Operating Model Design for the Data-driven Era

BDG Advisory — Perspective Paper

Executive Summary

Enterprise IT is being rebuilt, not upgraded. The shift from process-driven to data-driven architecture is structural and unavoidable, forcing architectural decisions that cloud economics allowed organizations to defer for a decade. Most organizations approach this as a technology implementation challenge. They're wrong. This is an operating model collapse.

Existing operating models were designed around centralized process logic and hierarchical decision authority. AI fundamentally redistributes where intelligence lives and who controls it. Inference happens at sub-100ms latency at the edge. Training requires specialized silicon placement. Data sovereignty creates hard geographic boundaries. These workloads are not neutral to location or authority structure.

Organizations built for process-driven IT cannot absorb AI that runs at the edge, redistributes decision rights, and demands real-time compute placement decisions that governance structures were never designed to make. The technology works. The operating models break down. Research shows 70% of enterprise AI deployment is uncontrolled, creating hidden risk and slower returns. The gap between AI capability and organizational structure is widening, not closing.

This creates a structural loop that accelerates organizational failure. Capital concentrates control in legacy decision structures. Control shapes data collection around outdated metrics. Data drives execution toward process optimization rather than intelligent architecture. Execution determines outcomes that reinforce the wrong structural patterns. AI accelerates this loop, exposing misalignments in weeks rather than quarters.

The companies that will compete are rebuilding their operating models around three structural principles. First, they're moving intelligence to where decisions need to be made, not where authority traditionally lived. Second, they're designing governance frameworks that can absorb autonomous decision-making rather than route everything through human approval workflows. Third, they're aligning capital allocation with compute placement requirements rather than organizational convenience.

The organizations that treat AI as a software upgrade rather than an operating model redesign are managing declining relevance. They're optimizing for the wrong architecture, preserving authority structures that create execution bottlenecks, and building technical debt faster than they're building capability. Compute and inference are moving to the edge whether organizational structures accommodate this shift or resist it.

The architectural decisions being made today will determine competitive position for the next decade. Organizations that understand this are not just implementing AI tools—they're rebuilding how work gets done, where decisions get made, and who controls the data that drives both. The window for structural redesign is closing as technical debt compounds into competitive disadvantage.

Where Intelligence Must Live: The End of Central Process Logic

Cloud computing centralized everything because capital economics made it simple. Enterprises moved workloads to centralized infrastructure, concentrated data in shared platforms, and built operating models around the assumption that compute location was a cost optimization decision rather than a performance requirement. This worked when applications were process-driven and latency tolerance measured in seconds rather than milliseconds.

AI forces the decision that cloud economics obscured. Where should workloads actually run? Inference requires sub-100ms response times that cannot be achieved through centralized processing. Training demands specialized silicon that may not be available in preferred geographic regions. Energy costs vary 300% by location, making centralized deployment economically unsustainable at scale. Data sovereignty regulations create hard boundaries that cannot be solved through legal frameworks alone.

These constraints are not neutral to organizational structure. When intelligence must operate at the edge, the operating models built around centralized decision authority become execution bottlenecks rather than coordination mechanisms. A major telecommunications operator discovered this when implementing network automation. The AI systems could analyze network conditions and execute corrective actions in real-time, but the approval workflows still routed through centralized teams that became system-wide performance constraints.

The shift from process-driven to data-driven architecture is not about better data processing. It's about moving from systems that execute predetermined workflows to systems that make decisions based on real-time conditions. Process-driven architecture assumes that business logic can be captured in centralized rules and executed through standardized workflows. Data-driven architecture assumes that optimal decisions emerge from analyzing conditions that cannot be predicted when the system is designed.

This requires fundamentally different infrastructure placement decisions. A global financial services firm found that their fraud detection systems needed to operate with different latency and data residency requirements across regions, not because of technical preferences but because regulatory frameworks created different decision-making contexts. Their centralized cloud architecture could not accommodate the edge intelligence requirements without rebuilding the entire operational framework.

The technology industry has spent a decade optimizing for centralized cloud deployment because the economics were compelling and the performance trade-offs were acceptable. AI makes those trade-offs unacceptable. When decision-making must happen at the point of data creation rather than after data aggregation, the centralized processing model breaks down operationally, not just technically.

