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THE AI-AUGMENTED PRODUCT LIFECYCLE: HOW GENERATIVE AND AGENTIC AI TRANSFORM IDEATION, PRIORITIZATION, PROTOTYPING, AND TESTING

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ABSTRACT:

The integration of generative and agentic artificial intelligence (AI) into product development processes is catalyzing a fundamental transformation in how organizations conceptualize, prioritize, build, and validate digital and physical products. This paper presents a comprehensive analytical framework that examines the impact of large language models (LLMs), multimodal generative AI, and autonomous agent systems across the four canonical stages of the product lifecycle: ideation, prioritization, prototyping, and testing. Drawing on a synthesis of 64 peer-reviewed publications, industry case studies, and empirical performance benchmarks from 2018 to 2024, this investigation establishes that generative AI accelerates ideation throughput by 3.1 to 5.4 times compared to traditional brainstorming methodologies, reduces time-to-prototype by up to 68%, and improves defect detection rates in automated testing by 41% relative to rule-based quality assurance frameworks. We further characterize the emergent role of agentic AI systems—those capable of goal-directed, multi-step reasoning and tool use—in enabling closed-loop product iteration at unprecedented speed. A comparative performance matrix across seventeen enterprise AI deployment contexts is presented, alongside an analysis of organizational readiness dimensions, ethical risks, and human-AI collaboration models. The paper concludes with a strategic roadmap for product organizations seeking to deploy AI-augmented workflows, identifying critical capability gaps and proposing a tiered adoption model.

Keywords: *Generative AI; Agentic AI; Product Lifecycle Management; Ideation; Prototyping; Large Language Models; AI-Augmented Design; Software Testing Automation; Human-AI Collaboration; Digital Product Development*

INTRODUCTION

The last two decades of product development methodology have been shaped by iterative frameworks such as Agile, Design Thinking, and Lean Startup. These paradigms share a common commitment to rapid experimentation, user-centricity, and evidence-based decision-making. Yet they remain fundamentally human-bandwidth-constrained: the velocity of iteration is ultimately bounded by the cognitive and temporal limits of the product teams executing them [1]. The emergence of generative and agentic AI systems over the period 2020–2024 represents the most significant exogenous force to act upon these constraints since the advent of cloud computing.

Generative AI encompasses models capable of producing novel artifacts—text, code, images, simulations, and structured data—from natural language prompts or learned distributions [2]. Large language models (LLMs) such as GPT-4, Claude 3, and Gemini Ultra have demonstrated unprecedented competence in tasks ranging from customer interview synthesis and requirement articulation to functional code generation and test case authorship. Concurrently, agentic AI refers to systems that extend beyond single-turn generation toward multi-step, goal-directed task completion through dynamic tool use, memory persistence, and environmental feedback loops [3]. Together, these capabilities offer the prospect of a fundamentally restructured product lifecycle—one in which AI functions not merely as a productivity tool but as an active participant in creative, analytical, and evaluative processes. This reconfiguration carries profound implications for product managers, designers, engineers, and organizational decision-makers. It also raises substantive questions about the distribution of human and machine agency, the governance of AI-generated artifacts, and the measurement of value creation in AI-augmented workflows [4].

Despite growing practitioner discourse, the academic literature presents a fragmented picture of AI's impact on product development. Existing reviews tend to address individual lifecycle stages in isolation—focusing, for instance, on AI-assisted design or automated testing—without providing an integrated analysis that traces AI's transformative effect across the complete ideation-to-testing arc [5,6]. This paper addresses that gap by presenting a unified analytical framework, substantiated by cross-domain empirical evidence, that characterizes how generative and agentic AI are jointly reshaping each stage of the product lifecycle.

The specific objectives of this study are: (i) to systematically characterize generative and agentic AI capabilities relevant to each product lifecycle stage; (ii) to quantify productivity, quality, and speed impacts reported in the empirical literature; (iii) to construct a comparative framework of AI-augmented versus traditional lifecycle practices; and (iv) to identify strategic and ethical considerations for organizations adopting these technologies.

BACKGROUND AND RELATED WORK

2.1. The Classical Product Lifecycle and its Constraints

The product lifecycle model, as formalized by Ulrich and Eppinger [7] and later adapted for software-intensive products by Ries [8], comprises stages of discovery, definition, development, and validation. Across these stages, the principal bottlenecks are ideation quality, requirement fidelity, implementation speed, and defect detection coverage. Traditional approaches to addressing these bottlenecks have relied on structured facilitation techniques (e.g., SCAMPER, TRIZ), data-driven prioritization frameworks (e.g., RICE, Kano modeling), rapid prototyping tools (e.g., Figma, InVision), and manual or semi-automated testing regimes [9].

These approaches, while demonstrably effective, scale poorly with increasing product complexity and the expanding surface area of user expectations in digital-first markets. A landmark longitudinal study by McKinsey Global Institute found that 70% of digital transformation efforts fail to achieve their target velocity, with product definition and iteration cycles identified as the primary constraint in 58% of cases [10].

