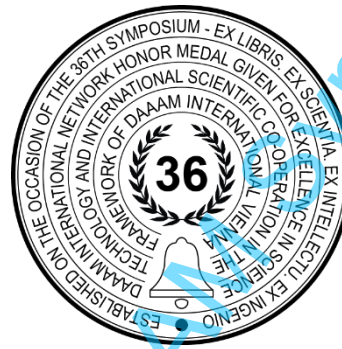


ARTIFICIAL INTELLIGENCE AND INDUSTRY TRANSFORMATION: WHY ITS COMPETITIVE IMPACT DIFFERS ACROSS INDUSTRIES

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Abstract

Generative artificial intelligence can improve established offerings, reduce the scarcity of expertise and enable alternative delivery arrangements. These developments need not constitute disruptive innovation or produce incumbent displacement. This conceptual, evidence-informed paper compares industrial automation, translation and localisation, legal services, and consumer web search. Christensen's distinction between sustaining and disruptive innovation provides the principal lens, supported by capability change, complementary assets and organisational adaptation. Four conditions organise the comparison: customer requirements and entry position, incumbent capability change, access to complementary assets, and business-model and organisational compatibility. The reviewed evidence documents incumbent integration, task-substitution pressure, alternative provision and interface change. It does not establish a foothold-to-mainstream disruptive sequence or consistently identify recipients of net efficiency gains. The comparison identifies residual requirements of complete delivery as a link between task-level improvements and commercial consequences. Three propositions connect task substitution to entry, foothold development to incumbent response, and reconfiguration to value capture. Conditional scenarios specify observable signals and evidence that would challenge the proposed mechanisms.

Keywords: generative artificial intelligence; disruptive innovation; competitive advantage; complementary assets; industry evolution.

1. Introduction

Generative artificial intelligence (AI) supports activities across industries, but its competitive consequences depend on more than technical capability. An application may improve an established supplier's offering while also reducing the scarcity of expertise, enabling customer self-service or changing relationships between organisations. These effects can coexist, so a tool that complements an automation platform may simultaneously reduce demand for programming services supplied by its partners.

Industry-evolution research provides a starting structure for examining these relationships between technological change and organisational adaptation [1]. Describing AI as disruptive, however, can obscure the distinctions between

technological novelty, capability change and competitive consequences. Disruption concerns a particular market trajectory rather than radical technology, rapid diffusion or harm to incumbents [2], with the theory emphasising how customer priorities, resource allocation, performance trajectories and competitive responses shape that trajectory [3]. An incumbent may therefore recognise a technology yet give limited support to a commercially different offering [4].

Against this background, the paper asks: *Under what industry and organisational conditions do generative-AI-enabled offerings follow sustaining or disruptive trajectories, and how do these conditions shape incumbent advantage and industry structure?* It also examines when AI-driven capability or architectural change alters competitive positions without constituting disruption in Christensen's sense.

To address these questions, the paper compares industrial automation, translation and localisation, legal services, and consumer web search. Although industries provide the comparative cases, disruption is assessed at the level of a defined offering, customer segment and incumbent business model. This distinction also requires separating broad model availability from effective access, which may differ substantially with data rights, deployment costs, integration and customer access.

The intended contribution is a conditional explanation of how technical improvements connect to commercial delivery. By distinguishing task-level assistance from entry trajectories and competitive outcomes, the analysis avoids inferring incumbent reinforcement from survival or value capture from productivity alone.

2. Theoretical Background and Positioning

2.1. Disruption, capabilities and complementary assets

Sustaining innovations improve performance valued by established customers, even when they are technically radical, whereas disruptive offerings develop through low-end or new-market positions and may subsequently progress towards mainstream competition [2], [3]. Customer relationships and organisational allocation processes help explain why incumbents may favour established markets [4]. Incorporating an assistant into an existing offering therefore represents a different commitment from supporting an alternative delivery model.

To assess disruptive development, the paper distinguishes four evidential stages: disruptive potential, an established foothold, mainstream progression and attributable displacement. These distinctions organise the evidence rather than describe a sequence through which every innovation must pass. In particular, establishing a commercially credible foothold requires evidence of overservice or previous non-consumption alongside viable delivery economics; low prices, funding or growing usage alone do not demonstrate such a position.

