CHALLENGING MULTI-VECTOR EXCLUSION BY IMPROVING ROI ADOPTION IN APPLIED AI SYSTEMS: THE E.A.S.E. FRAMEWORK AS A SYSTEMIC EVALUATION TOOL FOR INTERSECTING AI BIAS AND DIGITAL EXCLUSION

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ABSTRACT

This paper addresses the core challenge of multi-vector exclusion in applied AI systems, arguing that the industry's singular focus on Return on Investment (ROI) constitutes a systemic failure in evaluation (Chen, 2025). This crisis is exacerbated by the progression to autonomous agentic systems, which intensify the risk to human agency by relying on workflows that have not been adequately understood. Mixed-methods research reveals distinct, intersecting harms across two axes: Neurodiversity/Disability (evidenced by systemic technical friction and the "disability tax") and Racial Bias(evidenced by significant algorithmic preference bias and job displacement risk for Black heritage professionals). These findings demonstrate that AI adoption is separating functional rollouts from the critical need for co-creative change management. To resolve this, the paper introduces the E.A.S.E. Framework (Equity of Access, Agency & Participation, Succession Continuity, and Employment Impact)—a novel governance methodology designed to integrate human-centered, auditable metrics across the product lifecycle, ensuring technology supports equitable and resilient organizational transformation.

KEYWORDS

Multi-vector Exclusion, Algorithmic Bias, AI Governance, Digital Exclusion, Agentic Systems

1. INTRODUCTION

The rapid global expansion of Generative AI (GenAI) into professional services is frequently measured by a singular, narrow metric: Return on Investment (ROI), focusing on efficiency, speed, and productivity gains. This approach fundamentally fails to capture the systemic costs of multi-vector exclusion (Chen, 2025), treating systems as successfully validated within controlled or simulation environments without sufficient attention to long-term, real-world performance or user-facing outcomes (Myllyaho et al., 2021). The consequence of prioritizing efficiency is the measurable scaling of structural biases and the deepening of digital inequality. Digital exclusion is not merely a matter of access; rather, the lack of real-world evaluation permits exclusionary systems to persist, thus creating a cascade of impacts across economic, social, cultural, and personal domains (Helsper, 2012). When effectiveness is narrowly defined by productivity alone, critical factors like inclusion, trust, and continuity are relegated to peripheral concerns, yet these factors ultimately determine whether GenAI adoption bridges or exacerbates societal inequality.

This paper addresses the core challenge facing organizational leadership: How can AI leaders in mid- to large-scale companies implementing GenAI effectively drive value, culture change, and

ROI by systemically addressing inequality and accessibility?

The research trajectory is rooted in foundational studies of complex design problems and the role of technology in facilitating human agency (Spellman, 2010). This early focus informed a practical investigation into a GenAI implementation with a disability charity, which highlighted precisely how a technologically complex system fails to uphold equitable outcomes. This initial challenge—diagnosing the technical friction faced by disabled and neurodivergent users—directly established the problem mandate and informed a subsequent, expanded Diversity and Inclusion (D&I) research conducted within a major consultancy. This later study provided undeniable evidence that AI systems introduce algorithmic bias and disproportionate risk to Black heritage professionals throughout the entire employment lifecycle.

1.1. The Escalation of Existential Risk

The evaluation crisis is now compounded by escalating commercial and national security risks, transforming the social justice imperative into a matter of organizational stability and viability. This shift is crucial, as the failure of governance protocols affects the entire ecosystem. AI has proved to be a "double-edged sword," accelerating cybercrime capacity and generating severe, unmanaged risks that industry leaders have struggled to contain. The widespread adoption of Generative AI (GenAI) creates a massive new attack surface, significantly escalating the potential for data pollution and compliance failures. These failures expose firms to a critical risk concerning both reputation and the security of client data. This pressure forces leaders to acknowledge the severe consequences posed by unreliable AI outputs (hallucination) and the difficulty of auditing Black Box systems, which hinder effective due diligence and accountability.

