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Editorial

1+1 > 2: Integrating Analytical Techniques in the Age of AI

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INTRODUCTION

The premise that combining analytical techniques yields results greater than the sum of their parts, captured in the expression 1+1 > 2, has gained renewed urgency in an era marked by the proliferation of artificial intelligence (AI), the explosion of unstructured data, and mounting pressure on researchers to demonstrate both rigor and relevance. However, integrating methods remains more promising than practice in many fields. Survey evidence indicates that while 87 percent of organizations have adopted AI for task automation, only 23 percent employ it in strategic decision-making (McKinsey & Company, 2024; MIT Sloan Management Review, 2024). Similarly, despite decades of methodological pluralism in the social sciences, the dominant mode of inquiry continues to privilege single-technique approaches that sacrifice contextual richness for analytical tractability. This editorial argues that the contemporary landscape demands a different paradigm: one in which hybrid architectures — combining frequentist and Bayesian inference, structured and unstructured data, human judgment, and machine computation — are the norm rather than the exception.

Three interrelated crises provide a backdrop for this argument. The reproducibility crisis, thrust into prominence by large-scale replication failures in psychology, medicine, and economics, exposes the fragility of findings produced under conditions of low statistical power, analytical flexibility, and publication bias (Ioannidis, 2005; Open Science Collaboration, 2015). The accountability crisis in marketing reflects persistent managerial skepticism regarding whether investments in brands, advertising, and customer experience generate measurable financial returns (Hanssens & Pauwels, 2016; Morgan et al., 2022). Furthermore, the data access crisis stems from increasingly restrictive privacy regulations and declining consumer willingness to participate in research, both of which constrain the granular behavioral data on which much marketing science depends (Toubia et al., 2025). None of these crises admits a single-method solution; each calls for analytical architectures that combine complementary strengths while mitigating individual weaknesses.

These concerns motivated the special session "1+1 > 2: Integration of Analytical Techniques in AI Times," convened at EnANPAD 2025, which brought together four complementary perspectives on hybrid analytical architectures. The following sections develop each perspective in turn: the historical evolution from unimodal to multimodal integration; the progressive layering of techniques in financial risk management; the MESH framework for human-AI collaboration; and a four-step workflow for addressing reproducibility, accountability, and data scarcity. The concluding section synthesizes these contributions and articulates an agenda for future research.

THE AGE OF ANALYTICAL INTEGRATION

The integration of analytical techniques has transformed decision-making across public and private organizations and academic research; however, in practice, this movement remains incipient in many domains. The convergence of big data, generative AI (GenAI), geospatial artificial intelligence (GeoAI), text mining, deep learning, Bayesian modeling, and social network analysis (SNA) has substantially expanded the repertoire of applications in areas such as spatial marketing, credit risk, pricing, asset valuation, and omnichannel strategy. The simultaneous advancement of these methodological frontiers not only increases analytical efficiency but also enables hybrid architectures that strengthen contextual interpretation and predictive robustness (Bertsimas & Kallus, 2019; Wedel & Kannan, 2016). Unlike isolated approaches, these architectures do not merely aggregate capabilities but mutually potentiate the results.

Recent literature supports this direction. The combination of GeoAnalytics and NLP enables the contextualized capture of consumer spatial perceptions (Ghasemaghaei et al., 2018); text mining techniques integrated with SNA graphs help identify thematic clusters in social networks; and Bayesian models have incorporated spatial and semi-structured variables for inference in highly complex environments (Ghasemaghaei, 2019; Rai & Tang, 2010). Similarly, the emergence of GeoAI has brought deep learning closer to georeferenced data, enabling precise insights into credit, mobility, retail, and consumer behavior (Boutayeb et al., 2024). At the frontier of computational modeling, GenAI has been applied to complex financial decisions (Liu et al., 2024), risk assessment (Joshi, 2025), and the transformation of digital marketing strategies (Popescu et al., 2025), while simultaneously raising new ethical concerns.

