167$. All expected counts exceeded five, so a Fisher sensitivity test was not required.

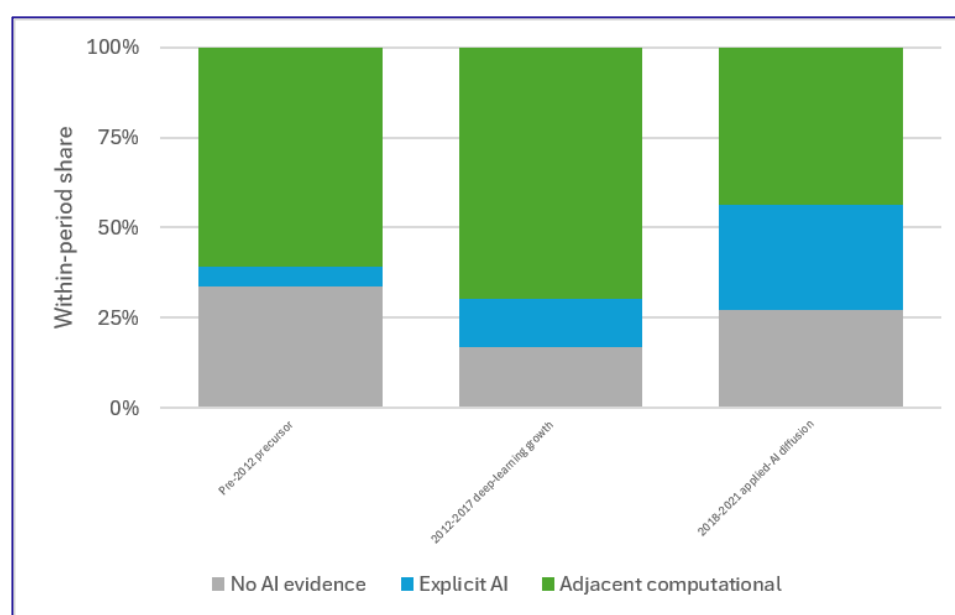


Figure 3. AI relevance by technological period.

Table 2. Computational engagement across technological periods

Period	Projects	Explicit AI	Explicit + adjacent computational
Pre-2012 precursor	1,191	65 (5.5%)	726 (61.0%)
2012-2017 deep-learning growth	1,478	198 (13.4%)	1,029 (69.6%)
2018-2021 applied-AI diffusion	426	124 (29.1%)	186 (72.8%)

Note. Period and three-category AI relevance: $\chi^2(4) = 172.68$, $n = 3,095$, $p < .001$, Cramer's $V = .167$.

Figure 4 shows the annual explicit-AI share overlaid on the combined explicit AI-plus-adjacent computational project share. The annual series is shown through 2019, the last year before project counts fall sharply due to a partial record in the source data. Explicit AI rose from approximately 4-7% during 2009-2012 to 11.6% in 2014, 18.6% in 2016 and 29.2% in 2019. Combined computational engagement remained much higher and reached 81.2% in 2019. This indicates a compositional shift within an already computationally intensive programme rather than a simple appearance of computation where none existed previously.

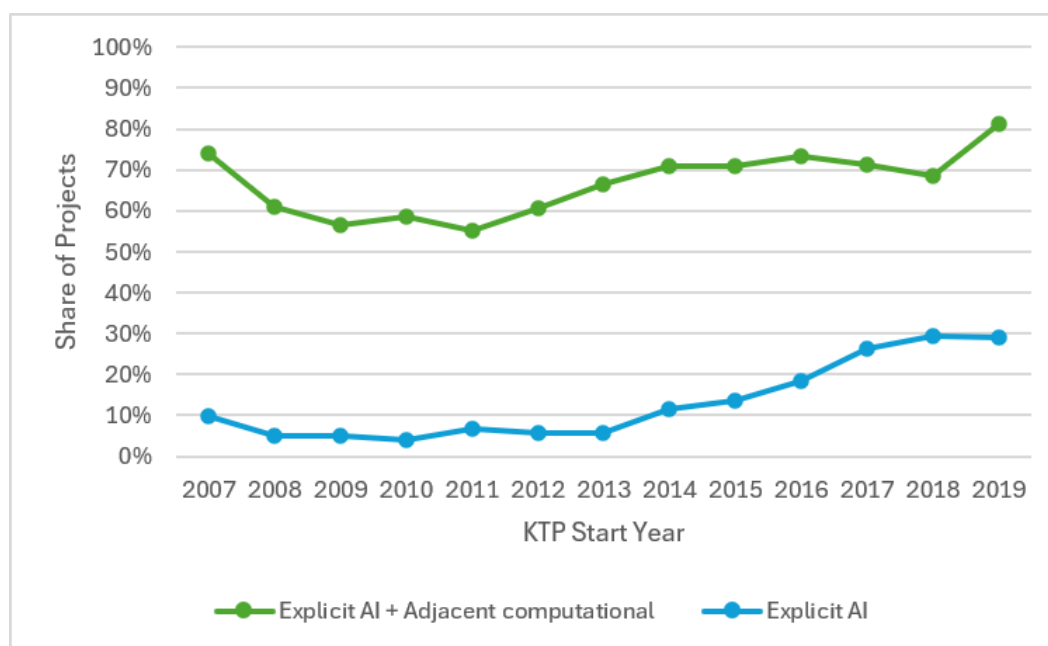


Figure 4. Annual explicit-AI and combined computational engagement, 2007-2019.

4.2 Persistence of novelty and technical sophistication

H2 was not supported. Among explicit-AI projects, the highest technical-sophistication category (3) increased from 26.2% in the precursor period to 41.4% in 2012-2017 and 45.1% in 2018-2021. Category 2 projects, the next lowest technical level, declined correspondingly from 72.3% to 57.6% and 53.3%. Period differences in the ordered distribution were statistically significant, Kruskal-Wallis $H(2) = 6.40$, $n = 385$, $p = .041$. Figure 5 shows the ordered category shares by period. Figure 6 shows annual category shares for years with adequate explicit-AI counts. The evidence indicates persistence and, if anything, an upward shift rather than a decline in technical sophistication.

First-of-kind claims, shown in Figure 7, were uncommon and non-monotonic: 12.3% (8/65), 7.6% (15/197) and 10.6% (13/123). The overall association was not significant, chi-square(2) = 1.59, $n = 385$, $p = .452$, $V = .064$. Bias-reduced linear and quadratic period contrasts were also non-significant. With only 36 positive cases, the test has limited power. The defensible conclusion is that no decline was observed, not that a decline cannot exist. Together, the two indicators show that diffusion in explicit-AI volume coexisted with continued technical ambition.

Table 3 and

Table 4 provide a summary of the data.

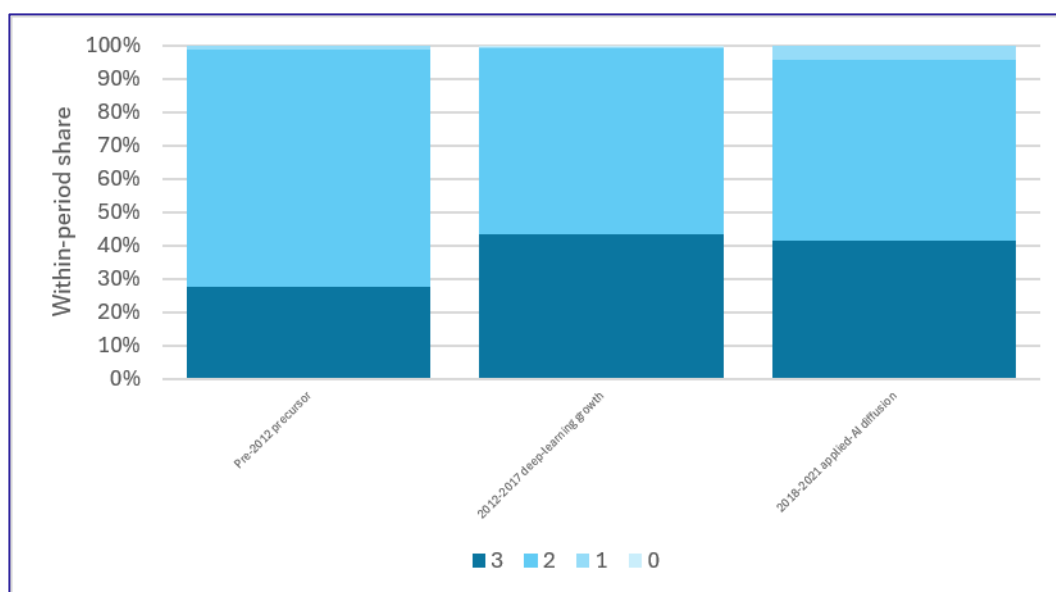


Figure 5. Technical sophistication (0-3) of explicit-AI projects by period.