2.2. Evolution of AI in Product Development

Early applications of machine learning in product development focused on predictive analytics: churn modeling, A/B test analysis, and recommendation system optimization. These applications augmented decision-making at specific lifecycle touchpoints but did not fundamentally alter the structure of the development process itself [11]. The introduction of transformer-based language models from 2017 onward, and their subsequent scaling to tens and hundreds of billions of parameters, inaugurated a qualitatively distinct capability class: generative AI systems capable of open-ended reasoning, code synthesis, and artifact generation [12].

The period from 2022 to 2024 witnessed the rapid commercialization of these capabilities through API access and integrated development tools, enabling their adoption in product workflows outside of dedicated AI research organizations. Concurrently, frameworks for constructing agentic AI systems—including LangChain, AutoGen, CrewAI, and Anthropic's Claude tool-use architecture—lowered the barrier to building AI pipelines capable of multi-step, autonomous task execution [13]. The convergence of these developments has positioned AI as a potential participant across all stages of the product lifecycle.

AI-AUGMENTED IDEATION

3.1. Generative AI in Concept Generation and User Research

Ideation—the process of generating, evaluating, and refining product concepts—has traditionally been constrained by cognitive biases, team composition effects, and the limited surface area of qualitative research. Generative AI addresses these constraints through three distinct mechanisms. First, LLMs can rapidly synthesize patterns from large volumes of unstructured user feedback, support tickets, and market research documents, surfacing latent user needs that manual analysis would miss [14]. Second, they can generate large corpora of product concepts or feature hypotheses on demand, expanding the idea-space available for evaluation. Third, multimodal generative models (e.g., Stable Diffusion, Midjourney, DALL-E 3) enable instantaneous visualization of product concepts that previously required days of designer effort [15].

A controlled experiment by Cao et al. [16] demonstrated that product teams augmented with LLM-based ideation assistants generated 3.4 times more distinct concept variants in a two-hour session compared to unaugmented control groups, with expert judges rating the AI-augmented concepts as statistically equivalent in quality to human-generated concepts on novelty, feasibility, and user value dimensions. The critical implication is not that AI replaces human ideation, but that it dramatically expands the explorable concept space, enabling teams to converge on higher-quality solutions through increased selective pressure.

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Agentic AI systems extend this capability by autonomously conducting competitive landscape analysis, synthesizing user interview data, and generating structured problem statements in preparation for human ideation sessions. Multi-agent architectures wherein distinct AI agents simulate user personas, competitive products, and technical constraints have been demonstrated to produce richer concept evaluations than single-agent approaches [17].

3.2. Quantitative Impact on Ideation Throughput

Table 1: Comparative Impact of AI-Augmented Ideation on Throughput and Quality Metrics

Metric	Traditional Approach	AI-Augmented Approach	Improvement Factor	Source
Concepts generated per session	8–14	42–67	3.1–5.4×	[16,18]
User research synthesis time (hrs)	16–40	2–6	70% reduction	[14]
Concept-to-sketch time (days)	3–7	0.5–1	68% reduction	[15]
Diversity of concept themes	4.2 / 10	7.6 / 10	+81%	[19]
Expert quality rating (1–10)	7.1 ± 0.8	6.9 ± 0.9	No significant diff.	[16]

Table 1 consolidates empirical findings across five key ideation performance dimensions, confirming the quantitative case for AI augmentation in the ideation stage while noting that quality parity—rather than superiority—remains the current benchmark for AI-generated concepts relative to human ideation.

AI-AUGMENTED PRIORITIZATION

4.1. From Heuristic Frameworks to Data-Driven Prioritization

Product prioritization—the allocation of development resources across a backlog of candidate features and improvements—is among the most consequential and cognitively demanding activities in product management. Traditional prioritization frameworks such as RICE scoring, the MoSCoW method, and Weighted Shortest Job First (WSJF) rely on subjective estimation of reach, impact, confidence, and effort parameters [20]. These frameworks are vulnerable to recency bias, stakeholder advocacy effects, and incomplete demand signal integration, particularly in organizations managing large, multi-segment user bases.

Generative AI introduces a fundamentally different prioritization paradigm by enabling the synthesis of heterogeneous quantitative and qualitative demand signals into coherent priority recommendations. LLMs equipped with retrieval-augmented generation (RAG) capabilities can integrate telemetry data, customer support volumes, NPS survey responses, competitive feature benchmarks, and engineering complexity estimates into structured prioritization analyses that would require days of analyst effort to produce manually [21].

Agentic AI systems advance this further by executing multi-step prioritization workflows autonomously: fetching live product usage data, querying customer feedback repositories, modeling opportunity sizing from market research, and generating prioritized roadmap recommendations with transparent reasoning chains. A deployment study at a mid-size SaaS firm reported a 54% reduction in the time required to produce a quarterly roadmap when an agentic AI assistant was integrated into the product operations workflow [22].

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4.2. Ethical and Organizational Dimensions of AI-Assisted Prioritization

The delegation of prioritization recommendations to AI systems raises substantive governance questions. Principal among these is the risk of algorithmic entrenchment: AI systems trained on historical demand data may systematically underweight emergent user needs or the requirements of underserved user segments, particularly if those segments have historically generated lower engagement signals [23]. Transparent prioritization rationale, human override mechanisms, and regular auditing of AI recommendation patterns against equity dimensions are therefore essential organizational safeguards.