These convergences also manifest in text-mining applications for technological roadmapping, anticipating the trends and impacts of new architectures (Porter et al., 2024; Singh et al., 2024). Hybrid models have already advanced risk measurement, portfolio allocation, and default prediction by combining AI with macroeconomic analyses and ESG-related decision-making (Li et al., 2024; Wamba-Taguimdje et al., 2020). GenAI integrated with Bayesian models has been applied to predict health and environmental crises, whereas NLP algorithms evaluate reports, social media, and news in near real time, influencing financial decisions (Khattak et al., 2023). Furthermore, the combined use of consumption geolocation, environmental data, and social networks enhances pricing strategies and risk management, thereby configuring a more market-responsive toolkit.

Multimodal analytical integration and GeoAI

The integration of analytical techniques has occurred incrementally. In various areas of Business Administration, researchers have combined methods such as bibliometrics, social network analysis, and GeoAnalytics, using bibliographic data, co-authorship relations, and spatial metrics to investigate structural patterns and research dynamics (Favaretto & Francisco, 2017; Francisco, 2011). Examples include the intersection of geodesic distances and collaboration network structures, spatial modeling of article relevance using kriging, thematic cartography applied to non-geographic domains, and the construction of three-dimensional similarity surfaces among themes, institutions, or keywords. These combinations are essential for revealing hidden interdependencies, offering multidimensional views of phenomena traditionally analyzed in a unidimensional fashion.

The integration of analytical techniques has evolved from traditional, consistent combinations to hybrid architectures that integrate multiple data modalities. This transition reflects a paradigm shift from statistical analyses to pipelines that integrate text, location, images, time series, sensor data, trajectories, and socioeconomic data. A landmark of this evolution is the advancement of GeoAI, a field that emerged from the convergence of geospatial big data, machine learning, and GIScience principles. According to Li (2020), GeoAI combines two methodological traditions — data-driven and knowledge-driven — allowing models to learn complex spatial patterns while simultaneously incorporating semantic knowledge using ontologies and knowledge graphs. This hybrid approach overcomes the limitations of traditional techniques, expanding both predictive capacity and interpretability.

From an applied standpoint, recent advances have demonstrated that multimodal integration generates substantial gains. In the context of disasters, Hanny et al. (2025) found that combining text, spatial, and temporal features significantly improves the classification of relevance in social media posts by allowing the model to simultaneously consider distance to the event, temporal co-occurrence, and text semantic context. Integration, not the isolated use of each modality, is the central element for capturing complex patterns. These capabilities extend to the market and consumer domains. The study on AI-powered geospatial market analysis shows how the fusion of satellite imagery, urban mobility, transactional data, and digital activity enables the identification of retail hotspots, demand forecasting, guidance on expansion decisions, and urban growth modeling with unprecedented granularity (Ali et al., 2025). Thus, analytical integration evolves from 'modal' approaches — space with statistics or networks with text — to multimodal architectures in which spatial, temporal, and semantic elements are articulated as parts of a single system. GeoAI symbolizes this change by offering a framework for spatially explicit analyses that has the potential to transform investigations in marketing, operations, logistics, credit, and organizational behavior.

Hybrid analytical architectures in financial risk management

Financial risk management is a fertile domain for the transformative potential of hybrid analytical architectures. For many years, the measurement and management of risk relied predominantly on traditional econometric models that processed exclusively historical structured data on prices, returns, and volatilities. Although these approaches served reasonably well during periods of relative stability and even occasional disruptions, their limitations become far more apparent in the context of structural breaks and extreme events. Value-at-risk (VaR) is an example that illustrates this methodological evolution. As a standard risk management metric that estimates the maximum expected losses over a given time horizon and confidence level, VaR has traditionally been calculated through historical simulations, parametric models assuming specific return distributions, or Monte Carlo simulations with parameters estimated from past series. All these approaches share a fundamental limitation: they depend exclusively on observed historical patterns, ignoring contextual information, relevant non-financial events, and the possibility of future scenarios that are qualitatively distinct from the past.