While policy frameworks such as the EU AI Act (EU, 2024) aim to couple innovation with rights-preserving governance (Brattberg, 2020), they lack clear mandates for accessibility or participatory design. This is a critical omission, given that the European Investment Bank (EIB, 2025) has emphasized that inclusion is a competitiveness factor, not solely a rights concern. Existing standards, such as WCAG 2.2 and ISO 30071-1, remain inconsistently applied, particularly in dynamic, conversational GenAI systems, where their application to emergent, probabilistic outputs poses a significant challenge. Without enforceable requirements, accessibility risks remaining aspirational rather than operational.

This study introduces the E.A.S.E. Framework (Equity of Access, Agency & Participation, Succession Continuity, and Employment Impact) as a systemic evaluation tool designed to translate the complex realities of multi-vector exclusion and external risk into auditable, architectural criteria.

2. Empirical Foundations: The Reality of Multi-Vector Exclusion

The necessity of the E.A.S.E. Framework is grounded in the distinct, quantified harms that AI imposes across different marginalized groups, demonstrating that accessibility is not an inherent property of GenAI but a design choice. While AI systems have delivered tangible benefits in areas such as perception, mobility, and communication for disabled users (Wang et al., 2023; Smith et al., 2023; Voutsakelis et al., 2025), their widespread adoption remains fragmented by affordability, uneven usability, and limited inclusive design practices (Chemnad et al., 2024).

The evaluation crisis is compounded by the following systemic issues:

- Erosion of Trust and Data Integrity: Information environments are increasingly polluted by low-quality, machine-generated content—often termed "AI slop"—that actively undermines knowledge infrastructures and user confidence (Shao et al., 2017).
- Governance Failures: Failures in governance protocol multiply barriers to participation, particularly for individuals reliant on assistive technologies or with limited digital literacy. Examples include documented risks of unsafe conversational AI interactions with minors (Reuters, 2025) and exposed private chatbot conversations (McMahon, 2025).
- Policy Gaps in Implementation: In high-stakes sectors like healthcare and education, AI-enabled tools can enhance autonomy and adaptive learning, yet gaps in privacy, governance, teacher training, and data governance risks constrain impact and trust (Giansanti et al., 2025; Kooli et al., 2025). Rights-based critiques emphasise that accessibility must be embedded across standards, procurement, and lifecycle governance, not relegated to retrofitted add-ons (Scully et al., 2025).

2.1. Vector 1: Neurodiversity and the Technical Access Barrier

Neurodivergent users represent a critical vector of exclusion because their reliance on consistent, predictable, and interoperable digital environments directly highlights the friction created by the divergence between consumer and enterprise GenAI maturity.

Between 2022 and 2025, GenAI adoption moved from flexible, consumer-facing tools (e.g., ChatGPT) to regulated enterprise deployments. Early consumer systems were largely unregulated, placing the responsibility for accessibility on individuals who relied on mature personal assistive technologies (PATs). However, the subsequent introduction of enterprise offerings (e.g., ChatGPT Enterprise) into workplaces brought stronger guardrails and compliance measures but often featured weaker interoperability with PATs.

This divergence created a persistent dissonance: Consumer tools rapidly became multimodal (e.g., voice, image, text), promising a fluidity that enterprise systems could not match, especially in critical areas like accessibility and retrieval-augmented grounding (RAG). For neurodivergent staff who depend on predictable digital patterns, the weaker interoperability and slower evolution of enterprise systems compared unfavourably to faster-evolving consumer tools. This gap means that enterprise deployments are experienced as constrained, less reliable, and harder to align with existing accessibility ecosystems, ultimately creating technical friction that prevents equitable access to these essential productivity tools.

2.2. Vector 2: Racial Bias and Allocative Harm

The initial diagnostic findings—particularly the low platform engagement resulting from technical friction—immediately raised questions about whether this crisis of confidence would extend to groups navigating racial bias and systemic allocative harm, where anonymity and data integrity are prerequisites for fair evaluation. The ensuing large-scale Diversity and Inclusion (D&I) research confirmed that this foundational lack of trust in AI systems manifests as explicit, measurable harm across the full employee lifecycle for Black heritage professionals. The primary vector of exclusion is allocative harm—the systematic denial of opportunities that results in measurable job displacement and gatekeeping:

Displacement Risk: Black workers are 10% more likely to face job displacement from AI-related automation due to historical concentration in vulnerable roles (McKinsey, 2022).