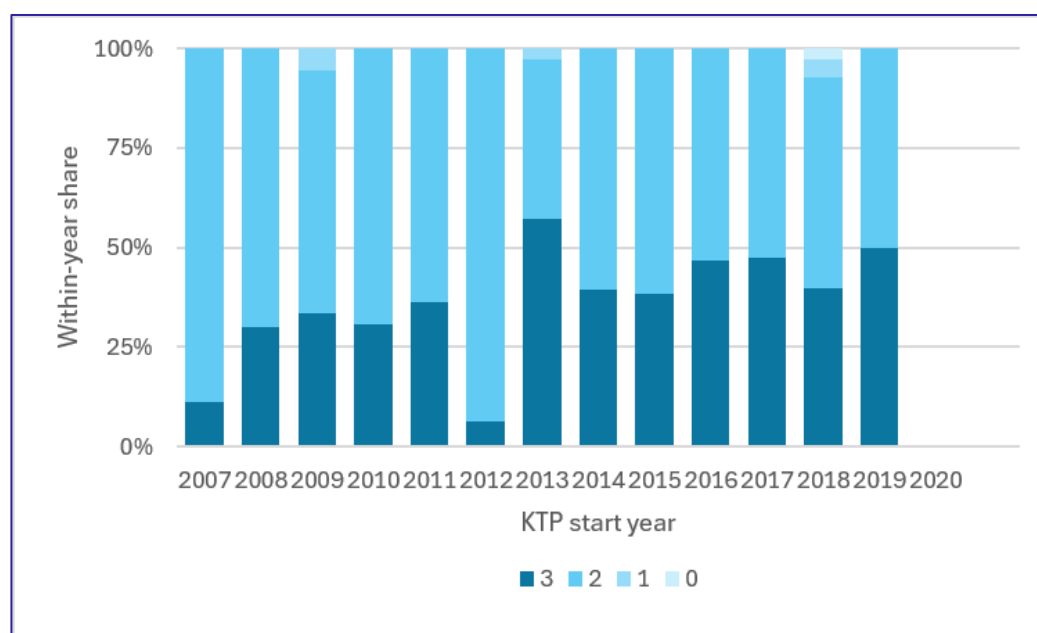


Figure 6. Annual technical-sophistication (0-3) distribution among explicit-AI projects.

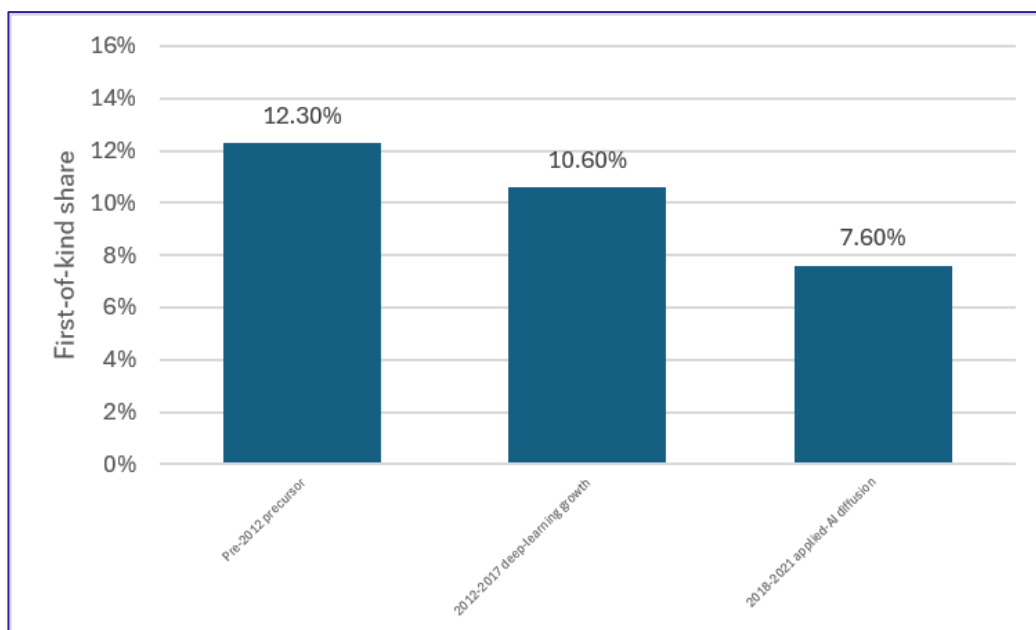


Figure 7. Explicit first-of-kind share among explicit-AI projects by period.

Table 3. Technical sophistication among explicit-AI projects

Period	Level 0-1	Level 2	Level 3	n
Pre-2012 precursor	1 (1.5%)	47 (72.3%)	17 (26.2%)	65
2012-2017 growth	2 (1.0%)	114 (57.6%)	82 (41.4%)	198
2018-2021 diffusion	2 (1.6%)	65 (53.3%)	55 (45.1%)	122

Note. Kruskal-Wallis $H(2) = 6.40$, $n = 385$, $p = .041$.

Table 4. Explicit first-of-kind claims among explicit-AI projects

Period	First-of-kind n	Explicit-AI n	Share
Pre-2012 precursor	8	65	12.3%
2012-2017 growth	15	197	7.6%
2018-2021 diffusion	13	123	10.6%

Note. chi-square(2) = 1.59, $n = 385$, $p = .452$, Cramer's $V = .064$.

4.3 Concentration and entry among participating KBs

4.3.1 Knowledge Base

H3 was partially supported. Figure 8 shows the top-ten share under the AI-active and all-KTP-active denominators. The percentage share of projects undertaken by the top-ten KBs active in the explicit-Ai category fell sharply from 61.3% in the precursor period to 36.4% in 2012-2017, before increasing moderately to 40.7% in 2018-2021. When all KTP-active KB formed the denominator, the Gini coefficient for explicit-Ai project counts fell from .820 to .656 and .643. These patterns indicate substantial broadening beyond the initial base, but not a monotonic fall in every concentration indicator.

The number of KBs observed undertaking explicit-AI projects increased from 23 in the precursor period, to 74 in 2012-2017, and then stood at 58 in 2018-2021. Figure 9 shows the annual active KBs and first-time entrants after the initial 'burn-in' period described in 3.3 Coding of AI and technological character. First-time engagement in explicit-Ai projects was high in 2013 (12 of 15 active KBs, 80.0%) and generally declined to 4 of 31 (12.9%) in 2019, with a temporary rise in 2017. A total of 89 KBs (61% of the 144 active organisations in KTP in the study period) engaged in Ai projects. Broadening therefore occurred during the transition into the explicit-Ai growth period (2013 onwards) and was followed by consolidation rather than a continuously rising entrant share potentially reflecting the availability of Ai capabilities within the participating knowledge organisations.

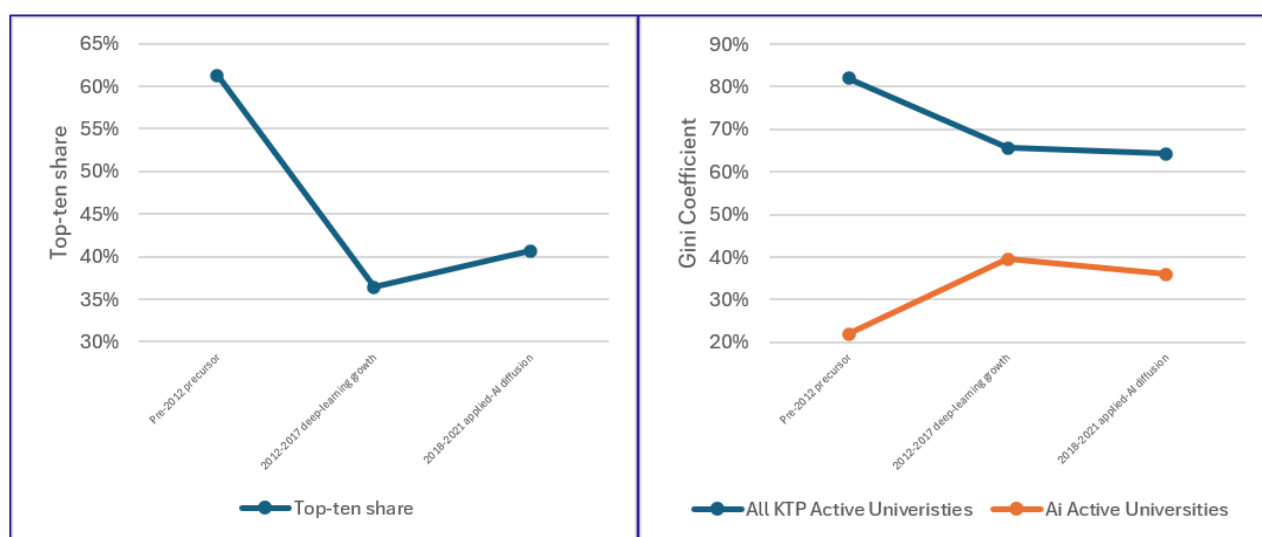


Figure 8 . Top-ten share and Gini concentration of explicit-AI projects by period.