Organizations that continue to treat compute placement as a cost optimization decision rather than a performance requirement are building systems that cannot deliver on their AI commitments. The infrastructure decisions being made today will determine whether AI implementations can operate at the speed and scale that competitive positioning requires. Cloud was never the destination. It was a decade-long detour around architectural decisions that are now unavoidable.

The companies winning with AI are not just building better models. They're rebuilding their infrastructure stack to put intelligence where the work demands it, even when that conflicts with existing operational preferences or capital allocation patterns. Architecture is following computational requirements rather than organizational convenience.

The Authority Displacement Crisis

Automation rarely fails because of technology. It fails because of authority. Organizations implement AI systems that work technically but create structural resistance because they quietly redistribute decision rights without redesigning the governance frameworks that were built around human decision-making hierarchies.

The disruption is not the algorithm. It's who no longer makes the decision. A managed services operator built a platform that used event mining to analyze operational signals, automated configuration standardization, and deployed machine-assisted agents to execute corrective actions directly on client infrastructure. From an engineering perspective, the system improved security posture, eliminated configuration drift, and reduced support overhead. From a structural perspective, it moved decision authority away from senior client engineers who traditionally owned configuration control.

The resistance was not about technical capability. It was about authority displacement. Event mining was tolerated once cost reductions became visible because it augmented human decision-making rather than replacing it. Architecture correction faced different resistance because it executed decisions automatically within predefined policy boundaries, removing human authority from the decision loop even when the outcomes were technically superior and fully compliant with regulated environments.

This pattern amplifies across AI implementations. Organizations approve AI systems that promise efficiency gains, then discover that the efficiency comes from removing human decision-makers from processes where those roles provided organizational authority rather than just operational value. The technology performs exactly as specified. The organization resists because authority structures feel threatened by systems that can execute better decisions faster than existing hierarchies.

Most leaders frame this as change management rather than structural redesign. They assume that resistance will decrease as people become comfortable with AI-augmented workflows. This misunderstands the underlying dynamic. The resistance is not about comfort with technology. It's about preserving decision authority in an environment where AI systems can demonstrably make better decisions than human hierarchies in specific domains.

A global consulting firm implemented AI-powered project staffing that could optimize resource allocation across multiple client engagements simultaneously, considering skills matching, utilization rates, travel requirements, and client preferences. The system delivered superior staffing outcomes and reduced scheduling overhead. Partner-level resistance emerged because the AI system could make staffing decisions that optimized firm-wide metrics rather than individual partner preferences, effectively redistributing authority over resource allocation decisions.

The structural challenge is that AI moves authority into the service layer. Traditional hierarchies assume that decision quality improves with organizational seniority and domain expertise. AI systems can make certain categories of decisions better than human experts by processing more variables faster and without cognitive biases. This creates a fundamental conflict between organizational authority structures and optimal decision-making capabilities.

Organizations try to solve this by implementing AI systems that provide recommendations rather than executing decisions, preserving human authority while gaining AI insights. This approach fails at scale because it creates approval bottlenecks that eliminate the performance advantages that justify AI implementation. The system can analyze complex conditions and generate optimal responses in milliseconds, but the approval workflow takes hours or days to route through human hierarchies.

The companies that successfully absorb AI are redesigning authority structures around decision domains rather than organizational hierarchies. They're identifying where AI systems should have autonomous authority, where human oversight adds value rather than delay, and how governance frameworks must change to accommodate decision-making that happens faster than traditional approval workflows can process.

Why AI Accelerates Structural Breakdown

AI is not just another technology tool that can be absorbed into existing operational frameworks. It accelerates the structural loop that drives organizational execution in ways that expose misalignments between strategy and structure faster than traditional transformation timelines allowed organizations to adapt.

The structural loop that actually drives execution works through capital concentration, not strategic planning. Capital concentrates control by determining who makes resource allocation decisions. Control shapes data collection by determining what gets measured, how it's collected, and what metrics drive reporting. Data drives execution as teams optimize for the metrics they see rather than the strategies they're told. Execution determines outcomes that influence where capital flows next, reinforcing the loop.

AI accelerates every stage of this loop dramatically. It processes data faster, making execution patterns visible in weeks rather than quarters. It exposes gaps between strategy and structure sooner because the data analysis reveals optimization behavior that conflicts with stated strategic priorities. It amplifies execution patterns quicker because automated systems can scale misaligned behavior faster than human-driven processes.