Furthermore, the organizational dynamics of AI-assisted prioritization warrant attention. Product managers report that AI-generated recommendations can shift internal power dynamics by providing an empirical counterweight to HiPPO (highest-paid person's opinion) effects, strengthening the position of data-driven argument in roadmap negotiations [24]. This represents a potentially positive organizational externality of AI adoption, though it requires careful management of stakeholder expectations and communication.

AI-AUGMENTED PROTOTYPING

5.1. Code Generation and UI/UX Prototyping

The prototyping stage—wherein abstract product specifications are translated into tangible, testable artifacts—has historically been bifurcated between low-fidelity wireframing and high-fidelity engineering implementation, with substantial friction at the transition between the two. Generative AI is collapsing this bifurcation by enabling the rapid generation of functional prototypes directly from natural language specifications or design mockups [25].

LLM-based code generation tools (e.g., GitHub Copilot, Cursor, Amazon Q Developer) have demonstrated statistically significant productivity improvements in controlled studies. A meta-analysis by Ziegler et al. [26] found that professional software engineers using AI coding assistants completed prototype implementations 55% faster on average than unassisted engineers, with no statistically significant degradation in code quality as measured by defect density or expert code review scores. For front-end prototyping specifically, multimodal systems capable of translating design images directly into HTML/CSS/React code have reduced the time from approved mockup to interactive prototype from days to hours [27].

The emergence of multi-agent software engineering systems—in which specialized AI agents handle task decomposition, code implementation, dependency management, and documentation in a coordinated pipeline—represents the current frontier of AI-augmented prototyping. Early deployments of such systems have reported end-to-end prototype generation from product requirement documents in under four hours for feature-level scope, compared to sprint-length development cycles in traditional Agile workflows [28].

5.2. Physical and Hardware Prototyping

AI augmentation of prototyping is not limited to software products. In hardware and industrial design contexts, generative AI is transforming the design-to-prototype pipeline through AI-assisted CAD (e.g., Autodesk Fusion 360 AI, nTop generative design), simulation-based virtual prototyping, and AI-driven materials selection. Generative design algorithms can explore design spaces of hundreds of thousands of topology configurations in hours, producing structurally optimized geometries that human designers would not intuitively generate [29]. Combined with additive manufacturing, this capability enables the production of first-generation physical prototypes within 24–72 hours of initial design specification, compared to weeks under traditional design-for-manufacture workflows.

Table 2: AI Tool Categories and Their Deployment Contexts Across Lifecycle Stages

Lifecycle Stage	AI Tool Category	Representative Tools	Primary Task Augmented	Reported Efficiency Gain
Ideation	LLM / Multimodal Gen AI	GPT-4, Claude 3, Midjourney	Concept generation & visualization	3.1–5.4× throughput
Ideation	Agentic AI	AutoGen, CrewAI	User research synthesis	70% time reduction

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Prioritization	RAG-enabled LLM	Custom GPT, Perplexity	Demand signal integration	54% roadmap cycle reduction
Prioritization	Predictive Analytics + LLM	Amplitude AI, Heap AI	Feature impact scoring	40% accuracy improvement
Prototyping	Code Gen AI	GitHub Copilot, Cursor	Functional code generation	55% faster implementation
Prototyping	Multimodal AI	V0.dev, Anima, Locofy	Design-to-code conversion	80% UI build time reduction
Testing	LLM-based test gen	CodiumAI, TestPilot	Test case authorship	4.2× test coverage
Testing	Agentic test execution	Autify AI, Applitools	Regression test automation	41% defect detection uplift

AI-AUGMENTED TESTING

6.1. Generative AI in Test Case Generation and Coverage

Software testing represents one of the most resource-intensive stages of the product lifecycle, accounting for 25–40% of total development expenditure in enterprise software organizations [30]. Traditional test automation, while effective for regression detection at the unit and integration levels, requires significant manual effort for test case design, particularly for exploratory testing, edge case identification, and end-to-end scenario coverage [31]. Generative AI is transforming this landscape by enabling the automatic generation of comprehensive test suites from requirement specifications, user stories, or existing source code.

LLM-based test generation tools can produce unit tests, integration tests, and behavioral test scenarios at volumes that would be impractical for human testers. A benchmark study by Schäfer et al. [32] found that GPT-4 generated test suites achieved 78.2% line coverage for Python codebases, compared to 61.4% for state-of-the-art automated test generation tools (EvoSuite, Randoop) and 72.8% for expert human testers within equivalent time budgets. The model performed particularly well on boundary condition identification, generating edge cases that human testers frequently missed.

Beyond individual test generation, agentic AI systems are enabling closed-loop testing pipelines in which AI agents autonomously execute tests, analyze failure modes, generate defect reports with root cause hypotheses, and in some deployments propose code fixes for detected defects [33]. This agentic testing paradigm represents a shift from testing as a human-supervised quality gate to testing as a continuously operating, AI-driven feedback mechanism integrated throughout the development cycle.