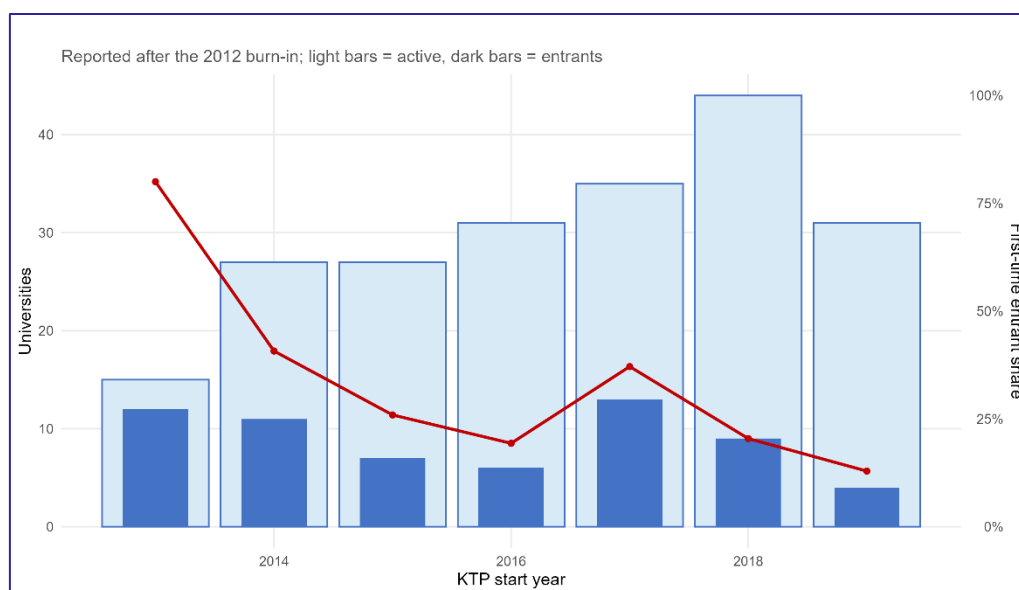


Figure 9. Annual active explicit-AI KBs and first-time entrants after the 2012 burn-in

Mission-group composition was comparatively stable across the study period. Figure 10 shows that Russell-group institutions represented 35.5%, 26.5% and 30.8% of explicit-AI projects with observed grouping. MillionPlus or University Alliance institutions represented 19.4%, 24.3% and 24.8%, while unaffiliated institutions remained the largest category. Of the unaffiliated institutions, 3 (3% of the 85 institutions undertaking AI projects) were not Universities, participating in 3 (0.7%) of the AI projects. The broadening pattern is best described as expansion across many KBs than a transfer of engagement between institutional mission groups. Table 5 provides the Explicit Ai data in the context of all active KTP KBs.

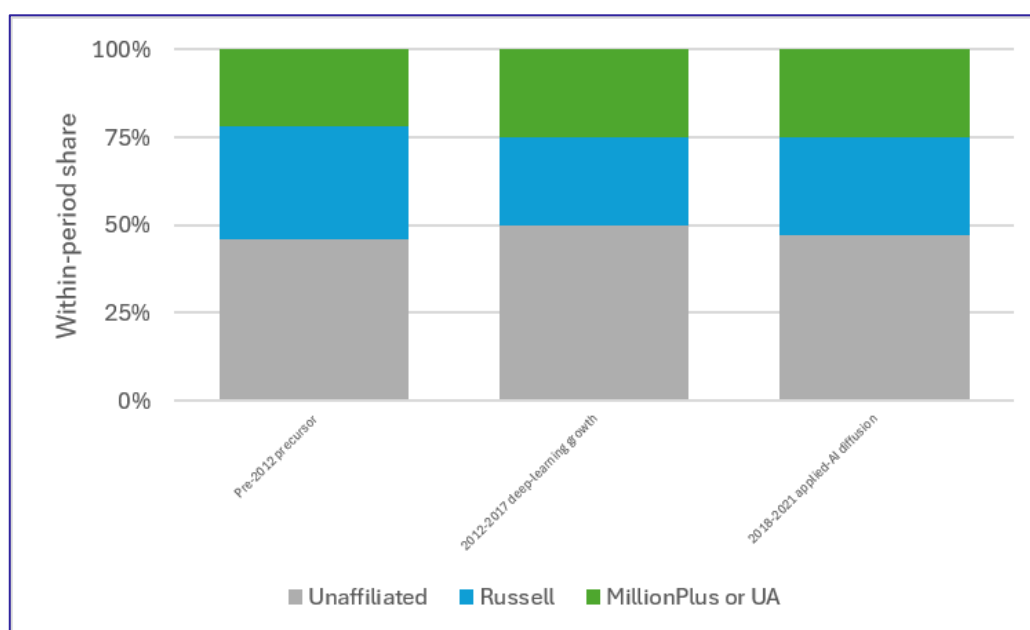


Figure 10. Mission-group composition of explicit-AI projects by period.

Table 5. Institutional breadth and concentration of explicit-AI KTPs

Period	All KTP-active KBs	Explicit-AI KBs	Top-ten share	Gini
Pre-2012 precursor	95	23	61.3%	.820
2012-2017 growth	129	74	36.4%	.656
2018-2021 diffusion	105	58	40.7%	.643

Note. The Gini uses all KBs active in KTPs in the period; KBs with no explicit-AI project receive zero.

4.3.2 Company Partner

Figure 11 shows the company participation in explicit-AI KTP periods across the whole study period. Most of the companies (93%) participated in a single explicit-Ai project. Just 25 companies (7%) participated in more than one project. Of these 25 companies, 16 were with the same KB partner, with both companies participating in three Ai projects doing so with the same KB partner.

Figure 12 shows the company size in the partnerships engaging in explicit-AI projects. Company size was determined by employee head count according to the EU size definition currently used by Innovate UK. Participation in AI projects was broad based across all size categories across all periods but with the participation of both micro and small companies increasing over the period. In line with the overall programme experience more than 75% of explicit-Ai projects were undertaken by micro and SME businesses across all three time periods.

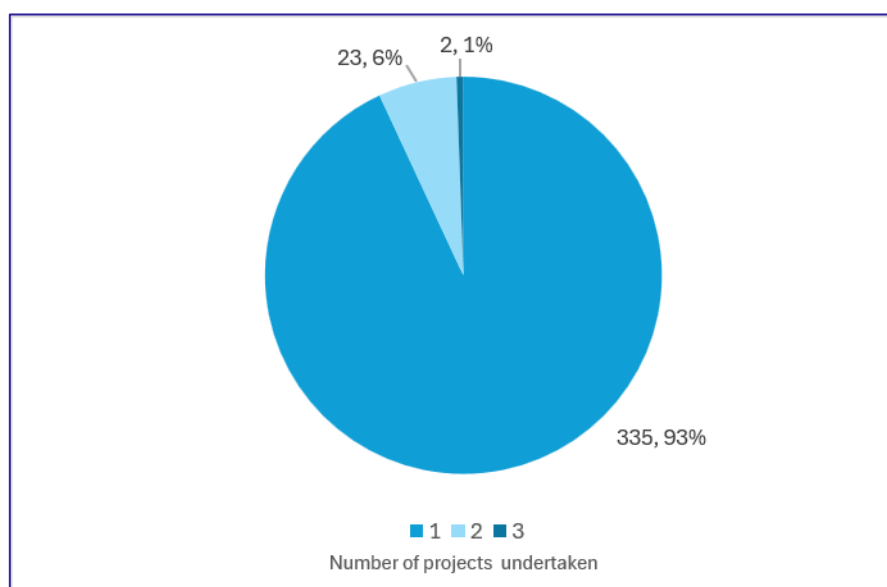


Figure 11. Company participation in Explicit Ai KTP projects.