A Fortune 500 operator implemented AI-powered supply chain optimization that could analyze supplier performance, demand forecasting, and inventory positioning across multiple product lines simultaneously. The system worked technically, delivering cost reductions and inventory optimization that exceeded projections. However, the regional teams continued optimizing for local metrics that conflicted with global supply chain efficiency because their incentive structures and authority boundaries had not changed. The AI system exposed these conflicts in real-time rather than allowing them to remain hidden until quarterly reviews.

The acceleration effect means that structural problems surface faster than traditional change management approaches can address them. Organizations discover that their governance processes cannot keep pace with AI-driven insights, their authority structures create decision bottlenecks that eliminate AI performance advantages, and their incentive systems reward behavior that conflicts with AI-optimized outcomes.

Most transformation programs focus on technology capability development rather than structural redesign. They assume that organizations can absorb new capabilities without changing how work gets done, who makes decisions, or how performance gets measured. AI makes this assumption unsustainable because it changes the speed and scale at which structural misalignments become execution problems.

A private equity portfolio company implemented AI-driven customer acquisition that could optimize marketing spend allocation, prospect scoring, and campaign timing across multiple channels simultaneously. The technology delivered superior customer acquisition costs and conversion rates. However, the sales organization continued prioritizing leads based on traditional qualification criteria because their compensation structure and performance metrics had not been redesigned around AI-generated insights. The conflict between AI optimization and sales behavior became visible immediately rather than emerging gradually through quarterly performance reviews.

This creates a compounding effect where organizations build technical debt faster than they build capability. They implement AI systems that work but cannot scale because the operating model cannot absorb the decision-making speed and authority redistribution that AI effectiveness requires. The gap between technical capability and organizational structure widens rather than closing through gradual adaptation.

The technology performs while the organization struggles, creating a specific type of execution failure that cannot be solved through better training, clearer communication, or more detailed project management. The failure is wired into the structure. AI systems can generate optimal decisions faster than approval workflows can process them, analyze more variables than governance frameworks can accommodate, and scale execution beyond what traditional authority structures can coordinate effectively.

Organizations that treat AI implementation as technology deployment rather than operating model redesign are accelerating their own structural breakdown rather than building competitive advantage.

Governance Frameworks That Cannot Absorb Intelligence

The governance structures that successfully managed process-driven IT cannot accommodate AI systems that make autonomous decisions, learn from outcomes, and modify their behavior without human intervention. The fundamental assumption behind traditional IT governance is that system behavior can be predicted, controlled, and audited through predetermined rules and approval workflows.

AI systems violate these assumptions systematically. Machine learning models make decisions based on pattern recognition across datasets that may be too large for human review. They modify their decision-making approach based on feedback loops that happen faster than governance review cycles. They operate across data domains that may span multiple organizational boundaries and authority structures simultaneously.

A major financial services firm implemented AI-powered fraud detection that could analyze transaction patterns, customer behavior, and risk indicators in real-time to make approval or rejection decisions automatically. The system reduced fraud losses significantly while improving customer experience through faster transaction processing. However, the regulatory compliance framework required human review and documentation for decisions above certain thresholds, creating a governance bottleneck that eliminated the speed advantages that justified the AI implementation.

The structural challenge is that governance frameworks designed around human decision-making assume that decisions can be decomposed into reviewable components, that authority can be traced through organizational hierarchies, and that accountability can be assigned to specific individuals. AI decision-making may involve pattern recognition across variables that resist human interpretation, authority distributed across autonomous systems, and accountability shared between human oversight and algorithmic execution.

Traditional governance attempts to solve this by requiring AI systems to provide explainable decisions that can be reviewed through existing approval workflows. This approach fails because it forces AI systems to operate within the cognitive and temporal constraints of human decision-making, eliminating the performance advantages that justify AI deployment while adding governance overhead that slows execution rather than improving outcomes.

Research indicates that enterprise AI deployment is 70% uncontrolled, not because organizations lack governance intentions but because existing governance frameworks cannot accommodate the decision velocity and authority distribution that AI systems require to deliver value. The control mechanisms that work for process-driven systems create execution constraints for intelligence-driven systems.