Capability and architectural change provide related but distinct perspectives. Tushman and Anderson distinguish competence-enhancing from competence-destroying discontinuities [5], while Henderson and Clark examine changes in relationships among product components and the organisational knowledge needed to integrate them [6]. Neither distinction by itself establishes disruption. Moreover, product or system architecture must be separated from industry architecture, which concerns the distribution and coordination of activities among organisations.

These changes become commercially consequential partly through complementary assets, which affect both commercialisation and the capture of returns [7]. Historical evidence accordingly shows that capability erosion need not eliminate an incumbent's commercial position [8]. What matters is access as well as ownership: entrants may assemble complements through contracts, partnerships or qualified personnel, while incumbents may fail to deploy assets they already possess.

2.2. Artificial intelligence and competitive advantage

Research on AI extends these arguments by examining how established capabilities and new complementarities interact. Evidence from chess competitions shows AI substituting for established capabilities while creating new human-machine complementarities [9], offering a mechanism analogue rather than a direct test of generative AI in the selected industries. Kemp's situated-AI argument further emphasises how AI becomes embedded in firm-specific organisational systems [10]. Together, these perspectives explain why access to a general model is insufficient on its own to secure competitive advantage.

Agrawal, Gans and Goldfarb develop a related argument by modelling AI adoption across interdependent decisions and showing how modularity and coordination affect the returns to adoption and organisational redesign [11]. Because their model concerns AI prediction, applying it to generative-AI delivery constitutes an analytical extension. The present paper makes that extension explicit while examining who can assemble commercially viable delivery and how changing relationships may affect returns, treating system redesign and value capture as overlapping questions.

This positioning must also account for research that already addresses generative AI and business-model innovation through propositions and industry examples [12], appropriability and complements within the AI industry [13], and competitive dynamics in downstream markets [14]. A recent typology extends this coverage by distinguishing existing-business enhancement, new-business enablement and configurations of human-AI collaboration [15].

The proposed contribution therefore lies in applying disruption criteria consistently alongside an assessment of residual delivery requirements, organisational responses and competitive consequences, rather than in identifying varied

AI applications or asserting that complements matter. As a bounded conceptual synthesis, the paper connects these perspectives without claiming that no prior study has examined their relationships.

3. Method

The study uses theory-guided comparative analysis of secondary evidence available through 14 October 2026. Its purpose is to develop a conceptual perspective rather than conduct a statistical test or an exhaustive systematic review.

Case selection was purposive, drawing on application maturity, theoretical contrast, incumbent resources, alternative propositions, architectural change and evidence availability. The four cases offer contrasting delivery conditions rather than predetermined outcomes: automation embeds outputs in physical systems, translation and legal services provide a paired comparison of language-related work, and search concerns information intermediation. The translation–legal pairing allows comparison without assuming that technology or customer requirements are held constant.

Targeted web searches combined theory terms—disruptive innovation, complementary assets, capability change and business-model innovation—with generative AI and industry-specific terms. Publisher records, institutional repositories and original regulatory and company sources were prioritised, with references in retrieved material providing further leads. Because a bibliographic-database originality review was not completed, conclusions about literature coverage and novelty remain limited.

Sources were selected according to the offering and claim they could substantiate: technical benchmarks inform capabilities, workplace studies inform bounded task effects, surveys describe respondent experience, and filings document reported financial outcomes. Company announcements establish reported activity without independently verifying benefits. Wherever material was accessible, the review examined methods, evaluated tasks, populations, versions and stated limitations; sources lacking sufficient detail supported only narrower claims or were omitted. Conflicting observations were retained to expose uncertainty rather than resolved by counting supportive sources.

Within each case, the analysis defines the offering, customers and incumbent model before identifying demonstrated changes, evaluating the four conditions, and assessing responses, trajectories and consequences alongside contrary evidence. Empirical findings and company-reported results are distinguished from theory-based interpretations and conditional expectations. Timing, technological performance, deployment economics and other market changes are considered as rival explanations, while regulation is examined through the requirements or access conditions it changes. The heterogeneous, jurisdiction-specific evidence does not permit estimation of a common causal effect, and organisational allocation decisions and comparative returns are often unobserved. Assessments of these mechanisms consequently remain prospective, particularly because the short observation period limits trajectory assessment: the absence of a documented disruptive sequence does not establish that one cannot develop.