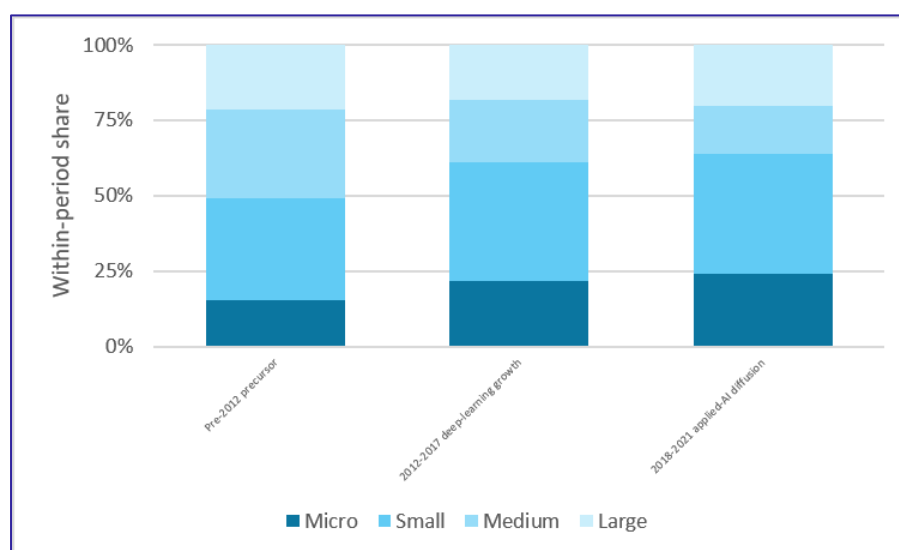
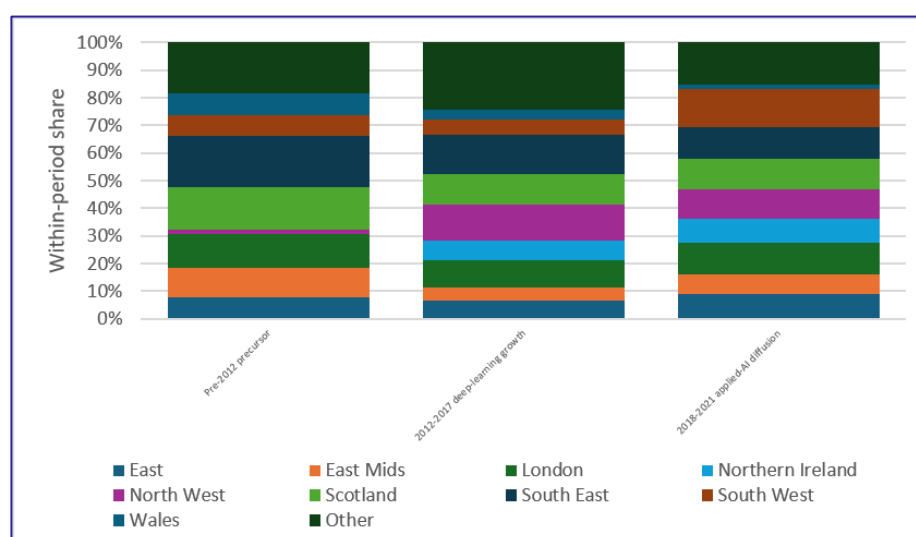
Figure 12. Participation in explicit-AI projects by company size.

Figure 13 shows the regional distribution of explicit-AI projects over the three periods considered. A broad-based regional engagement can be observed from the earliest period, with regional participation continuing to broaden as project volumes increase in post 2018 period.

**Figure 13 Regional distribution of explicit-AI projects.**

4.4 Domain-specific and general institutional experience

H4 and H5 were supported in the revised bias-reduced logic model. The model used 1,043 projects with observed KB grouping and complete five-year GtR+ history, including 245 explicit-AI projects. Prior explicit-AI and prior other KTP counts were entered together and standardised within the model sample. The distribution period of these projects is shown in Figure 14. Their Pearson correlation was .372 and Spearman correlation was .560. Variance-inflation factors ranged from 1.09 to 1.46, indicating no problematic collinearity.

A one-standard-deviation increase in prior explicit-AI KTP experience was associated with 36.8% higher odds of an explicit-AI focal project (OR = 1.368, 95% CI [1.165, 1.605], $p < .001$). Prior other KTP experience was associated with lower odds (OR = .765, 95% CI [.630, .927], $p = .006$). This is a conditional specialisation result: among KBs with equivalent AI-specific histories, larger portfolios of other KTP activity did not mean that they were more likely to undertake an explicit-Ai project. Figure 15 shows the odds ratios and confidence intervals from the selection model. The data is summarised in Table 6.

Mission group was not independently associated with entry. Relative to MillionPlus or University Alliance institutions, Russell-group universities had OR = .801 (95% CI [.515, 1.247], $p = .326$) and unaffiliated institutions had OR = .958 (95% CI [.659, 1.392], $p = .821$). The result supports the domain-specific formulation of absorptive capacity: related accumulation mattered more than broad institutional status or general collaborative throughput.

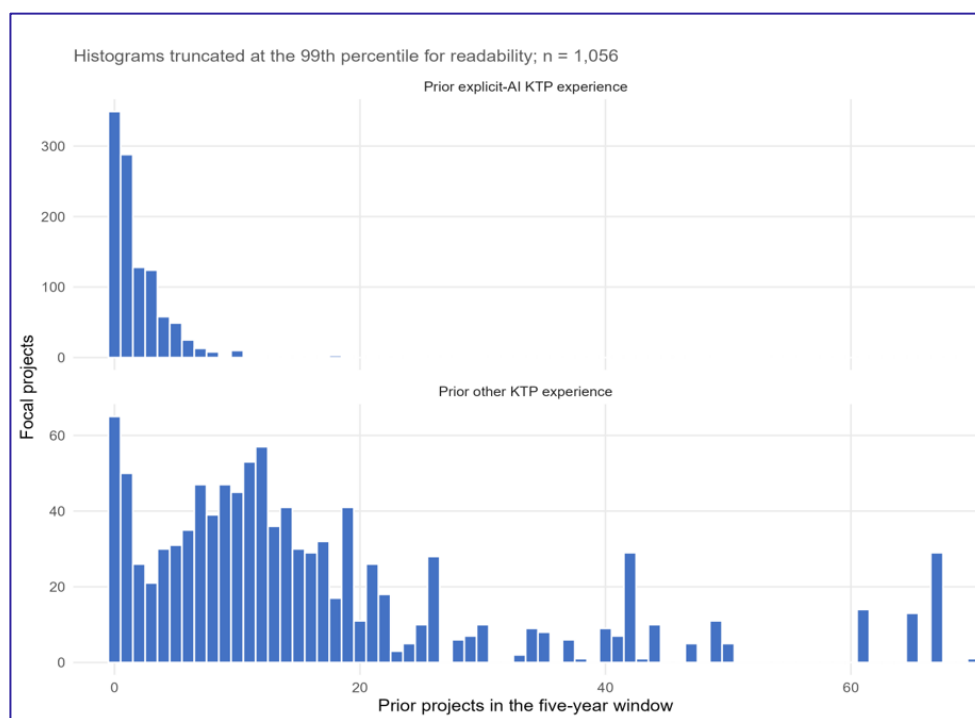


Figure 14. Distributions of five-year prior explicit-AI and prior other KTP experience.

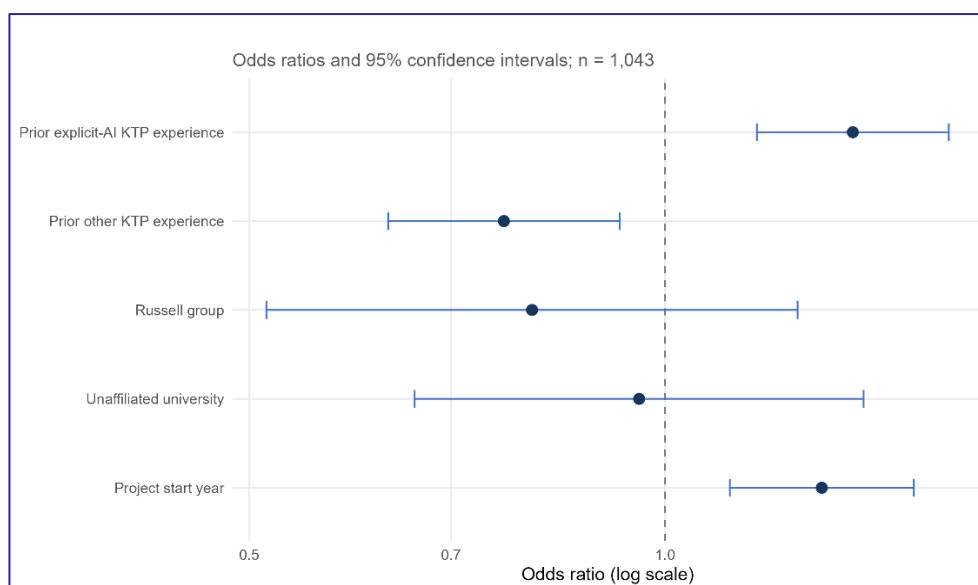


Figure 15. Bias-reduced logistic model of explicit-AI entry: odds ratios and 95% confidence intervals.