A progressive hybrid architecture for VaR estimation can be constructed by sequentially and complementarily integrating different analytical techniques. The first layer of sophistication incorporates text mining and sentiment analysis of financial news. Critical events such as the COVID-19 pandemic, geopolitical conflicts, banking crises, and abrupt changes in monetary policies can precede extreme market movements. However, this contextual information is not captured in historical price series until the impact has materialized. By extracting sentiment from a broad set of news through text processing, one can identify potentially forward-looking informational signals regarding changes in the market regime (Song et al., 2025). As an additional layer, generative artificial intelligence can be applied to data augmentation by generating synthetic data (Cheng et al., 2025). Generative models can create synthetic scenarios with realistic logic that preserve the correlation and dependence structures observed in different volatility regimes while exploring underrepresented regions of the state space in historical data. The third layer introduces Bayesian inference for uncertainty quantification (Martín et al., 2025). Bayesian models characterize posterior distributions over quantiles of interest, incorporating prior knowledge and continuously updating beliefs as new data become available, providing base estimates and confidence intervals that quantify prediction uncertainty.

The integration of multiple analytical techniques can improve predictive capacity and robustness. Text mining captures the qualitative context and non-financial events that are absent from numerical price data. Generative AI expands the sample space beyond historical limitations, enabling the preparation of plausible yet unobserved scenarios. Bayesian inference quantifies uncertainty and allows the incorporation of prior knowledge. Similar hybrid architectures can be applied to credit risk assessment, asset pricing, and portfolio management. The convergence between traditional financial econometric techniques and new methodological frontiers of data science, generative artificial intelligence, and Bayesian inference represents not merely a marginal technical refinement but rather a paradigmatic shift in how we understand, measure, and manage financial risks in increasingly complex and interconnected environments.

Hybrid intelligence and the MESH framework

Beyond the integration of analytical techniques lies a more fundamental question: how can humans and artificial intelligence systems effectively collaborate in research and decision-making processes? The prevailing approach to AI adoption has largely followed what might be termed substitution logic: human processes are mapped, transferred to AI systems, and then executed autonomously by machines. This asymmetry suggests that the dominant paradigm treats AI as a replacement technology rather than as a collaborative partner, thereby forfeiting the potential integration that emerges when human and machine capabilities are deliberately combined. The conceptual foundations of human–AI collaboration have deep historical roots. Licklider (1960) first articulated the vision of 'man–computer symbiosis,' proposing that humans and machines could form partnerships in which each contributes what the other lacks. Hutchins (1995) extended this perspective through the framework of distributed cognition, demonstrating that cognitive processes can be distributed across individuals and artifacts. Latour (2005) further elaborated on this view through actor–network theory, treating human and non-human actors as symmetrical participants in networks of action. More recently, Mollick (2024) synthesized these perspectives into the concept of 'co-intelligence,' arguing that the partnership between humans and AI systems can exceed the sum of its parts when properly designed.

A useful heuristic for understanding the division of labor between humans and AI emerges from mapping cognitive tasks onto Bloom's taxonomy of educational objectives. At lower cognitive levels, such as memory and understanding, AI systems outperform humans in speed, scale, and consistency. At the intermediate levels of applying and analyzing, the relationship becomes genuinely hybrid. At higher cognitive levels, such as evaluation and creation, humans retain decisive advantages in contextual judgment, ethical reasoning, and the generation of genuine novelty. The MESH framework — map, explore, sift, harmonize — operationalizes these principles into a structured workflow for hybrid human–AI research. In the 'map' phase (approximately 80 percent human-led), researchers define the problem, establish context, and articulate values and criteria. In the 'explore' phase (approximately 70 percent AI-led), AI systems process large-scale data, scale analysis by orders of magnitude, and detect patterns across multiple sources. In the 'sift' phase (approximately 70 percent human-led), researchers validate contextual appropriateness, detect potential biases, and exercise ethical judgment. Finally, in the 'harmonize' phase (genuinely a 50–50 hybrid), humans decide on strategy, while AI optimizes implementation through simulation, forecasting, and scenario analysis.