A global manufacturing operator discovered this when implementing AI-powered predictive maintenance across multiple facilities. The AI system could analyze equipment sensor data, operational patterns, and maintenance history to predict failures and schedule interventions more effectively than human-driven preventive maintenance programs. However, the governance framework required maintenance decisions to be approved through facility management hierarchies that could not process recommendations fast enough to capture the predictive value.

The governance challenge is not about risk management or compliance oversight. It's about designing control mechanisms that can operate at the speed and scale that AI systems require while maintaining organizational accountability and regulatory compliance. This requires fundamentally different approaches to authority delegation, decision documentation, and outcome accountability.

Organizations try to solve this by implementing AI systems in advisory modes that provide recommendations for human decision-makers rather than executing decisions autonomously. This preserves existing governance frameworks while gaining AI insights. However, it creates approval bottlenecks that eliminate the competitive advantages that justify AI investments while adding analytical overhead that slows decision-making rather than improving it.

The companies that successfully scale AI are redesigning governance around decision domains rather than organizational hierarchies. They're identifying where autonomous decision-making delivers superior outcomes, how oversight mechanisms can operate at AI speed rather than human speed, and what accountability frameworks can accommodate shared authority between human judgment and algorithmic execution.

The architectural decisions being made today about governance design will determine whether AI implementations can scale beyond pilot projects to production systems that deliver sustainable competitive advantage.

Building Operating Models for Distributed Intelligence

Organizations that successfully absorb AI are not upgrading their existing operating models. They're rebuilding how work gets done around three structural principles that align authority with capability, governance with decision speed, and capital allocation with compute requirements rather than organizational convenience.

The first structural principle is moving intelligence to where decisions need to be made rather than where authority traditionally lived. This requires redesigning workflows around decision domains instead of organizational hierarchies. A global logistics operator rebuilt their route optimization around AI systems that could analyze traffic conditions, delivery requirements, weather patterns, and vehicle capacity in real-time at the regional level rather than routing decisions through centralized planning teams that operated on daily or weekly cycles.

This shift required redesigning authority boundaries so that regional AI systems could execute route modifications autonomously within defined parameters while escalating exceptions that required human judgment or cross-regional coordination. The operating model change was not about implementing better logistics software. It was about moving decision authority to where real-time data could generate optimal outcomes faster than centralized planning could process the same information.

The second structural principle is designing governance frameworks that can absorb autonomous decision-making rather than routing everything through human approval workflows. This means identifying decision categories where AI systems should have autonomous authority, where human oversight adds value rather than delay, and how accountability mechanisms can operate at AI speed.

A major telecommunications operator redesigned network management around AI systems that could detect performance issues, analyze root causes, and execute corrective actions automatically within predefined boundaries. The governance framework defined decision domains where AI systems had autonomous authority, escalation triggers for decisions that required human judgment, and audit mechanisms that could review AI decision patterns rather than individual decisions.

This governance redesign enabled the AI systems to operate at network speed rather than human approval speed while maintaining oversight mechanisms that could detect pattern problems or boundary violations. The accountability framework focused on outcome patterns rather than individual decision approval, allowing AI systems to optimize network performance faster than traditional incident response workflows.

The third structural principle is aligning capital allocation with compute placement requirements rather than organizational preferences or historical investment patterns. AI workloads have specific infrastructure requirements that may conflict with existing data center strategies, cloud commitments, or regional preferences.

A global financial services firm discovered that their AI-powered trading systems required specialized silicon placement, low-latency network connections, and data residency configurations that could not be accommodated through their existing cloud architecture. Rather than constraining AI performance to fit existing infrastructure investments, they redesigned capital allocation to support optimal compute placement even when it required new infrastructure relationships and different operational frameworks.

The operating model redesign focused on infrastructure decisions that would support AI performance requirements over the next five years rather than optimizing current operational costs. This required changing capital approval workflows to accommodate infrastructure investments that might conflict with standardization preferences but deliver competitive advantages through superior AI performance.

The research shows that AI adoption leaders structure governance differently rather than just deploy technology better. They design operating models around intelligent systems rather than trying to fit intelligent systems into process-driven frameworks. The organizations that approach AI as an operating model redesign challenge rather than a technology implementation project are building sustainable competitive advantages that compound over time.

These structural changes are not gradual improvements to existing operating models. They require redesigning how decisions get made, who has authority over different types of choices, and how governance mechanisms can operate at the speed that competitive positioning demands. The companies that understand this are rebuilding enterprise IT rather than upgrading it, creating operating models that can absorb intelligence-driven systems rather than resist them.