Table 6. Bias-reduced logistic model of entry into explicit-AI KTPs

Predictor	OR [95% CI]	p
Prior explicit-AI KTP experience	1.368 [1.165, 1.605]	<.001
Prior other KTP experience	.765 [.630, .927]	.006
Russell group	.801 [.515, 1.247]	.326
Unaffiliated KB	.958 [.659, 1.392]	.821
Project start year	1.299 [1.114, 1.514]	<.001

Note. n = 1,043; explicit-AI events = 245. Continuous predictors were standardized. Reference mission group: MillionPlus or University Alliance.

4.5 Output orientation across subdomains and institutions

The group of Explicit-AI KTP projects were predominantly focused on creating market-facing capabilities across technical and institutional categories. Ai application subdomains of Automation and Control, Data Modelling, Language and Knowledge (e.g. LLMs), Optimisation and Search, and Perception (e.g. Machine Vision) were classified. The market-facing share in each of these sub-domains ranged from 70.6% for data modelling to 85.9% for perception. Figure 16 shows these proportions along with 95% confidence intervals.

The same uniformity appeared across mission groups. Market-facing shares were 72.5% for MillionPlus or University Alliance projects, 75.8% for Russell-group projects and 74.4% for unaffiliated projects. Figure 17 shows the group proportions and confidence intervals. Rather

than treating these as isolated null results, the pattern is interpreted as a property of the KTP funding requirements where particular emphasis is placed on business growth: knowledge transfer activity, in this case in explicit-Ai activities being tied to commercial or service-oriented organisational objectives regardless of subdomain or mission group.

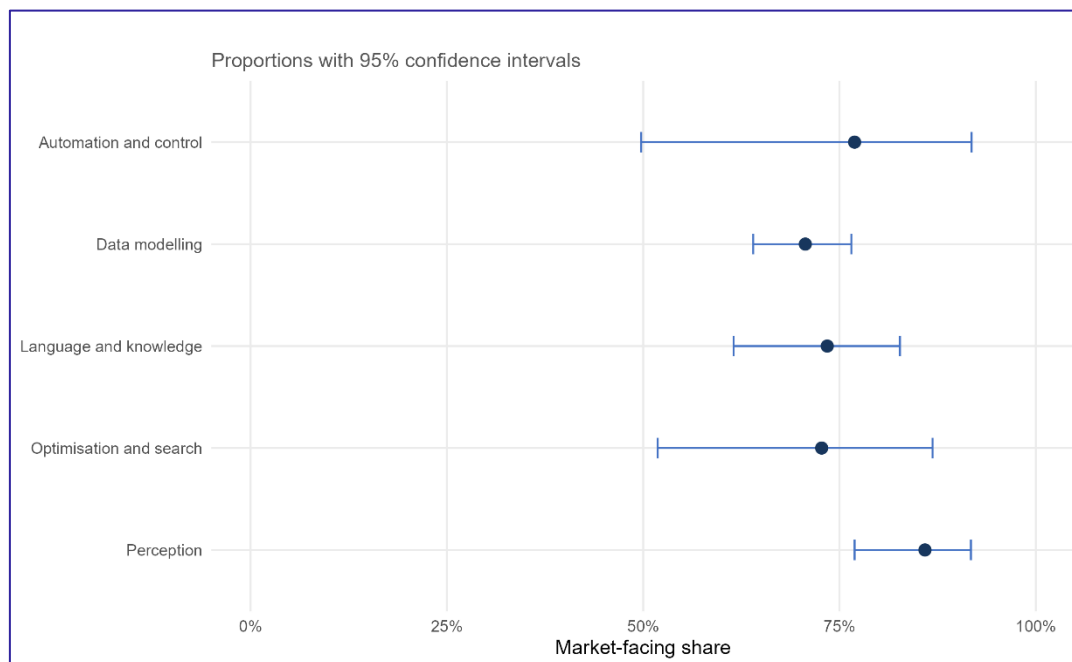


Figure 16. Market-facing output orientation by AI subdomain with 95% confidence intervals.

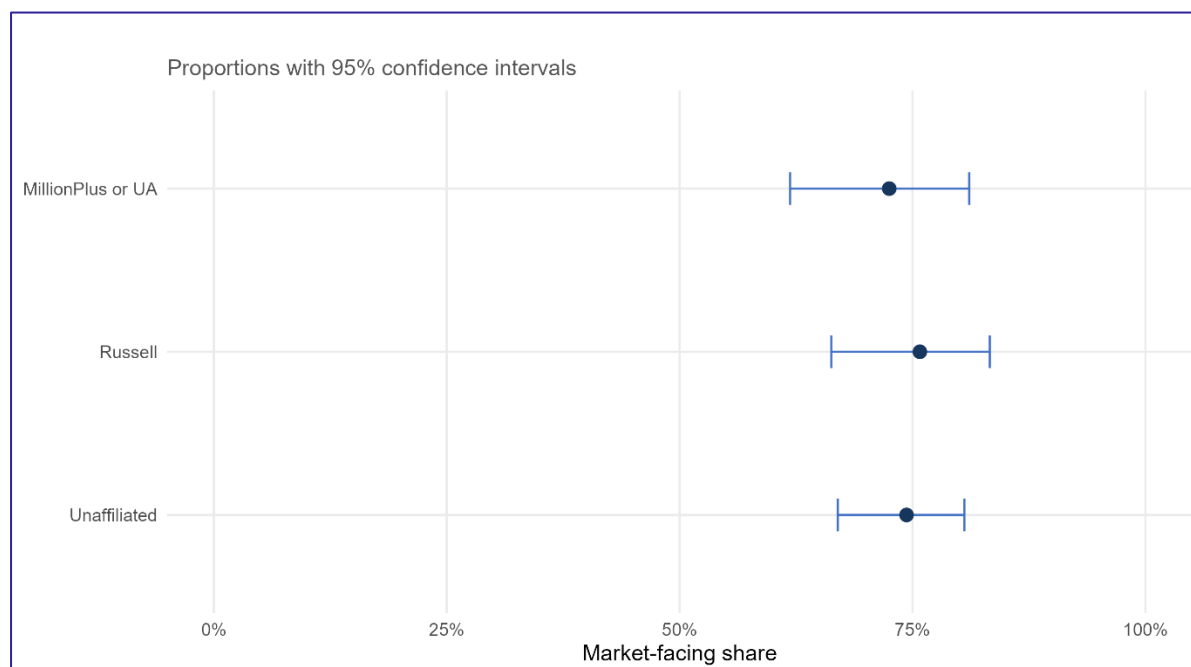


Figure 17. Market-facing output orientation by KB mission group with 95% confidence intervals.

Table 7. Market-facing output orientation by AI subdomain

AI subdomain	Market-facing n/N	Share	95% CI
Automation and control	10/13	76.9%	[49.7, 91.8]
Data modelling	142/201	70.6%	[64.0, 76.5]
Language and knowledge	47/64	73.4%	[61.5, 82.7]
Optimisation and search	16/22	72.7%	[51.8, 86.8]
Perception	73/85	85.9%	[76.9, 91.7]

Note. Omnibus chi-square(12) = 9.42, $p = .667$, Cramer's $V = .090$; Monte Carlo Fisher $p = .554$.

Table 8. Market-facing output orientation by mission group

Mission group	Market-facing n/N	Share	95% CI
MillionPlus or University Alliance	58/80	72.5%	[61.9, 81.1]
Russell group	72/95	75.8%	[66.3, 83.3]
Unaffiliated	116/156	74.4%	[67.0, 80.6]

Note. Omnibus chi-square(6) = 6.12, $p = .410$, Cramer's $V = .096$; Monte Carlo Fisher $p = .461$.

4.6 Summary of hypothesis outcomes

Table 9 summarises the outcomes of the hypotheses made at the outset of this study and described in Section 2.

Table 9. Summary of hypothesis outcomes

Hypothesis	Decision	Evidence
H1	Supported	Explicit AI rose from 5.5% to 29.1%; broader computational engagement rose more modestly.
H2	Not supported	First-of-kind claims were non-monotonic and sophistication shifted upward.
H3	Partially supported	Concentration fell strongly after the precursor period, followed by consolidation rather than continuous entry.
H4	Supported	Prior explicit-AI KTP experience was positively associated with explicit-AI entry.
H5	Supported	Prior other KTP experience was negative and mission-group effects were null.