The implications of hybrid intelligence frameworks extend beyond efficiency gains to fundamental and methodological questions. If research processes are distributed across human and machine agents, traditional notions of authorship, accountability, and reproducibility must be reconceptualized. The challenge is not merely technical (i.e., developing better AI tools) but methodological: designing research workflows that preserve human judgment on questions of meaning, ethics, and interpretation while leveraging machine capabilities for scale, speed, and pattern detection. The transition from substitution to genuine hybridization represents a paradigm shift in how we conceptualize the research enterprise, positioning humans and AI as complementary rather than competing intelligences.

Addressing three crises through mixed analytical techniques

Reproducibility crisis. Reproducibility has always been a defining feature of science — the ability of independent researchers to obtain the same findings when repeating a study using the same methods, procedures, and conditions. The reproducibility crisis, although widely publicized only in the 2010s, has deep historical roots. Early warnings appeared long before the term existed: Cohen (1962) demonstrated that many psychological studies were critically underpowered; Rosenthal (1979) described the file-drawer problem, which suppressed non-significant findings; and Meehl (1990) argued that flexible theorizing rendered many psychological claims unfalsifiable. By the early 2010s, the crisis became impossible to ignore. Begley and Ellis (2012) replicated only six of 53 landmark cancer studies, while Camerer et al. (2016) found that a third of studies published in top-tier economics journals did not replicate. The Reproducibility Project: Psychology found that only 36 percent of 100 studies yielded statistically significant results upon replication, with effect sizes roughly half those of the original work (Open Science Collaboration, 2015). A substantial portion of the methodological criticism has focused on the misuse of frequentist statistics, particularly the overreliance on null-hypothesis significance testing and the misinterpretation of p-values (Cohen, 1994; Ioannidis, 2005; Wasserstein & Lazar, 2016).

Accountability crisis. The accountability crisis in marketing reflects a persistent lack of confidence in whether marketing investments truly generate financial returns, a concern repeatedly voiced by managers who struggle to justify budgets in the absence of credible, decision-relevant evidence. Foundational research by Srinivasan and Hanssens (2009) shows that firms often fail to link marketing actions to their long-term financial performance. Hanssens and Pauwels (2016) further argue that marketers face escalating pressure to demonstrate economic impact because traditional attitudinal and behavioral metrics often fail to translate into predictable financial results. Morgan et al. (2022) document that many organizations continue to underinvest or systematically misallocate marketing resources due to weaknesses in their marketing performance assessment systems. Methodologically, the most significant response has been the rapid adoption of modern causal inference techniques — graphical models, counterfactual reasoning, and identification strategies — which provide more robust estimates of marketing's actual impact (Morgan & Winship, 2014; Pearl et al., 2016; Pearl & Mackenzie, 2018).

Access to primary consumer data. The third challenge is the growing difficulty in collecting primary consumer data. Regulatory environments have become much stricter, with frameworks such as the GDPR limiting the conditions under which organizations can store, process, or share personal information. Consumers have become more skeptical and less motivated to participate in research. One promising response is the development of synthetic data pipelines, particularly those based on digital twins. A central recent contribution is the work of Toubia et al. (2025), who assembled and publicly released a large-scale dataset specifically designed to support the construction and validation of digital twins, including more than 500 psychological, cognitive, economic, and behavioral items per respondent.