Hiring Gatekeeping: Algorithmic systems exhibit direct bias, favoring white-associated names in resume screening 85% of the time (University of Washington News, 2024).

Progression Barriers: Post-hire AI tools structurally suppress careers; for example, 63% of Black professionals reported AI platforms underestimated their academic credentials (Thomson Reuters/UPenn Law, 2025).

Compliance Failure: Automated algorithms used by the US IRS targeted Black taxpayers for audits at a rate at least three times higher than others (Goldin & Ramesh, 2025).

2.3. Cross-Cutting Implications: Labor Impact and Knowledge Succession

The quantification of allocative harm is magnified by macro-level labour market shifts that intersect with exclusion across both vectors. This efficiency-inclusion gap disproportionately harms disabled workers, who are often the first displaced, and neurodivergent professionals, who risk being sidelined as "non-adaptive."

This phenomenon is reflected in executive rhetoric that frames AI adoption in terms of pure productivity, with leaders urging workers to adapt or lose their jobs and noting Ginni Rometty stated that AI systems "doesn't strike or ask for pay raises." This aligns with broader labour market trends where jobs in sectors like software engineering and customer service contract while new roles cluster in narrow tech hubs. AI's labour impacts thus extend beyond job losses to threaten operational continuity and knowledge succession, as GenAI rollouts frequently coincide with workforce reductions without clear retraining commitments. Inclusion often ranks low in AI development because accessibility benefits are seen as long-term and harder to quantify than immediate productivity gains, allowing accessibility to remain treated as an "add-on" rather than a core design principle.

3. METHODOLOGY

The case study followed a mixed-methods design over six months during an enterprise GenAI rollout. This approach provided both quantitative measures and rich qualitative depth, consistent with theory-building through contextual inquiry (Eisenhardt, 1989; Orlikowski, 1992).

Surveys (n=50): Captured changes in trust, accessibility, workload impact, and adoption readiness.

- Interviews: Explored lived experiences, focusing on cognitive load, perceptions of control, and specific accessibility needs.
- Focus Groups (with 35 total staff): Multiple focus groups, including visually impaired, neurodivergent, and mobility-impaired participants, provided collective feedback on usability and integration.
- Accessibility Audit: Assessed the platform against WCAG 2.2 and ISO 30071-1, highlighting strengths and systemic barriers.
- Ethical protocols ensured informed consent and safe participation, especially for staff with accessibility needs. Consistent with non-probabilistic sampling, the findings offer contextual insights but are not statistically generalizable.

3.1. Findings

The empirical data revealed three critical points of friction that undermine the intended value proposition of the enterprise GenAI deployment.

3.1.1. Accessibility Conflicts

Staff immediately derived value from features such as summarisation, email drafting, and tone adjustment, which successfully reduced cognitive strain, a significant benefit particularly for dyslexic and autistic participants. However, this intended value was compromised by challenges related to inconsistent interoperability. Mature personal assistive technologies (PATs) such as screen readers and dictation software exhibited friction when interacting with the GenAI interface, resulting in increased cognitive load. The accompanying WCAG audit substantiated these findings, confirming structural gaps related to non-text content (1.1.1), reflow (1.4.10), resizing (1.4.4), and focus order (2.4.3), even where baseline compliance on contrast and keyboard navigation was met. As one participant observed, the system did not read outputs cleanly, effectively "doubling the work". The necessary functional support for accessibility was, therefore, perceived not as an inherent system property but as a challenging retrofit.

3.1.2. Trust Fragility

Trust in the system's output remained a challenging variable to stabilize (e.g., trust was rated low on a 5-point scale, mean 2.0). While staff valued the controlled, ring-fenced environment designed to ensure security, confidence was undermined by output issues: inconsistent responses, hallucinations, and truncated content required constant human verification. This reliance on constant verification led many to revert to external, trusted tools when reliability was paramount. Furthermore, the conversational design, often based on unexamined neurotypical assumptions, increased ambiguity and cognitive strain for neurodivergent participants. This phenomenon was exacerbated by the perception that the enterprise model was “outdated” compared to rapidly evolving consumer versions. Consequently, trust was established as a structural challenge, influenced by system maturity and the dissonance between user expectations and real-world performance.