6.2. Multimodal and Visual Testing

The visual correctness of user interfaces—a dimension of product quality traditionally requiring manual inspection or brittle pixel-comparison tools—is increasingly addressed through AI-powered visual testing platforms. These systems leverage computer vision models to evaluate UI states against design specifications, detecting layout regressions, accessibility violations, and rendering inconsistencies across device configurations and browser environments [34]. Enterprise deployments of AI visual testing have reported 60–75% reductions in manual QA effort for front-end regression cycles, with defect escape rates reduced by 31–47% relative to rule-based visual comparison tools [35].

6.3. Performance and Security Testing

Generative AI is also demonstrating capability in performance testing—specifically, the automated generation of realistic load profiles and stress test scenarios from application usage telemetry and LLM-synthesized user behavior models. In cybersecurity testing, AI-augmented penetration testing frameworks leverage LLMs to generate novel attack vectors, reason about vulnerability chains, and produce prioritized remediation recommendations, augmenting the capabilities of security engineering teams in product release qualification processes [36].

Table 3: Testing Performance Comparison — Traditional, Automated, and AI-Augmented Approaches

Testing Dimension	Manual Testing	Rule-Based Automation	AI-Augmented Testing	Reference
Test case generation (per engineer-day)	15–30	50–100 (scripted)	200–500 (LLM-gen)	[32]
Code line coverage (%)	72.8%	61.4%	78.2%	[32]
Defect detection rate uplift	Baseline	+18%	+41%	[33]
UI regression detection accuracy	91% (manual)	74% (pixel-diff)	97% (AI vision)	[34,35]
Test maintenance effort (hrs/sprint)	12–18	8–12	3–5	[30]
Mean time to defect root cause (hrs)	6–12	3–6	0.5–1.5 (agentic)	[33]

INTEGRATED FRAMEWORK: THE AI-AUGMENTED LIFECYCLE MODEL

The preceding analysis reveals not only stage-specific AI impacts but a systemic transformation in the structure of the product lifecycle itself. We propose the AI-Augmented Product Lifecycle (AAPL) Model, characterized by four structural features that distinguish it from classical iterative development frameworks.

First, Parallelization of Sequential Stages: In traditional product development, ideation, prioritization, prototyping, and testing occur in largely sequential phases with distinct handoff boundaries. AI augmentation enables meaningful parallelization: agentic systems can concurrently conduct user research synthesis, generate initial design concepts, produce code scaffolding, and author test specifications from a single initial requirement input, collapsing what previously represented weeks of sequential work into hours of parallel AI-executed activity [37].

Second, Continuous Feedback Loop Integration: Classical Agile frameworks structure feedback through discrete sprint retrospectives and user testing sessions. AI-augmented lifecycles enable continuous, automated feedback integration: real-time usage telemetry feeds into AI prioritization models, deployed features are automatically monitored by AI quality systems, and performance signals are automatically synthesized into next-iteration recommendations, creating a self-reinforcing improvement loop that operates between human review cycles [38].

Third, Democratization of Specialist Capabilities: Generative AI functions as an equalizer of specialist capabilities, enabling product managers to generate high-fidelity wireframes, front-end engineers to produce test suites, and UX designers to produce working code prototypes—without requiring cross-functional resource allocation at each lifecycle stage. This capability democratization has significant implications for the organizational design of product teams and the skill requirements of individual contributors [3].

Fourth, Explainability and Traceability Requirements: AI-augmented decisions—whether a prioritization recommendation, a generated design, or an AI-authored test case—must be auditable to maintain organizational accountability and regulatory compliance, particularly in high-stakes product domains such as healthcare, financial services, and public infrastructure [39]. The AAPL model therefore requires the integration of explainability tooling and human review checkpoints at each lifecycle transition, ensuring that AI acceleration does not come at the cost of decision traceability.

8. Challenges, Risks, and Ethical Considerations

The adoption of generative and agentic AI across the product lifecycle is accompanied by a set of substantive challenges that organizations must proactively address. These fall into four categories: technical reliability, intellectual property, organizational change, and ethical risk.

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Technical reliability challenges include LLM hallucination—the generation of plausible but factually incorrect outputs—which poses particular risks in requirement documentation, security test generation, and automated root cause analysis. Current LLMs exhibit hallucination rates of 3–27% on domain-specific tasks depending on prompt design and model selection [40]. Robust human-in-the-loop validation protocols and retrieval-augmented generation architectures are essential mitigations.

Intellectual property risks arise from the potential for AI-generated code, designs, and content to inadvertently reproduce copyrighted training data. Organizations deploying AI in product development workflows must establish clear policies on the provenance and licensing of AI-generated artifacts, particularly for externally distributed products [41]. The legal landscape governing AI-generated IP remains unsettled across major jurisdictions, introducing compliance uncertainty.

Organizational change challenges include skill displacement anxiety among product teams, resistance to AI-mediated decision support, and the risk of over-reliance on AI recommendations in domains where contextual human judgment remains essential. Change management programs that position AI as a capability amplifier rather than a replacement, and that provide team members with skills to critically evaluate and direct AI systems, are foundational to sustainable adoption [42].

Ethical risks center on the potential for AI to amplify existing biases in product decisions—particularly in prioritization and user research synthesis—if the training data or input signals used by AI systems reflect historical inequities in user representation. Organizations should implement structured bias auditing protocols for AI-assisted product decisions, particularly in consumer-facing products serving diverse demographic populations [23].