Solutions to the three crises. A tentative four-step solution combines analytical approaches in a cumulative and complementary sequence (presentation, case study, and code available at https://osf.io/cgv6e). Step 1 focuses on reproducibility and model transparency by beginning with a simple frequentist effect test, typically an ordinary least squares (OLS) estimation, which provides a baseline estimate under explicit, well-understood statistical assumptions. Step 2 moves from association to causation through formal causal inference tests, such as difference-in-differences designs, and then proceeds to a structured counterfactual analysis. Step 3 addresses the accountability crisis through Bayesian marketing mix modeling, which quantifies the financial impact of multiple marketing variables simultaneously and yields posterior distributions that enable decision-makers to interpret uncertainty and long-term effects more effectively. Step 4 addresses the growing scarcity of primary consumer data by combining real and synthetic data and integrating privacy-compliant empirical data with digital twin-based behavioral simulations. This integrated analytical workflow combines transparent baseline estimation, credible causal identification, rigorous financial attribution, and innovative data augmentation into a coherent toolset to navigate contemporary challenges in marketing science.

CONVERGENCE OF PERSPECTIVES AND AN AGENDA FOR THE FUTURE

The four perspectives presented in this editorial converge on a central thesis: the integration of analytical techniques is not merely an incremental refinement but a paradigmatic shift in how research and decision-making should be conducted. Francisco's account of the evolution from unimodal to multimodal architectures, Almeida's demonstration of progressive layering in financial risk measurement, Limongi's framework for human–AI collaboration, and Brei's workflow for addressing the reproducibility, accountability, and data access crises all share a common logic: deliberately designed combinations of methods compensate for individual limitations while amplifying collective strengths. This convergence reflects the structural demands of an environment characterized by data abundance, methodological pluralism, and the imperative to produce findings that are rigorous, interpretable, and actionable.

Several unifying principles have emerged from these contributions. First, 'sequentiality matters': the order in which techniques are combined shapes the quality and interpretability of the results. Second, 'complementarity trumps substitution': rather than replacing human judgment with AI or traditional methods with novel ones, the most productive architectures allocate tasks according to comparative advantage. Third, 'uncertainty must be quantified, not ignored': Bayesian approaches, confidence intervals, posterior distributions, and scenario simulations all help to operationalize epistemic humility. Fourth, 'transparency is non-negotiable': hybrid architectures risk becoming black boxes unless each step is documented in sufficient detail to permit scrutiny and replication.

However, significant methodological questions remain. How should researchers calibrate the relative weights of different information sources within integrated models? What validation criteria apply to the synthetic scenarios generated by generative AI? When human judgment and machine output diverge, what protocols should govern the resolution? How should authorship, accountability, and credit be attributed to research processes distributed across human and artificial agents? An agenda for future research might productively address several fronts: empirically, comparative studies benchmarking hybrid architectures against single-method approaches; methodologically, standardized protocols for documenting hybrid workflows; theoretically, deeper engagement with the epistemological foundations of integration; and practically, case studies of implementation challenges and governance structures.

However, a note of caution is warranted. The enthusiasm for hybrid architectures should not obscure the risks of methodological opportunism — the temptation to combine techniques in ad hoc ways that maximize apparent sophistication while sacrificing coherence. Integration for its own sake, without a clear justification for each component's necessity, amounts to methodological theater that undermines rather than advances scientific credibility. The guiding principle is not 'more is better' but rather 'each addition must earn its place by solving a problem that simpler approaches cannot address.'

The panel from which this editorial was derived was titled '1+1 > 2' as a provocation: can the combination of analytical techniques genuinely yield more than the sum of their parts? The contributions assembled here suggest that the answer is conditionally affirmative in this case. When integration is designed with attention to sequentiality, complementarity, uncertainty quantification, and transparency — and when it is motivated by substantive problems rather than methodological fashion — hybrid architectures can generate insights, predictions, and decisions that no single approach could produce. The challenge now is to move from demonstration to institutionalization: to develop training programs, publication standards, review criteria, and collaborative practices that make rigorous integration the norm rather than the exception in business administration research. If this editorial contributes to this transition, it will have served its purpose.

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