3.1.3. Succession and Continuity

Organizational capacity in key areas was highly concentrated. Specifically, expertise in accessibility and Quality Assurance (QA) testing was thinly distributed across the organization. As the pace of GenAI adoption accelerated, these specialized staff became demonstrably overstretched, revealing immediate risks to knowledge preservation and operational continuity. Focus groups highlighted this vulnerability, noting the institutional memory risk: “When the one person who knows the accessibility setup leaves, we’re stuck”. The absence of structured succession planning indicated that the acceleration of GenAI adoption posed a measurable risk to long-term operational resilience, as institutional knowledge risked being lost faster than it could be embedded.

3.2. Synthesis and Implications

The case study confirms that the value derived from this enterprise GenAI deployment—including reduced cognitive load, productivity gains, and a safer environment compared to public tools—was fragile and contingent. This fragility stemmed directly from the three structural challenges observed: accessibility conflicts, trust fragility, and risks to succession continuity.

The findings illustrate that GenAI adoption intersects with systemic organizational and social conditions rather than occurring in isolation. The challenge of technical friction for disabled and neurodivergent users resulting in an operational penalty (the "disability tax") is a failure to integrate accessibility across the development lifecycle, a systemic issue well-documented in literature (Chemnad et al., 2024) .

This structural failure, where usability is undermined by neurotypical assumptions and compliance gaps, is compounded by the larger economic narrative. The operational penalty is exacerbated by the macro-level trend of workforce displacement. Executive rhetoric, such as the statement that AI "doesn't strike or ask for pay raises" (Futurism, 2025), frames AI adoption solely in terms of pure efficiency. This environment reinforces the risk that accessibility expertise is under-resourced and succession planning remains absent.

Consequently, when effectiveness is measured too narrowly—prioritizing efficiency above all—trust becomes the overlooked determinant of system success. This trust erosion is driven not only by output errors and liability-driven guardrails but also by the proliferation of "AI slop"—low-quality, machine-generated content that pollutes knowledge infrastructures and dilutes public trust. For individuals navigating disability or limited digital literacy, such polluted information ecosystems heighten barriers to participation and compound epistemic exclusion, making platform accountability an urgent governance necessity.

4. THE E.A.S.E. FRAMEWORK METHODOLOGY: AGNOSTIC INTERVENTION

The E.A.S.E. Framework is a novel governance and evaluation methodology positioned to address the full spectrum of multi-vector exclusion by demanding accountability across four pillars. As a meta-design tool for reframing AI effectiveness. The framework reorients evaluation toward these overlooked dimensions, offering a rights-based, human-centred lens for assessing the systemic impacts of current and future AI systems

Table 1. E.A.S.E. framework

E.A.S.E. Pillar	**Function and Mitigation Strategy**	**Addresses Exclusion Vector(s)**
E: Equity of Access	Mandates technical fairness and guarantees interoperability. Requires testing against WCAG 2.2 and ISO 30071-1 (European Commission, 2015).	Neurodiversity, Disability. Directly mitigates the "disability tax" by making access a precondition for launch.
A: Agency & Participation	Ensures user control and the right to contest AI outputs. Metric: Logging of override actions as a governance signal.	Race, Neurodiversity. Counteracts algorithmic bias by mandating human accountability before irreversible harm occurs.
S: Succession Continuity	Preserves tacit knowledge by mandating formal handover and reskilling plans for automated roles.	All Groups. Stabilizes the diversity pipeline by mitigating the loss of organizational expertise.
E: Employment Impact	Shifts evaluation from displacement to mandated augmentation and reskilling. Metric: Employment Retention Rate for displaced staff.	Race. Directly addresses the 10% higher job displacement risk by mandating reskilling investment for vulnerable groups.