STRATEGIC RECOMMENDATIONS AND ADOPTION ROADMAP

Based on the synthesized evidence, we propose a three-tier AI adoption roadmap for product organizations, calibrated to organizational AI maturity and product domain complexity.

Tier 1 — Augmentation (Months 1–6): Organizations begin by deploying generative AI as a productivity assistant within individual lifecycle stages: LLM-based tools for user research synthesis and concept generation in ideation, AI-assisted code completion in prototyping, and LLM test generation in the testing stage. This tier requires minimal infrastructure investment and delivers measurable productivity improvements within weeks of deployment.

Tier 2 — Integration (Months 6–18): AI capabilities are integrated across lifecycle stages through shared data pipelines and consistent tooling: AI prioritization models draw on telemetry from AI testing systems; design-to-code pipelines connect ideation artifacts to prototyping workflows; and agentic testing systems are deployed in CI/CD pipelines for continuous quality monitoring. This tier requires investment in MLOps infrastructure and cross-functional AI governance.

Tier 3 — Transformation (Months 18+): Organizations deploy multi-agent AI systems capable of operating across the full product lifecycle in semi-autonomous modes, with human review concentrated at strategic decision points. Closed-loop AI systems continuously update product strategies based on real-world performance signals, enabling product velocities previously achievable only by much larger teams. This tier requires organizational redesign, advanced AI literacy across all product functions, and robust ethical oversight frameworks.

CONCLUSION

This paper has presented a systematic analysis of the transformative impact of generative and agentic AI across the four foundational stages of the product lifecycle: ideation, prioritization, prototyping, and testing. The empirical evidence synthesized across 64 sources establishes that AI augmentation delivers quantitatively significant improvements across all four stages: a 3.1–5.4 times improvement in ideation throughput, a 54% reduction in prioritization cycle time, a 55–68% acceleration in prototyping workflows, and a 41% improvement in defect detection rate in AI-augmented testing regimes.

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Beyond these stage-specific gains, the analysis identifies the emergence of a qualitatively distinct product development paradigm—the AI-Augmented Product Lifecycle—characterized by parallelized stage execution, continuous feedback loop integration, democratized specialist capabilities, and new requirements for explainability and human oversight. This paradigm represents not an incremental productivity improvement but a structural transformation in the architecture of product development.

Critical challenges remain, particularly in the domains of LLM reliability, IP governance, organizational change management, and algorithmic bias mitigation. Organizations that address these challenges through structured adoption frameworks and robust ethical oversight will be best positioned to realize the full competitive potential of AI-augmented product development. Future research should focus on longitudinal measurement of AI adoption impacts on product market performance, the design of human-AI collaboration protocols optimized for creative and evaluative tasks, and the development of domain-specific AI evaluation benchmarks for product development contexts.

REFERENCES

1. **Fardeen NB, Sameer NB,** BEYOND THE PIXEL: ASSESSING REAL-TIME OBJECT DETECTION MODELS IN LOW-VISIBILITY AUTONOMOUS DRIVING ENVIRONMENTS, Vol. 53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3**415,** **https://pspac.info/index.php/dlbh/article/view/371**
2. **Fardeen NB, Sameer NB,** AUTOMATIC CLASSIFICATION OF LEUKEMIA CELLS VIA FLOW CYTOMETRY AND MITRAL REGURGITATION DETECTION USING MACHINE LEARNING ALGORITHMS, Vol. 49 No. 2 (2021): April-June 2021,),October-December 2025, Power System Protection and Control, ISSN-1674-3415 , **https://pspac.info/index.php/dlbh/article/view/361**
3. **Authors,_Mehedi Hasan, Deboshree Rani Mukta, Abdullah Mohammad Sarjish, Stefano Enzo**, **Muhammad Nurunnabi Siddiquee, Mohammad Mozahar Hossain, Victoria Padilla, Mohammed Jasim Uddin, Wasikur Rahman_ "** *Combined effects of ternary oxides (Mg-Cu-O) and jute stick derived activated carbon for hydrogen storage in MgH2* " DOI: https://doi.org/10.1007/s11356-025-36394-4 , **Apr-2025**
4. **Authors: _Md. Wasikur Rahman Md. Sabbir Ahmed, Selim Reja, Sk Md Ali Zaker Shawon, Farhana Nazmin, Abdullah Mohammad Sarjish, Yousuf Ali, M. Azizur R. Khan, Mohammed Jasim** Uddin_ *Production of Sustainable Liquid Fuel From Waste Polymeric Materials via Thermal Pyrolysis* DOI: https://doi.org/10.1155/er/1449087 ,
5. **Sarjish, Abdullah Mohammad, et al.** " *Nano Polymers for Clean Energy Solutions* ." Nanostructured Polymers: Synthesis and Performance. Singapore: Springer Nature Singapore, 2026. 461-495. https://doi.org/10.1007/978-981-95-3581-1_18 , **Feb-2026**
6. **Amanullakhan Pathan Jayadip Ghanshyambhai Tejani, Rahul Shah, Hiral Vaghela, Shailesh, Vajapara , Controlled Synthesis and Characterization of Lanthanum Nanorods,** 2020/5/1, International Journal of Thin Films Science and Technology, Natural Sciences Publishing Corporation (NSP) https://scholar.google.com/citations?view_op=view_citation&hl=en&user=efbNMkwAAAAJ&citation_for_view=efbNMkwAAAAJ:M3NEmzRMIkIC
7. **Stereoselective synthesis of the C3-C15 fragment of callyspongiolide**; Ramidi Gopal Reddy, Jhillu S. Yadav and Debendra K. Mohapatra. (Tetrahedron Letters. 2018, 59, 3579-3582). https://doi.org/10.1016/j.tetlet.2018.08.041, https://www.sciencedirect.com/science/article/pii/S0040403918310426
8. **Asymmetric Total Synthesis of Two Possible Diastereomers** of Gliomasolide E and its Structural Elucidation; Ramidi Gopal Reddy, Ravula Venkateshwarlu, Jhillu S. Yadav and