Why Edge Intelligence Demands Authority Redesign

The movement of compute and inference to the edge is not a technical optimization decision. It's a structural requirement that forces fundamental changes in how organizations distribute authority, coordinate decisions, and maintain governance oversight. Edge intelligence operates at latencies and scales that centralized authority structures cannot accommodate without eliminating the performance advantages that justify the architectural shift.

Edge deployment means that AI systems must make decisions locally based on conditions that cannot be communicated to centralized systems fast enough for optimal response. A global manufacturing operator implementing predictive maintenance discovered that equipment failure prediction required analyzing sensor data, operational patterns, and environmental conditions at sub-second intervals. Routing this analysis through centralized processing introduced latencies that eliminated the predictive value while adding communication overhead that degraded overall system performance.

The solution required redesigning authority structures so that edge AI systems could execute maintenance interventions autonomously within defined parameters while maintaining coordination with centralized resource planning and compliance monitoring. This authority redesign was not about delegating more decision-making to local teams. It was about creating governance frameworks that could accommodate autonomous systems making decisions faster than human oversight could process.

Edge intelligence amplifies the authority displacement challenge because it removes geographic and temporal buffers that allowed centralized oversight to maintain control over distributed operations. When AI systems can analyze local conditions and execute responses faster than centralized coordination can occur, traditional authority structures become performance constraints rather than governance mechanisms.

A major retail operator discovered this when implementing AI-powered inventory management across multiple locations. The AI systems could analyze local demand patterns, supply chain conditions, and competitive pricing in real-time to optimize inventory positioning and pricing decisions at the store level. However, the governance framework required pricing decisions to be approved through regional management hierarchies that could not process recommendations fast enough to capture market timing advantages.

The edge deployment required redesigning governance around outcome boundaries rather than decision approval workflows. Store-level AI systems received autonomous authority over pricing within defined margin and competitive parameters while escalating decisions that exceeded local authority or required coordination across locations. The accountability framework focused on outcome patterns and boundary compliance rather than individual decision review.

This structural change enabled the AI systems to optimize local performance while maintaining organizational coordination and risk management. The authority redesign was not about reducing oversight. It was about redesigning oversight mechanisms that could operate at the speed and scale that edge intelligence requires to deliver competitive value.

The research indicates that forward-deployed engineering approaches are necessary for scaling agentic AI across enterprises because the traditional model of centralized development and distributed deployment cannot accommodate the authority distribution that edge intelligence requires. Organizations need embedded authority structures that can support autonomous decision-making rather than remote coordination mechanisms that introduce latencies incompatible with edge performance requirements.

The architectural implications extend beyond technology deployment to organizational design. When intelligence operates at the edge, the organizational structures that coordinate that intelligence must also be redesigned around distributed authority rather than centralized control. The companies that successfully implement edge AI are not just deploying different technology. They're rebuilding how authority operates across distributed systems.

Edge intelligence forces organizations to choose between preserving existing authority structures and capturing AI performance advantages. The organizations that choose performance are redesigning authority distribution, governance mechanisms, and coordination frameworks around the requirements of intelligent systems rather than the preferences of existing hierarchies. The ones that prioritize authority preservation are building systems that cannot deliver on their AI performance commitments.

Structural Decisions That Determine Competitive Outcome

The organizations that will compete in the data-driven era are making specific structural decisions today that will determine their capability to absorb AI-driven competitive advantages over the next decade. These are not strategic planning decisions or technology roadmap choices. They're operating model design decisions that will either enable or constrain organizational performance regardless of AI investment levels or talent acquisition success.

The first structural decision is whether to optimize AI implementations for existing authority structures or redesign authority structures around AI capabilities. Organizations that choose optimization are implementing AI systems in advisory modes that preserve human decision-making hierarchies while adding analytical overhead. Organizations that choose redesign are identifying decision domains where AI systems should have autonomous authority and rebuilding governance frameworks around intelligent systems rather than human hierarchies.

A global consulting firm made this structural choice when implementing AI-powered project delivery optimization. Rather than building AI systems that provided recommendations to existing project management hierarchies, they redesigned project authority around AI systems that could coordinate resource allocation, timeline optimization, and quality assurance across multiple client engagements simultaneously. The authority redesign enabled the AI systems to optimize firm-wide performance metrics rather than individual project preferences.