4. Analytical Framework

The framework connects an offering's changes in tasks, cost and performance to four conditions:

- 1. Customer requirements and entry position:** whose needs are served, on which dimensions, and from which initial position.
- 2. Incumbent capability change:** which capabilities become more valuable, less scarce or inadequate.
- 3. Access to complementary assets:** whether alternative providers can assemble necessary commercial delivery on viable terms.
- 4. Business-model and organisational compatibility:** whether incumbents can support the offering within their economics, incentives and organisational arrangements.

Figure 1 summarises how these conditions connect offering changes to organisational responses and market trajectories, with consequences for relative position, value capture, customer access and activity boundaries. The relationships may also be reciprocal, as entry can change customer requirements and adaptation can change access to complements.

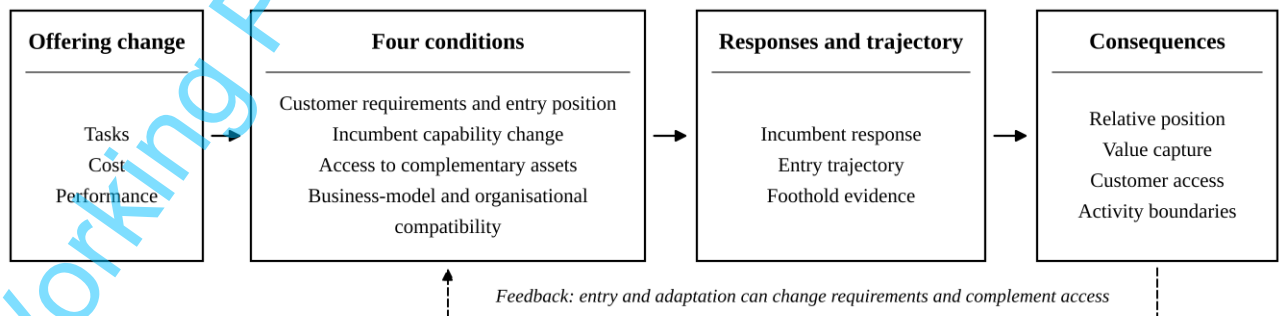


Fig. 1. Proposed relationships between offering changes, conditions, responses and consequences; the dashed arrow indicates feedback; arrows do not represent estimated causal effects.

The assessment separates trajectory type from evidence of disruptive development. Sustaining, potentially disruptive, other identified and indeterminate trajectories describe different possibilities rather than positions on an ordinal scale. Similarly, entrant origin—*de novo* or *de alio*—is distinct from delivery through external provision, customer self-service or hybrid arrangements, and neither origin nor delivery arrangement determines the classification.

Assessing incumbent reinforcement requires evidence of an improved relative position or greater value capture, since productivity gains may be shared by competitors or captured by customers and suppliers. The analysis therefore examines residual delivery requirements: the integration, contextual evaluation, accountability and other requirements needed to make generated outputs acceptable and commercially usable. These requirements must be evidenced for each application, with their persistence treated as an empirical question.

5. Comparative Analysis

5.1. Industrial automation

The automation case concerns control-code generation, debugging and project engineering for machine builders, integrators and manufacturing customers. It assesses two incumbent models: integrated control-hardware and engineering-software provision, and engineering services sold by integrators. Within this setting, Tran and colleagues evaluate language models on 21 programmable logic controller (PLC) programming examples [16], while Adnyana and Schwung examine prompting across 25 industrial use cases and distinguish logical and semantic verification from runtime and physical validation [17]. Together, these results support bounded engineering assistance without establishing dependable autonomous delivery of complete production systems.

Established suppliers are incorporating such assistance into their engineering environments. Siemens reported general availability of an engineering agent connected to TIA Portal following pilots [18], and Beckhoff describes an assistant integrated within its engineering environment and offering a choice of underlying models [19]. These announcements document supplier activity, although the claimed benefits remain company-reported.

The distinction between assistance and complete delivery matters because generated code can reduce selected tasks while leaving project specification, integration and verification unresolved. Existing engineering environments offer deployment routes, but their use does not demonstrate exclusive control of necessary assets, especially when customers and integrators also possess project knowledge. Similar tools could become standard features across suppliers, assist smaller integrators or support customer insourcing, with different consequences for platform suppliers and engineering-service providers.