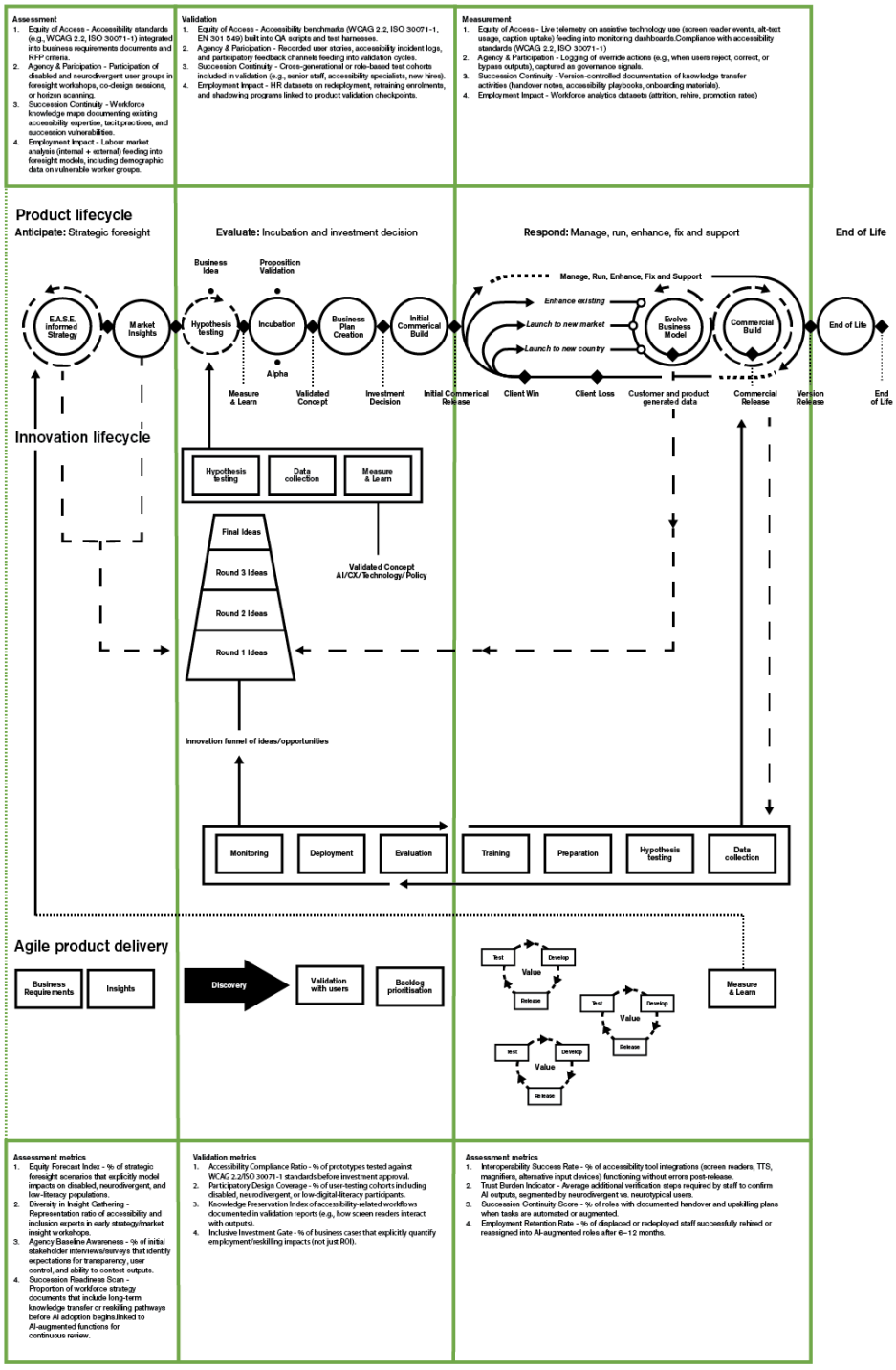

Figure 1.0 E.A.S.E. Framework

4.1. Integration Across the Product Lifecycle

The framework operates as a mandatory governance overlay across the full product lifecycle, ensuring accountability is architectural rather than retrospective.

Anticipate (Assessment): This phase requires using tools, such as the Equity Forecast Index, to proactively model potential multi-vector harm before development begins. This shifts the emphasis from fixing harm to preventing it.

Evaluate (Validation): This phase imposes the Inclusive Investment Gate, requiring formal validation against E.A.S.E. criteria (e.g., Accessibility Compliance Ratio) before resource commitment. This ensures that inclusion metrics are prioritized alongside business metrics.