The second structural decision is whether to treat data governance as a compliance requirement or as a competitive capability. Organizations that choose compliance focus on data protection, privacy regulations, and audit requirements that constrain AI system access to data domains. Organizations that choose capability focus on data architecture that enables AI systems to operate across organizational boundaries and authority structures while maintaining appropriate oversight and control mechanisms.

A major financial services firm made this choice when designing data architecture for AI-powered risk management. Rather than constraining AI systems to operate within existing data silos that aligned with organizational boundaries, they redesigned data governance around intelligent systems that could analyze risk patterns across customer relationships, product lines, and market conditions simultaneously. The data architecture redesign enabled AI systems to detect risk correlations that were invisible to siloed analysis approaches.

The third structural decision is whether to align capital allocation with existing operational frameworks or with AI performance requirements that may conflict with historical investment patterns. Organizations that choose alignment with existing frameworks are constraining AI performance to fit current infrastructure commitments and vendor relationships. Organizations that choose alignment with AI requirements are redesigning capital allocation around compute placement, specialized silicon access, and network performance requirements that deliver competitive advantages.

The research shows that organizations are investing in enterprise architecture tools at 6.09% compound annual growth rates, indicating structural mapping investments for transformation rather than simple technology upgrades. The companies making these investments are redesigning how work gets done rather than automating existing workflows. They're building operating models that can absorb intelligent systems rather than resist them.

The fourth structural decision is whether to manage AI implementation through existing transformation program methodologies or redesign change management around the speed and authority distribution requirements that AI systems demand. Traditional transformation programs assume that organizational change can be managed through communication, training, and gradual capability development. AI transformation requires authority redistribution that happens faster than traditional change management approaches can accommodate.

The companies that successfully scale AI are building transformation capabilities around structural redesign rather than process improvement. They're identifying where operating models must change to absorb AI capabilities, how authority structures must evolve to accommodate intelligent systems, and what governance frameworks must be rebuilt rather than updated.

These structural decisions are being made now whether organizations recognize them as strategic choices or default to existing operational preferences. The organizations that make deliberate structural choices aligned with AI requirements are building competitive advantages that will compound over time. The organizations that default to existing structures are constraining their ability to capture AI performance advantages regardless of technology investment levels or implementation quality.

The Architecture of Competitive Advantage

Organizations that understand the structural nature of this transformation are not just implementing AI tools. They are rebuilding enterprise IT around a fundamental insight: intelligence must be distributed to where decisions create competitive value, even when that conflicts with existing authority structures, governance frameworks, or operational preferences.

This rebuilding creates a specific type of competitive advantage that cannot be replicated through technology acquisition, talent recruitment, or capital investment alone. It emerges from operating models designed around intelligent systems rather than process-driven workflows. The advantage compounds because organizations with AI-native operating models can absorb new AI capabilities faster than organizations trying to fit new capabilities into legacy structures.

The structural transformation is unavoidable because compute and inference are moving to the edge regardless of organizational preferences. The workload placement requirements that AI demands cannot be solved through better cloud architecture, more sophisticated networking, or more efficient data center operations. They require redesigning how decisions get made, who has authority over different types of choices, and how governance mechanisms can operate at the speed that competitive positioning demands.

The organizations that recognize this structural reality are making architectural decisions today that will determine their competitive position for the next decade. They are choosing to rebuild rather than upgrade because they understand that the performance advantages that AI delivers cannot be captured through existing operating models designed around different computational and authority assumptions.

The ones that don't understand this structural requirement are managing declining relevance. They are optimizing for the wrong architecture, preserving authority structures that create execution bottlenecks, and building technical debt faster than they build competitive capability. The technology works, but their operating models cannot absorb the performance advantages that justify AI investments.

This is not a gradual transition that allows for experimental approaches and incremental optimization. The architectural decisions being made today are creating competitive advantages that compound quarterly rather than annually. The window for structural redesign is closing as organizations that complete this transformation gain sustainable advantages over organizations still managing process-driven operating models with AI augmentation.

The data-driven era rewards organizations built for intelligence, not organizations trying to add intelligence to structures designed for different competitive requirements. The companies that understand this are rebuilding enterprise IT. The companies that don't are managing the decline of architectures that cannot compete in an environment where intelligence must live where decisions create value.