On current evidence, the documented incumbent offerings have a predominantly sustaining orientation, while reinforcement, commercial parity and easier entry remain competing possibilities. Open, software-defined automation offers a rival source of change that may interact with AI, further complicating attribution. The reviewed evidence establishes neither a disruptive foothold nor attributable redistribution of returns. Earlier descriptive findings from 141 Slovenian manufacturers show variation in broad AI use by firm size and supply-chain role [20], providing context for deployment heterogeneity rather than evidence of generative-AI reinforcement.

5.2. Translation and localisation

The translation case examines purchased text-translation services, contrasting routine output with work requiring contextual, specialist or confidential delivery. Its incumbent model is paid human translation or managed language services, while software providers occupy a distinct commercial position. Attribution to generative AI is complicated by earlier machine translation: a working paper covering 695 US local labour markets reports a negative relationship between Google Translate adoption and employment growth among translators and interpreters, using search activity as an adoption proxy and an instrumental-variable strategy [21]. Although relevant to historical substitution, this finding depends on the proxy and identification assumptions and does not establish a disruptive market trajectory.

More recent task-level evidence comes from a Finnish public-sector team of four in-house translators using GPT-4. Pooled translation speed was approximately 14% higher when post-editing GPT-4 output than when translating from scratch, although individual results varied substantially and terminology and contextual problems persisted [22]. The study thus demonstrates a bounded task effect without establishing superiority over earlier machine translation or productivity gains across the industry. Online-platform research provides complementary evidence of demand pressure, reporting declines of 20–50% relative to the counterfactual trend for substitutable skill categories, including writing and translation [23]. This range depends on skill classification and the comparison trend rather than measuring translation-industry contraction; related findings of adverse employment and earnings outcomes in exposed occupations likewise concern bounded labour markets [24].

The European Language Industry Survey adds descriptive evidence of difficult business conditions and changing workflows, while acknowledging that its measures blur machine translation and generative AI [25]. Negotiated post-editing discounts centred around 20% coexist with stable or improved gross margins among surveyed language companies [25], challenging a uniform margin-erosion interpretation. These observations nevertheless come from a voluntary sample mainly representing smaller European providers and freelancers, so they describe respondent experience rather than estimate generative AI's incremental causal effect.

These findings illustrate how professional assistance and substitution pressure can coexist when customer requirements vary with intended use. Fluency alone may be insufficient, as terminology, contextual evaluation, workflow integration and relationships can matter beyond certified work. The commercial implications also depend on pricing and costs: per-word pricing can remain compatible with AI if lower costs improve margins, although buyer pressure, verification costs and competition may offset those gains. Discounts alone reveal little about the allocation of net benefits.

Commercial examples further illustrate alternative provision alongside incumbent adaptation. DeepL reported more than 100,000 organisational customers in 2024 [26], but this customer base does not establish their previous alternatives or the effects on incumbent suppliers. RWS, meanwhile, reported group revenue growth of about 5% in the first half of 2026 and an increased AI-related revenue share driven by TrainAI, even as its Transform segment declined in organic constant-currency terms [27]. Transform's adjusted operating profit nevertheless increased, which the company attributed to delivery efficiencies and overhead savings [27]. The contrast within these company-reported results demonstrates why revenue change alone cannot establish competitive reinforcement or erosion.

Taken together, the case supports assistance, substitution pressure and possible changes in activity boundaries more clearly than a generative-AI-specific disruptive sequence. Historical automation, demand changes and channel migration remain alternative explanations, while evidence of preserved expertise also challenges an interpretation of uniform competence destruction.

5.3. Legal services

The legal-services case concerns research, analysis and document preparation supplied through lawyer-led services under hourly or fixed fees. Because the evidence is concentrated in the United States and England and Wales, its interpretation must account for jurisdictional and task differences.

Within this scope, Choi, Monahan and Schwarcz find speed gains but small and inconsistent quality improvements in a randomised study of law students using GPT-4 [28]. A later experiment with law students using reasoning and retrieval-based tools reports gains in both quality and productivity [29], although neither study estimates complete client-service performance. Magesh and colleagues also identify material errors in tested commercial research systems despite their retrieval-based design [30]. These version-specific findings qualify the demonstrated gains without establishing permanent technological limits.