Respond (Measurement): This phase mandates the use of live telemetry (e.g., Trust Burden Indicator and Interoperability Success Rate) to ensure continuous ethical performance in production and provide auditable records of systemic failures and human interventions.

4.2. Final Synthesis: Conclusion

The E.A.S.E. Framework provides the prescriptive response necessary to bridge the gap between AI's technological innovation and its systemic socio-economic consequences. By translating the complex realities of allocative harm and structural technical friction into auditable criteria, the framework offers a methodology for achieving an AI deployment that is not only profitable but also equitable and resilient.

5. CONCLUSION AND FUTURE RESEARCH

5.1. The Systemic Mandate for Equitable AI Governance

This paper demonstrated that adherence to narrow Return on Investment (ROI) metrics actively contributes to systemic injustice, evidenced by quantified bias in hiring and systemic accessibility failures. The inherent limitations of single-vector evaluation necessitate a shift in organizational accountability. The E.A.S.E. Framework is essential not only for mitigating regulatory liability but for establishing a new standard of social and ethical resilience that is architectural, auditable, and rights-preserving.

5.2. Translational Impact and Future Directions

The E.A.S.E. Framework is currently positioned for rigorous methodological validation (Phase III: Future Work). The proposed initial research—focusing on blind and dyslexic participants engaging with high-stakes applications like tax support—will serve as a targeted, agnostic test for the framework's Equity of Access and Agency pillars. This confirms the model’s universal capability to address systemic architectural deficits across multiple vectors of exclusion.

Future research must now focus on Translational Impact and Scalability by meeting the following strategic criteria:

- Scalability and High-Stakes Sectoral Transferability: Applying E.A.S.E. to high-stakes, complex visual domains like tax and financial compliance. This crucial step, conducted through partnerships with social agencies, will confirm the framework's agnostic efficacy and its scalability across diverse compliance environments where trust, regulatory

adherence, and the potential for allocative harm (e.g., algorithmic audit bias) are critical.

- Inter-Agency Governance and Agentic AI Systems: Testing the framework's efficacy in newly emerging agentic AI systems, where high levels of autonomy and delegation raise challenges for accountability, particularly when these systems operate and share data across multiple organizational and social agency boundaries.
- HEI Partnership for Global Comparative Studies: Conducting comparative implementation studies of E.A.S.E. across different regulatory jurisdictions (e.g., EU, US, UK). This work will be conducted in partnership with Higher Education Institutions (HEIs) to ensure independent validation, rigorous methodological refinement, and maximized academic and policy influence.
- By continuing this research trajectory—moving from quantified observation to prescribed methodological validation—the E.A.S.E. Framework offers a robust solution for equitable AI evaluation, ensuring that technological progress aligns with social justice and contributes to long-term societal resilience.

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1. Transparency Statement (Use of LLM)

This revision clarifies the LLM's role as a *refinement* tool, not a source of original argument, and incorporates the required APA 7 citation format for the specific model version used.

Transparency Statement: Use of Generative AI

This paper includes content generated in dialogue with the ChatGPT large language model (LLM)(OpenAI, 2025). The model served as a collaborative tool in the drafting process, primarily for structural refinement, language clarification, editing, and exploring contextual examples. The LLM was not used to develop critical arguments, theoretical framing, or empirical data analysis. All critical arguments, theoretical framing, validation, and final conclusions are the sole responsibility of the author.

2. Assistive Technology and Accessibility Statement (Inclusive Practice)

This revision tightens the language to focus on the tools as cognitive scaffolds and explicitly links their use to ethical research practice, addressing both neurodiversity and the specific tools used.

Assistive Technology and Accessibility Statement

The preparation of this paper utilized several assistive technologies, including generative AI tools such as ChatGPT (OpenAI, 2025) and Google Gemini, to accommodate the author's neurodivergent profile (dyslexia and autism). These tools functioned as cognitive scaffolds to aid in executive functions critical to academic writing, including language organization, memory recall, and iterative ideation. The use of such technology aligns with a commitment to inclusive research practices that actively validate the diverse ways in which rigorous knowledge is produced and communicated.

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