Note. Findings are associational. H3 captures early broadening followed by consolidation.

5. Discussion

This study asked two questions of the KTP archive. The first was how the technological composition of AI-related activity changed between 2007 and 2021, and whether volume, technological character and institutional base moved together in the way that diffusion theory predicts. The second was what kind of institutional experience predicted entry into explicit-AI collaboration. The answer to the first is that explicit AI grew rapidly as a share of the programme, but that this growth was compositional, occurring within a portfolio that was already computationally intensive, and that it was not accompanied by any movement towards routine work. The answer to the second is that entry was predicted by related prior experience and not by general collaborative throughput or institutional status. The remainder of this section takes each finding in turn, sets out what was observed, considers the interpretations available and draws out what follows for theory and for programme design.

5.1 Reading the measures

Before interpretation, it is worth restating what the measures represent, because the argument depends on treating three aspects of diffusion separately. Volume is the share of projects in a period that were coded as explicit AI, and it is read against the combined share of explicit and adjacent computational projects, which shows whether AI was arriving in a programme that had little computational content or was emerging from within one that already had a great deal. Character is captured by two indicators among explicit-AI projects only. Technical sophistication is an ordered scale from 0 to 3 in which category 3 denotes the most technically demanding work [insert one clause from the coding scheme defining category 3 and category 2]. First-of-kind status records whether the project narrative made an explicit claim that the work was the first of its type for the company, the sector or the technology. A shift of activity from category 3 towards category 2, or a fall in first-of-kind claims, would indicate that AI work was becoming more routine. Base is captured by three indicators of who was doing the work. The top-ten share is the proportion of explicit-AI projects undertaken by the ten most active knowledge bases in a period. The Gini coefficient measures how unevenly explicit-AI projects were distributed across all knowledge bases active in KTP in that period, with zero denoting equality and one denoting complete concentration. First-time entry records the year in which a knowledge base undertook its first observed explicit-AI project.

The second research question uses two counts and one categorical variable. Prior explicit-AI experience is the number of explicit-AI KTPs undertaken by the same knowledge base in the five years before the focal project. Prior other KTP experience is the number of all other KTPs in that window, including those whose narratives were too sparse to classify. Mission group, with categories of Russell Group, MillionPlus or University Alliance, and unaffiliated, is used as an aggregate proxy for broad institutional research intensity in the absence of data on the individual academics involved. Odds ratios above one indicate that a one standard deviation

increase in the count raised the likelihood that a focal project was explicit AI, and ratios below one indicate that it lowered that likelihood.

5.2 Volume: a compositional shift within a computational programme

Explicit-AI projects rose from 5.5 per cent of awards in the precursor period to 13.4 per cent in 2012-2017 and 29.1 per cent in 2018-2021, reaching 29.2 per cent of the annual series in 2019. Over the same interval the combined computational share rose only from 61.0 per cent to 72.8 per cent. Explicit AI was already visible in the archive in 2008, which suggests that the earliest business engagement with the topic predates the data.

Two readings of the rise in explicit AI were available at the outset. One is that firms began to seek a computational capability that they had not previously sought. The other is that analytical work already under way, in expert systems, optimisation, decision support and predictive modelling, was progressively re-described in AI terms as the label acquired currency. The comparison with the combined share favours the second reading in part but not entirely. Had the growth in explicit AI been wholly new capability, the combined share would have risen by a comparable amount. Had it been wholly re-labelling, the combined share would have been flat. The observed pattern, a large rise in the explicit share against a modest rise in the combined share, indicates that most of the growth occurred through the conversion of adjacent computational engagement into explicitly AI related engagement, with a smaller increment of genuinely new computational demand. This is what a cross-sectional adoption survey cannot see. A survey conducted in 2019 would record a high AI adoption rate without being able to say that a majority of the firms concerned had been doing closely related work under a different name for a decade.

The programme setting matters for this result. KTP is technology-agnostic and demand-led, and the company contributes to the cost of each project, so the subject of a project reflects a commercial judgement by the firm rather than a policy steer. The shift towards explicit AI therefore records a change in what firms thought they needed and were prepared to invest in. It also shows that an open programme registers such changes early, since AI was present in the record roughly a decade before dedicated UK AI policy. This point is developed in Section 5.6.

5.3 Character: diffusion without routinisation

Diffusion theory anticipates that as adoption spreads the character of adopted work moves from development towards adaptation and routine use, which was the basis for H2. The archive shows the opposite. Among explicit-AI projects the share in the highest sophistication category rose from 26.2 per cent in the precursor period to 41.4 per cent and then 45.1 per cent, while category 2 fell correspondingly from 72.3 per cent to 53.3 per cent. First-of-kind claims were uncommon throughout, at between 8 and 12 per cent, and showed no trend. With only 36 positive cases the first-of-kind test has limited power, so the defensible statement is that no

decline was observed rather than that none occurred. Taken together, the two indicators show that the tripling of explicit-AI volume coexisted with rising, not falling, technical ambition.

Three explanations deserve consideration. The first is that the technological frontier moved with the adopting population. Deep learning after 2012 and applied machine learning after 2017 created new capabilities faster than earlier ones could become routine, so firms continued to reach for the most recent developments even as the number of firms doing so grew. The second is selection by the programme. KTP assessment has consistently favoured innovative projects that require skills primarily held in the knowledge base, and a project proposing to adapt an established tool would be less likely to be funded. On this reading the absence of routine work in the archive reflects what the programme admits rather than what firms wanted. The third is that the sophistication coding captures the ambition described in the narrative rather than the difficulty of what was delivered, and narratives may have grown more ambitious in tone as AI became fashionable. The validation exercise reported in Section 3 gives some protection against the third explanation, since sophistication coded reliably against manual review. The first two explanations are not mutually exclusive and cannot be separated in these data. Both, however, lead to the same conclusion for the diffusion account: within this instrument, volume and character moved independently, and expansion did not entail routinisation.

The implication for policy is symmetrical. If the frontier explanation holds, KTP remained a frontier instrument for AI throughout the period and there is no basis in the evidence for assuming that AI activity should migrate to lighter-touch support as adoption widens. If the selection explanation holds, then adaptation and re-use by less ambitious firms is not being served by KTP at all, and a complementary instrument would be needed if wider adoption among such firms were a policy aim. Either way, the finding that a technology can spread without maturing out of a frontier instrument is one that programme designers should take into account.

5.4 Base: early broadening, later consolidation

H3 anticipated that the population of institutions undertaking AI work would broaden continuously as the explicit share rose. The evidence supports the first half of this expectation and qualifies the second. The top-ten share of explicit-AI projects fell sharply from 61.3 per cent in the precursor period to 36.4 per cent in 2012-2017, and the Gini coefficient across all KTP-active knowledge bases fell from 0.82 to 0.66. The number of knowledge bases active in explicit AI rose from 23 to 74. Broadening was therefore substantial and rapid at the point where explicit AI began to grow. In the final period, however, the top-ten share rose moderately to 40.7 per cent, the number of active knowledge bases fell to 58, and the first-time entrant share of active knowledge bases declined from 80 per cent in 2013 to 13 per cent in 2019. Broadening was followed by consolidation. Over the whole period 89 of the 144 knowledge bases active in KTP, or 61 per cent, undertook at least one explicit-AI project.

The most plausible mechanism is saturation. The set of UK institutions holding computational capability that could be transferred to a company partner is finite, and the early entrants are likely to have been those with the most readily accessible capability. As that pool was drawn down, the rate of new entry fell, and activity settled among institutions that had already established a track record. Two features of the base support this interpretation over an alternative in which engagement transferred between kinds of institution. Mission-group composition was stable across the three periods, with Russell Group institutions accounting for between 27 and 36 per cent of explicit-AI projects and MillionPlus or University Alliance institutions for between 19 and 25 per cent, so broadening occurred across many institutions rather than from one group to another. Regional participation was broad from the precursor period and continued to widen. The 23 knowledge bases active before 2012 were located across all UK regions, which indicates a latent and geographically dispersed capability that firms could reach once they had identified a need.

A second reading of the consolidation phase is worth stating because it bears on future entry. The saturation argument assumes that transferable AI capability resides in disciplines that were already computational. As AI is applied across the wider range of research activity, including the arts, humanities and social sciences, knowledge bases with no prior computational engagement may enter, and the decline in entry observed to 2019 may prove to be a pause rather than an end point. The data cannot distinguish these possibilities, and extension of the series beyond 2019 would be the natural test.