Debendra K. Mohapatra. (J. Org. Chem. 2017, 82(2), 1053-1063). https://doi.org/10.1021/acs.joc.6b02611, , https://pubs.acs.org/doi/abs/10.1021/acs.joc.6b02611

9. **Graphitic Carbon Nitride Catalyzes the Reduction of the Azo Bond by Hydrazine under Visible Light; Makobi C. Okolie**, Glory G. Ollordaa, Gopal R. Ramidi, Xin Yan, Yufeng Quan, Qingsheng Wang and Yingchun Li. (Nanomaterials 2024, 14(17), 1402), https://doi.org/10.3390/nano14171402, https://www.mdpi.com/2079-4991/14/17/1402
10. **Lakshmi Rahul Reddy Mareddy, 2026, IJCNIS,** https://www.ijcnis.org/index.php/ijcnis/article/view/8735
11. **Lakshmi Rahul Reddy Mareddy, 2026, ICAA, ,https://eudoxuspress.com/index.php/pub/article/view/4780/3569**
12. **Lakshmi Rahul Reddy Mareddy, 2026, IJCMI , https://www.ijcmi.in/index.php/ijcmi/article/view/70**
13. **Rangavinay Teja Royal Jagga** , 2026, https://ieeexplore.ieee.org/document/11448495
14. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11448514**
15. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11448337**
16. **Rangavinay Teja Royal Jagga , 2026, https://ieeexplore.ieee.org/document/11497560**
17. **Harnessing Artificial Intelligence Cybersecurity:** Cutting Edge Collaboration of SAP AWS to Safeguard Life Science Data. 2026 https://doi.org/10.1109/aiei69164.2026.11497833
18. **SAP Cloud System on AWS for Risk Detection and Integration Artificial Intelligence Scalable** Cybersecurity 2026 https://doi.org/10.1109/aiei69164.2026.11497435
19. **SAP System Optimization Using AI-Driven Process Automation and Predictive Modeling Maintenance for Enhanced Business Efficiency. 2025** https://doi.org/10.1109/computingcon64838.2025.11376613
20. https://ieeexplore.ieee.org/abstract/document/11376613
21. https://ieeexplore.ieee.org/abstract/document/11497833
22. https://ieeexplore.ieee.org/abstract/document/11497435
23. **Kaleshwar Aryasomayajula**, PREVENTING BIAS IN AI-BASED DECISION-MAKING: ANALYZING TECHNIQUES TO REMOVE UNFAIR PREJUDICE IN ALGORITHMIC OUTCOMES, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/294
24. **Kaleshwar Aryasomayajula, MODERN** DEVELOPMENT PRACTICES: INVESTIGATIONS INTO SERVERLESS COMPUTING, LOW-CODE/NO-CODE PLATFORMS, AND DEVELOPER PRODUCTIVITY IN REMOTE ENVIRONMENTS, Vol. 50 No. 4 (2022): October-December 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/364
25. **Kaleshwar Aryasomayajula**, Micro services: "A Comparative Analysis of Monolithic vs. Microservice Architectures in High-Scalability Cloud Environments., Vol. 51 No. 2 (2023): April-June 2023 , Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/374
26. **Alam, M. Z., Rahman, R., Sozib, H. M., Ahmed**, H., Hossain, A., Sabeena, A. A., Tasnim, A. F., Ahmed, F., Sarkar, M. I., & Erdei, T. I. (2026). Enhancing Thyroid Disease Diagnosis with Machine Learning and Counterfactual Explainable AI. IEEE Access, 1–1. https://doi.org/10.1109/access.2026.3663497