Complete delivery also requires accountability, but established firms do not hold exclusive access to it. The Solicitors Regulation Authority authorised an AI-driven debt-recovery provider with named solicitor accountability, client approval and monitoring [31], demonstrating that an alternative provider can assemble a regulated delivery arrangement. The authorisation does not, however, establish previous customer non-consumption, viable foothold economics or mainstream progression.

The resulting commercial effects depend on how faster work interacts with pricing, demand, utilisation and supervision: it may reduce hourly revenue per matter, increase capacity or improve fixed-fee margins. Professional guidance addressing actual time under hourly billing illustrates one institutional pathway through which these effects can arise [32], although that pathway cannot be generalised across jurisdictions or fee models.

The evidence therefore supports professional assistance and emerging alternative provision, challenging both complete replacement and permanent regulatory protection. In-house provision and tool suppliers may change activity boundaries, yet observed adoption does not establish reduced outside spending or stronger incumbent returns. The comparison with translation is grounded in differing delivery arrangements rather than an assumed universal hierarchy of accountability.

5.4. Consumer web search

Consumer web search represents an advertising-funded incumbent model serving information queries. Generated answers combine retrieval and synthesis, changing how users encounter information within and beyond conventional search. Kirsten and colleagues compare Google's organic search with five generative systems from three providers and identify differences in source selection and output stability [33]. Their findings establish technical variation, leaving commercial displacement to be assessed separately.

Evidence of changing referral behaviour comes from Pew's observational study of 900 US adults, which reports traditional-result clicks on 8% of visits with an AI summary and 15% without one, while summary citations received clicks on 1% [34]. Query differences and reconstructed results limit causal interpretation, and referral changes cannot be equated with revenue losses. At the same time, Alphabet reports 17% growth in Google Search & other revenue in the second quarter of 2026 [35]. This counters immediate-collapse claims without isolating AI's contribution or establishing search margins.

Integration of generated answers into an existing search offering is compatible with a sustaining response, although it does not show that cannibalisation is absent or costless. Research identifies willingness to cannibalise existing investments as an explanation of radical innovation [36], so incumbent adoption need not contradict that argument or Christensen's account.

The competitive effects also depend on distribution and information access, which remain contested complements in US search-remedy proceedings [37]. Regulation may change access alongside technical and commercial developments, although the eventual effects cannot be inferred simply from the existence of remedies.

These developments allow generated answers to improve established tasks while changing referral relationships, and alternative providers may substitute for search sessions. Neither possibility alone identifies a disruptive foothold: free access offers no low-end advantage where conventional search is already generally free, while a provider's origins outside search do not establish customer non-consumption.

The case thus documents output and interface change, referral differences and incumbent adaptation, without establishing a disruptive sequence or a transfer of net returns from publishers to the platform. Earlier direct answers, ranking changes, advertising demand and measurement coverage remain relevant alternative explanations.

5.5. Cross-industry comparison

Industry	Residual requirements and complements	Incumbent response	Trajectory assessment	Unresolved consequences
Industrial automation	Integration, validation and dependable operation; engineering environments and customer project knowledge	Integrated engineering assistants	Predominantly sustaining orientation; disruptive foothold not established	Relative advantage and returns across participants
Translation/localisation	Context, terminology and assurance varying by use; accessible generation and workflow assets	Workflow assistance and diversification	Sustaining assistance and substitution pressure; disruptive sequence not established	Incremental AI effect and net savings allocation
Legal services	Evaluation, client context and accountable delivery; regulated arrangements can be assembled	Professional assistance	Assistance and emerging alternative provision; foothold not established	Pricing, insourcing and competitive returns
Consumer search	Navigation, synthesis and verification varying by query; distribution and information access	Interface adaptation	Sustaining response and interface restructuring; disruptive sequence not established	Sustained switching and commercial redistribution

Table 1. Evidence-informed comparison; mechanism interpretations are not estimates of causal effects.

6. Discussion

6.1. Industrial automation

Three mechanisms organise the cross-industry comparison. First, reducing task difficulty does not necessarily reduce the requirements of complete delivery: code generation still differs from commissioning, just as drafting differs from accountable service provision. The cases make this distinction observable without establishing fixed barriers, because improved models, evaluation tools, contracts and changing customer expectations may themselves reduce residual requirements.