The firm side of the base shows a related pattern. Company partners of all size categories engaged in explicit-AI projects from the precursor period onwards, and micro and small firms accounted for a rising share, reaching 64 per cent of awards after 2018. This is consistent with the falling cost of AI tools and infrastructure and with the emergence of small firms formed around scarce AI skills. It coincided, however, with a change in KTP eligibility that admitted micro and start-up companies which earlier trading-history requirements had excluded, and the two effects cannot be separated. The rise in the small-firm share should therefore be read as evidence that eligibility rules shape access to knowledge transfer in an emerging technology as much as evidence of a change in demand. Most companies, 93 per cent, undertook a single explicit-AI project. Of the 25 that undertook more than one, 16 returned to the same knowledge base. One engagement appears in most cases to have established a foundation on which the firm then built without further programme support, while the minority that returned did so through an existing relationship rather than by searching the market. Whether a single engagement was sufficient to embed capability is a question the archive cannot answer, and it is taken up in Section 5.6.

5.5 Institutional experience: specialisation rather than status

The selection model addressed the second research question directly. Among the 1,043 projects with a validated knowledge base and a complete five-year history, a one standard deviation increase in prior explicit-AI KTP experience was associated with 37 per cent higher

odds that the focal project was explicit AI (OR = 1.368, 95 per cent CI [1.165, 1.605]). A one standard deviation increase in prior other KTP experience was associated with 24 per cent lower odds (OR = 0.765, 95 per cent CI [0.630, 0.927]). Mission group was not independently associated with entry once these two counts were included.

The negative coefficient on other KTP experience requires care. It does not mean that general collaborative activity reduced a knowledge base's ability to undertake AI work, and it does not mean that experienced knowledge bases were less capable than inexperienced ones. The two counts were entered together, so the comparison is between knowledge bases with equivalent AI-specific histories. Among such institutions, those whose portfolios were weighted towards other domains were less likely to produce an explicit-AI project. The contrast the model identifies is between specialisation and breadth, not between experience and inexperience. A knowledge base that had built routines for managing associates and translating academic knowledge across many projects gained no advantage in AI from those routines unless it also accumulated AI-related experience.

The null result for mission group carries the same message from a different direction. Research-intensive status indicates broad institutional capacity. It does not indicate accumulated experience of transferring AI knowledge to firms, and once that experience was measured directly, status added nothing. Two caveats apply. Mission group is a coarse proxy, and the study could not observe the individual academics involved, whose track record and career stage may matter a great deal. The result is also drawn from a single technology in a single programme. Within those limits, it supports the domain-specific formulation of absorptive capacity set out by Cohen and Levinthal (1990), in which the capacity to recognise and exploit external knowledge is grounded in prior related knowledge rather than in generic organisational capability.

The uniformity of output orientation reinforces the point that the programme, rather than the institution, shaped what was produced. Market-facing shares ranged only from 71 to 86 per cent across AI subdomains and from 73 to 76 per cent across mission groups, and neither difference approached significance. Whatever the subdomain and whatever the institution, explicit-AI KTPs were directed at commercial application because that is what KTP funds. Output orientation in this archive is therefore a property of the instrument and should not be read as evidence about the maturity of AI adoption in the wider economy.

5.6 Implications for theory

The study makes two theoretical contributions. The first concerns diffusion. Rogers' (2003) account is commonly read as a sequence in which rising volume, routinisation of content and broadening of the adopting population proceed together. The archive shows that they can be separated empirically and that, when they are, they need not move together. Volume rose steeply, character became more rather than less ambitious, and base broadened and then consolidated. The general lesson is that where a technological frontier continues to advance

during the diffusion period, the frontier moves with the adopting population, and volume-based indicators of adoption will overstate the extent to which the technology has become routine. Studies that infer diffusion stage from adoption rates alone, which includes most of the contemporary SME AI literature reviewed in Section 2, are liable to this error.

The second concerns absorptive capacity at the level of the knowledge-base institution. The literature has tended to treat absorptive capacity either as a generic organisational property or as a firm-level construct. The present result locates it at institutional level and shows that it is domain-specific: related accumulation predicted engagement, and neither collaborative throughput nor research intensity substituted for it. This has a direct bearing on how university engagement is explained. The relevant distinction is not between engaged and unengaged institutions, or between research-intensive and teaching-led ones, but between those that have and have not built experience in the specific domain that a firm is seeking.

A secondary methodological contribution follows from the validation exercise. Structured coding of archival narratives recovered explicit-AI status and technical sophistication reliably but was less reliable for more abstract constructs. This defines what a longitudinal analysis of this kind can and cannot claim, and it suggests that programme archives are a usable source for tracking the technological content of collaboration provided that constructs are chosen with this gradient in mind.

5.7 Implications for policy and practice

Six implications follow from the findings, each resting on a specific result.

First, open programmes are leading indicators. Because KTP is demand-led and technology-agnostic, explicit-AI demand appeared in the archive from 2008, roughly a decade before targeted UK AI policy. Programme design should track who participates, the technical ambition of supported projects and whether new companies and institutions continue to enter, and it should do so by routine structured coding of the narratives that the programme already collects. This would give the funder a low-cost early signal of emerging technology demand with industry, especially amongst the diverse and dispersed SME community, before it appears in adoption surveys, and it would identify major innovation trends while there is still time to respond to them.

Second, knowledge-base capability should be targeted by related experience, not by status. Prior explicit-AI KTPs raised the odds of entry; general KTP volume and mission group did not. Policy that seeks to widen the supply of institutions able to support firms in an emerging technology should seed first domain-specific engagements at knowledge bases with no such history, rather than routing support through research-intensive or high-throughput institutions on the assumption that capacity in one domain transfers to another. The technical ambition of industry-led projects should be monitored alongside this, so that knowledge-base capability is

both aligned to present industry need and nurtured to establish depth in the topics likely to form the next stage of engagement.

Third, provision should be made for entry from beyond the computational disciplines. First-time knowledge-base entry fell from 80 per cent of active institutions in 2013 to 13 per cent in 2019, consistent with saturation of the pool holding existing computational capability. Future entrants are more likely to come from disciplines newly applying AI, and eligibility and support arrangements should not presume that the relevant capability sits in computer science or engineering.

Fourth, a technology should not be assumed to mature out of the instrument. Sophistication rose as volume rose, so KTP remained a frontier instrument for AI throughout the period. There is no evidential basis for moving AI activity to lighter-touch instruments as adoption widens. Conversely, because KTP assessment selects for novelty, adaptation and re-use by less ambitious firms are not served by the programme, and a complementary instrument would be required if wider adoption among such firms were an objective.

Fifth, a follow-on route would test whether one engagement is enough. Ninety-three per cent of company partners undertook a single explicit-AI project, and those that returned mostly did so with the same knowledge base. A light-touch follow-on mechanism, together with tracking of firms' subsequent AI activity, would establish whether a single KTP embeds capability or whether the existing relationship channel is being under-used.

Sixth, accessibility is something the programme shapes as well as monitors. The micro and small-firm share of explicit-AI projects rose to 64 per cent after eligibility was widened to start-ups. Innovation does not follow a simple diffusion path, and funding programmes should evaluate their accessibility across firm sizes, regions and knowledge bases on the understanding that eligibility conditions are a direct lever on who gains access to knowledge transfer in an emerging technology.

A final implication concerns data. The study could not identify the academics involved, linkage between the Final Report archive and GtR+ was incomplete, and records before 2010 were partial. Consistent identifiers, named lead academics and retention of early records would allow open programmes to be evaluated longitudinally at very low marginal cost, and would make the kind of analysis reported here routine rather than exceptional.

6. Limitations and future research

6.1 Limitations

This study was undertaken using archival information on the delivery of the UK's KTP programme between 2007 and 2019. Archival reporting can be more complex than secondary research presenting challenges in the interpretation of available information, particularly where disclosure within the archive can be influenced by issues such as commercial confidentiality.

However, the KTP Final Report record used here was mandated by the funding body, in a standardized narrative framework, and was subsequently used by the funding body to assess and formally 'grade' project outcomes. With this critical and well managed capture of information at source it is expected that most records provide a faithful and descriptive record of each project.

It was not possible to comprehensively match the KTP Final Report and GtR+ datasets. Although an issue throughout the data range it was particularly apparent in the earliest records in the KTP Final Report dataset which predates the availability of related KTP records within the GtR+ dataset. Hence some analysis of earlier records, particularly the identification of explicit-AI projects in the record, relied solely upon the KTP Final Report dataset. Similarly, there were some minor differences in data between the two primary datasets, in fields such as project start date, which affected some records. This is likely caused by KTP projects that encountered practical issues when initiating or executing delivery (e.g. delays in associate recruitment, long-term absences of critical staff, etc.) which necessitated delayed starts or, in some cases, project restarts. A pragmatic approach to these anomalies has been adopted in the study but this may have affected some analysis, for example where disagreement over project dates spanned a reporting period (pre-2012, 2012-2017, 2018-2021).