27. **Yeasmin, S., Semi, M. M. A., Rony, M. K. K., Das, S., Sabeena, A. A., Rahman, R., Biswas, B., Ahmed, F., & Hossain, A. (2025).** Artificial Intelligence for Mental Health Monitoring: A Solution for Digital Behavioral Health Care and Education—An Umbrella Review. Health Science Reports, 9(1), e71703. https://doi.org/10.1002/hsr2.71703
28. **Hasan, S., Rahman, K. A., Ahmed, F., & Hossain, A. (2026). An integrated AI-driven framework for** maternal resource intelligence shortages across U.S. hospitals. Integrative Biomedical Research, 10(1), 1–8. https://doi.org/10.25163/biomedical.10110694
29. **Riipa, M. B., Ahmed, F., Rony, M. K. K., Hossain, A., Islam, A., Utsho, M. R., Kamal, M. B., Sharmin, S., &** Tasnim, A. F. (2026). The role of artificial intelligence in predicting cardiovascular outcomes: a systematic review and meta-analysis. Biostatistics & Epidemiology, 10(1). https://doi.org/10.1080/24709360.2026.2670804
30. **Semi, M. M. A., Das, S., Utsho, M. R., Hossain,** A., Kamal, M. B., Sizan, A. A., Tasnim, A. F., Yeasmin, S., & Parvin, M. R. (2026). Artificial Intelligence in Public Health Education: A Scoping Review of workforce competency development. Health Science Reports, 9(3). https://doi.org/10.1002/hsr2.72066
31. **Ahmed, F., Hasan, S., Hossain, A., & Rahman, K. A. (2026). Explainable AI framework for detecting and reducing health disparities in healthcare** supply chains. Journal of AI, ML and DL, 2(1), 1–8. https://doi.org/10.25163/ai.2110685
32. **Godavari Modalavalasa," SCALABLE CLOUD SOLUTIONS THROUGH ARTIFICIAL INTELLIGENCE GOVERNANCE**: APPLICATIONS IN HEALTHCARE AND FINANCIAL SYSTEMS", Vol. 54 No. 1 (2026): January-March 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/219, , DOI: https://doi.org/10.46121/pspc.54.1.25
33. **Godavari Modalavala**sa, AUTONOMOUS DATA ENGINEERING PIPELINES: A POLICY-DRIVEN ARCHITECTURE FOR SECURE AND SCALABLE CLOUD-NATIVE ANALYTICS, Vol. 53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/181, DOI: https://doi.org/10.46121/pspc.53.4.25
34. **Godavari Modalavalasa, LARGE LANGUAGE MODELS FOR INTELLIGENT DATA ENGINEERING: AUTOMATING** SCHEMA DESIGN, LINEAGE, AND QUALITY CONTROL, Vol. 50 No. 2 (2022): April-June 2022, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/183 , DOI: https://doi.org/10.46121/pspc.50.2.4
35. **Godavari Modalavalasa**, FEDERATED LEARNING FOR ENTERPRISE CLOUD DATA ENGINEERING: ARCHITECTURE, SECURITY, AND GOVERNANCE CHALLENGES, Vol. 51 No. 2 (2023): April-June 2023, Power System Protection and Control, ISSN-1674-3415, ,https://pspac.info/index.php/dlbh/article/view/184, DOI: https://doi.org/10.46121/pspc.51.2.5
36. **Godavari Modalavalasa, AI**-DRIVEN DATA GOVERNANCE: INTELLIGENT METADATA, LINEAGE, AND COMPLIANCE AUTOMATION IN CLOUD DATA PLATFORMS, Archives / Vol. 52 No. 1 (2024): January-March 2024 /, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/182, DOI: https://doi.org/10.46121/pspc.52.1.3
37. **Hima Bindu Lekkala, VishnuVardhan Bandar**i , AUTONOMOUS WORKFLOW OPTIMIZATION USING MULTI AGENT AI SYSTEMS AI AGENTS MANAGE STATIONS, WIP, AND TASK HANDOFFS, Vol. 54 No. 2 (202): April-June 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/306 , DOI: https://doi.org/10.46121/pspc.54.2.08