Second, the ability to access complements explains more than ownership alone. Entrants may assemble delivery through personnel, partnerships and existing infrastructure, while incumbents may possess relevant assets without organising them effectively. Whether regulation, installed bases or expertise protect incumbents must therefore be demonstrated for the application rather than inferred from possession of those assets.

Third, competitive consequences depend on where relationships change. Assistance within an incumbent can coexist with customer insourcing, independent provision and interface intermediation, exposing participants to different effects. Supplier-mediated entry and buyer power offer exploratory refinements to this account, but the evidence does not yet

establish which participants gain. Answering that question requires comparable measures of AI-generated net returns rather than treating revenues, discounts, profits and referrals as interchangeable indicators.

Together, these mechanisms provide a structured connection between capability change, delivery requirements, entry trajectories and competitive consequences. This synthesis neither ranks the conditions above technical performance nor establishes a new theory, and it does not infer resource-allocation failure from non-adoption. Equally, documented incorporation into existing offerings does not reject Christensen's mechanism, which concerns support for particular alternative markets and business models.

6.2. Propositions and contradictory evidence

P1. Reductions in task difficulty are more likely to enable competitive entry when alternative providers can meet residual customer requirements and access necessary complements on commercially viable terms.

The reviewed evidence is consistent with parts of this mechanism, although its competitive effects remain only partially assessable. Repeated failure to enter despite demonstrated demand, adequate performance and viable access would challenge the proposition, as would successful entry that bypasses requirements considered necessary. To avoid circular explanation, demand and access must be assessed independently of the entry outcomes they are intended to explain.

P2. Where a viable low-end or new-market foothold exists, mainstream progression is more plausible when performance improves relative to customer requirements and incumbent allocation leaves the alternative offering insufficiently served.

Although incumbent responses are partly observable, mainstream progression remains prospective in these cases. The proposition would be challenged if footholds remained persistently bounded despite the stated conditions, or if effective incumbent adaptation contradicted the proposed allocation constraint. Awareness and model access alone cannot resolve either assessment.

P3. Changes in activity boundaries or customer interfaces are more likely to redistribute commercial returns when they change bargaining alternatives or control over customer access.

The evidence makes reconfiguration partially observable, but establishes less about the redistribution of returns. Persistent changes without corresponding effects on bargaining alternatives or returns would challenge the proposition, as would outcomes explained more convincingly by unrelated demand and pricing movements.

6.3. Conditional scenarios

Incumbent reinforcement is plausible where AI improves delivery, organisations adapt effectively and valuable complements remain differentiated. Its assessment requires relative customer gains and attributable improvements in returns, since adoption alone cannot demonstrate a stronger competitive position.

Restructuring with continuing incumbent participation is plausible where tasks, interfaces or activity boundaries change while existing organisations remain involved. Insourcing, changed contracting, partnerships and referral dependencies provide observable signals of such reconfiguration, although net gains still require separate measurement.

Disruptive development requires a credible foothold among overserved customers or previous non-consumers, followed by mainstream progression. Repeat use, viable economics, documented customer movement and attributable incumbent losses would provide evidence of that development. These scenarios may coexist across segments and should be treated as conditional possibilities rather than predictions.

7. Conclusion

Across the selected cases, the reviewed evidence documents incumbent integration, bounded assistance, substitution pressure, alternative provision and interface change. These developments reveal commercially relevant changes without establishing a foothold-to-mainstream disruptive sequence or consistently identifying the recipients of net efficiency gains.

The framework connects these observations by explaining why technical improvements must be considered alongside residual customer requirements, access to complements and organisational arrangements before commercial consequences can be inferred. This connection preserves the distinctions central to the analysis: capability erosion need not imply displacement, restructuring need not constitute disruption, and incumbent survival need not mean reinforcement.

For practitioners, the implication is to assess both the tasks AI changes and the delivery requirements it leaves, including who can meet them and on what terms. Future research can develop this assessment by tracking customer histories, total delivery costs, incumbent allocation decisions and returns across participants. Such longitudinal evidence is particularly necessary given the present study's short observation period, uneven secondary evidence and non-exhaustive literature coverage. It would allow researchers to determine whether emerging alternatives remain bounded, become suppliers or progress towards mainstream competition.

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