In some cases, it was not possible to classify the nature of a KTP as explicit-AI, adjacent computational, or No AI evidence due to incomplete, sparse or incorrect narrative information. Such records are typically created within the KTP Final Report archive because of project failures, particularly when the company partner ceases trading during project execution and no staff are available to provide the company narrative contribution. This necessitated the use of the 'Other-KTP' category which was deliberately chosen to identify those records which could not be classified as AI but still could potentially be AI related. These records could provide additional contributions to the Ai record and hence impact the results and observations that have been drawn from them.

Although the principles and operational ethos of KTP have remained remarkably stable throughout its 50-year history, it has not been immune from factors that indirectly impact its delivery, and that might influence its outcomes. Over such an extended operational period, the scheme has experienced changing funding priorities, including both rapidly reducing and increasing core programme funding, changes to company eligibility, and occasional short funding hiatuses, for example during government spending reviews. The KTP programme has endured through such situations through its robust operational ethos and core focus on supporting UK businesses to access skills within the Knowledge Base that are required for their economic growth. However, such circumstances could have left trace effects on the KTP programme record, for instance projects being started on either side of a calendar year which could be misinterpreted in the search for meaningful trends. This is particularly relevant to studies, such as is reported here, observing the chronological growth of a linked cohort of records from its earliest origins.

There is no single record of changes that have influenced KTP delivery over the period of this study. However, despite this dataset being 10-20 years old there remains an informal programme knowledge which can identify potentially significant events. These include:

- » A significant Strategic Review in 2010 resulting to a significant (c.50%) budget reduction for the subsequent 3-5 years, and consequently resulting in a broad-based reduction in projects awards and loss of experienced KTP operational practitioners, and subsequent change in practices, within the KB community (Polkinghorne, 2010)
- » A recognition by KTP of micro and start-up businesses as important innovative contributors to economic growth during this period, leading to their inclusion as eligible company partners (with programme determined caveats on absorptive capacity on an individual company basis) when they had previously been effectively been excluded from participation due to mandates on financial robustness including the need for evidence of historic trading (such as 3 years annual accounts filed with Company House).
- » Changes in the application process, notably with KTP pioneering on-line applications within Innovate UK (c. 2013) using the _connect portal, which may have increased programme visibility and accessibility to elements of the business community.
- » Periodic reviews and amendments to the application development and assessment processes including the introduction of structured quantitative proposal assessment protocols aligned with research council practices c. 2015.
- » Trailing of 'Themed Calls' during 2013-2015, focusing some programme funding on a small number (5-10 off per topic cohort) of projects aligned with contemporary areas identified as being of national importance (e.g. power electronics, rail, user experience and space) (Innovate UK, 2014)

The potential impact of these events on the nature of funded projects has not been considered in this study. Comparison between intervals in the study period (pre-2012, 2012-2017, 2018-2021) has been enabled using 'within-period share' as a consistent measure.

6.2 Future research

The broad base of KB and business engagement in AI KTP projects in the pre 2012 period suggests AI activity pre-dates this period. Data prior to 2006 was not included in the IUK dataset provided by IUK to the University of Exeter as the secondary data source in this study. Also, the dataset only included partial records for the period from 2006-2010. The availability of this early data, now 20 years in the past, particularly in electronic format, is unlikely to be available, however, should this exist, it could provide additional insights into the earliest origins of industry engagement in AI within the UK. Such understanding could inform the early identification of

similar large-scale, long-term, knowledge acquisition events in the UK business community, particularly the SME community. Similarly, the provision of KTP Final Report data from later time periods would inform understanding of the evolution of this key technology topic as it continued to evolve and expand post 2019.

Understanding gained about technology transfer from the earliest engagements through to widespread adoption of technology available from the unique 50-year history of KTP could provide valuable insight into the evolving nature of innovative knowledge acquisition within the business community, particularly the SME community. This could inform both current and future policy and practice in support of skills acquisition within UK business.

This project has laid the foundation of combining, extracting and analysing the KTP and GtR+ records. If a reliable source of the named PI could be identified (2 academics, the Lead Academic and Academic Supervisor are named on KTP applications) then additional insight could be gained in the background of the academics engaging in knowledge transfer, specifically their research track record and career stage, through a technology innovation-to-adoption phase, such as AI, that is evident in the KTP record.

7. Conclusion

This study has used the long-running UK Knowledge Transfer Partnership archive to examine how AI-related knowledge transfer developed within a stable, demand-led university-business collaboration instrument. Drawing on the discussion above, its central conclusion is that AI diffusion through KTP cannot be understood simply as a rising adoption curve. The archive instead shows a compositional shift within an already computationally intensive programme, a persistence of technical ambition as explicit-AI activity expanded, and an institutional base that broadened rapidly before entering a phase of consolidation.

Explicit-AI projects became an increasingly visible part of KTP activity, rising from a modest precursor presence to almost one third of observed awards by 2019. This did not indicate the sudden interest in computational activity in business. Rather, comparison with the broader explicit-plus-adjacent computational category suggests that much of the increase reflected adjacent analytical, automation and modelling work becoming explicitly framed as AI, alongside a smaller increase in genuinely new computational demand. Because KTP is technology-agnostic and requires company co-investment, this shift records a meaningful change in what firms judged strategically important and were prepared to pursue through a formal knowledge transfer engagement.

The results therefore qualify a simple diffusion account. Volume, technological character and institutional base did not move together. Technical sophistication rose rather than declined, first-of-kind claims showed no clear downward pattern, and the base of participating knowledge organisations broadened initially before consolidating. This indicates diffusion without routinisation: expanding industry interest in AI coexisted with continuing technical ambition and

sector-specific problem solving, sustained both by a moving technological frontier and by the programme's selection for projects requiring knowledge-base capability.

The study also shows that AI-related KTP activity remained strongly application-oriented. Market-facing outputs were common across AI subdomains and across knowledge-base mission groups, indicating that commercial or service-oriented application was a property of the KTP instrument rather than of any one technology domain or institution type. On the company side, participation was broad across regions and firm sizes, with micro and small firms becoming more prominent. Most company partners undertook only one explicit-AI project, while repeat participants often returned to the same knowledge base, suggesting both the importance of relationship-based learning and the need to understand whether a single engagement is sufficient to embed lasting AI capability.

The study further supports a domain-specific view of absorptive capacity. Prior explicit-AI KTP experience increased the likelihood of later AI engagement, whereas general prior KTP activity and mission-group status did not. The negative association with other KTP experience should be read as a specialisation result rather than as evidence that collaboration lowers capability in knowledge transfer: among knowledge bases with equivalent AI-specific histories, portfolios weighted towards other domains were less likely to generate explicit-AI projects. Related accumulated experience, not institutional status or general collaborative throughput, positioned knowledge bases to enter and sustain AI-related knowledge transfer.

These findings have direct implications for policy and practice. Open, demand-led programmes can act not only as delivery mechanisms but also as early-warning observatories of emerging industrial capability, especially across the dispersed SME community. Evaluation should therefore track not only project volume, but also technical ambition, institutional entry, market-facing orientation, accessibility across firms and regions, and follow-on learning. Capability-building should seed domain-specific experience in a wider set of knowledge bases rather than relying on research intensity or prior programme volume as proxies for readiness. At the same time, AI should not be assumed to mature out of frontier instruments merely because adoption widens; if routine adaptation and re-use are policy priorities, they may require complementary forms of support. Follow-on mechanisms and stronger longitudinal engagement post project would also help determine whether a single KTP embeds AI capability in firms or whether additional relationship-based support is needed.

Finally, the study's limitations point to a wider opportunity. Incomplete linkage between programme records and GtR+, partial early records and the absence of named academic identifiers constrain what can be inferred about individual expertise, long-run firm outcomes and the earliest phase of AI engagement. Yet these limitations also show the value of improving programme data infrastructure. Consistent identifiers, retained early records and named academic participation would allow open innovation programmes to be evaluated longitudinally at low marginal cost, making analyses of emerging technology demand, institutional capability and business access routine rather than exceptional.

8. Data Availability

GtR+ data was accessed under the terms of the IRC GtR+ Secondary Data Analysis scheme and are available under those terms. The KTP Final Report data (covering the period 2007-2019) was provided to the University of Exeter under a Non-Disclosure Agreement permitting its use for research and reporting in aggregate form.

9. Code Availability

Processing and analysis were undertaken written in R and available on request.

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