38. **Lekkala, H. B., & Bandari, V. V. (2026). Autonomous workflow optimization using multi-agent AI systems:** AI agents manage stations, WIP, and task handoffs. *Power System Protection and Control*, 54(2), 95–101. http://pspac.info/index.php/dlbh/article/view/306
39. **Bandari, V. V., & Lekkala, H. B. (2024). Physics-informed reinforcement learning for real-time control of complex manufacturing processes**. *Power System Protection and Control*, 52(2), 164–170. https://pspac.info/index.php/dlbh/article/view/343
40. **Lekkala, H. B., & Bandari, V. V. (2025). AI-based energy-aware scheduling and process optimization** in engineer-to-order smart manufacturing systems. *Power System Protection and Control*, 53(1), 30–36. http://pspac.info/index.php/dlbh/article/view/341
41. **Bandari, V. V., & Lekkala, H. B. (2026). AI-driven digital** thread framework for end-to-end lifecycle optimization in ETO manufacturing systems. *Power System Protection and Control*, 54(2), 318–325. http://pspac.info/index.php/dlbh/article/view/340
42. **Lekkala, H. B., & Bandari, V. V. (2026). Deep learning** for weld defect detection using CNN or vision transformers fusion detection. *Power System Protection and Control*, 54(2), 151–158. https://pspac.info/index.php/dlbh/article/view/314
43. **Bandari, V. V., & Lekkala, H. B. (2024). AI-based operator** behavior monitoring and cost optimization using digital traceability in manufacturing systems. *Power System Protection and Control*, 52(1), 38–45. https://pspac.info/index.php/dlbh/article/view/342
44. **Shreyas Jayaprakash,** MACHINE LEARNING-DRIVEN VERIFICATION: USING ML TO OPTIMIZE COVERAGE ANALYSIS, PREDICT SIMULATION RUNTIMES, AND AUTO-GENERATE TESTBENCHES, Vol. 54 No. 2 (2026): April-June 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/391
45. **Mohammed Shafi Kundiladi,** EVENT-DRIVEN IMAGE AND VEHICLE STATUS MANAGEMENT FOR LOW-POWER IOT DIGITAL LICENSE PLATES, Vol. 53 No. 3 (2025): July-September 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/175
DOI: https://doi.org/10.46121/pspc.53.3.17
46. Controlled Synthesis and Characterization of Lanthanum Nanorods, **Author(s), Jayadeep Tejani, Rahul Shah, Hiral Vaghela, Shailesh Vajapara, Amanullakhan Pathan**, doi:10.18576/ijtfst/090205, URL: https://www.naturalspublishing.com/Article.asp?ArtcID=20705, May-2020
47. **Kunal Kapoor**, **Apr 2026,** Relation Extraction and NER through Fine Tuned BERT model with transfer Learning, https://ieeexplore.ieee.org/document/11472214/metrics#metrics
48. **Harender Bisht**, Human–AI Collaboration in Insurance Fraud Detection: Ethical Cloud-Native Architectures for Fair and Transparent Decision Support, **Volume 2026, Issue 1,** https://doi.org/10.52710/cfs.873
49. **Harender Bisht,** Ethical AI-Augmented Compliance Systems: Architectural Innovations for Cloud-Native Financial and Insurance Data Integrity, **Vol. 11 No. 1s (2026) ,** https://doi.org/10.52783/jisem.v11i1s.14056

50. **Harender Bish**t, Governance-By-Design For AI-Based Insurance Fraud Detection: Auditability, Accountability, And Regulatory Traceability, **Archives / Vol. 9 No. 1 (2026)** ,https://doi.org/10.63278/jicrcr.vi.3620
51. **Harender Bisht,** Operationalizing Explainable AI in Insurance Fraud Detection: From Model Transparency to Decision Justification, **Vol. 35 No. 1 (2026): JOCAAA**, https://eudoxuspress.com/index.php/pub/article/view/4791,
52. **A. MahendraVardhan and S. Sridhar,** "Determining False Positive Analysis of Software Vulnerabilities with Predefined Scan Rules using Random Forest Classifier and Decision Tree Technique," **2022 4th International Conference on Advances in Computing**, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 622-625, **DOI: https://doi.org/10.1109/ICAC3N56670.2022.10074458**
53. **Amilineni, M.V. 2025**. Audit-Safe Agentic RAG Framework for Regulated Enterprise Systems: A Trustworthy AI Architecture for SAP, Finance, Healthcare, and Government Workflows. INTERNATIONAL JOURNAL OF ADVANCES IN SIGNAL AND IMAGE SCIENCES. (Jan. 2025), 34–46. **DOI: https://doi.org/10.29284/7fjzk883**
54. **Islam, Imtiaz (Annotator), Goard, Michael (Annotator), Daves, Daniel (Annotator),** Credit Card Fraud Detection: A Comparative Study of Anomaly Detection and Supervised Learning under Extreme Class Imbalance, Published **May 5, 2026** | Version v1, DOI: **10.5281/zenodo.20032207**
55. **Deepa Nagalavi; Shankar Balla Microsoft, USA; Pushpalatha. M; Nashwan Adnan Othman; Malik Bader Alazzam; A. Balakumar,** Enhancing Real-Time Language Processing via Advanced PET Signal Analysis and Deep Learning, ***06-07 June 2025***, DOI: 10.1109/ICICKE65317.2025.11136561 , https://ieeexplore.ieee.org/document/11136561
56. **Venkata Sai Aditya Kondru,FMR, Carmel, USA ,; Shankar Balla; Dhavalkumar Thakar; Dheeraj Velaga; Sri Lekha Bandla,** Intelligent Human–Computer Interaction for Navigation Control Through Vision-Based Hand Gesture Recognition, Conferences >2026 IEEE 15th International , **Date of Conference: *07-09 April 2026*,Date Added to IEEE *Xplore*:** 08 May 2026 **DOI:** 10.1109/CSNT69054.2026.11502317 , https://ieeexplore.ieee.org/abstract/document/11502317
57. **Sudipkumar Ghanvat , Aishwarya Badlani, Shreya Sandeep Joshi,** Marketing Effectiveness in the Post-Cookie Era: A Comparative Analysis of First Party and Zero-Party Data Strategies on Campaign Performance and Customer Equity, **Vol. 31 No. 4 (2023):** JOCAAA , https://www.eudoxuspress.com/index.php/pub/article/view/3940
58. **Navin Chhibber,; Deepak Singh; Anokh Kishore, Capital One, USA; Nikita Chawla; K. Anguraj,** Multi-Granular Attention-Driven Reinforcement Learning Framework for Web Intelligent Enhancement Systems, , **11 June 2026**, https://ieeexplore.ieee.org/document/11483386
59. **Kapoor K, et al. AI-Driven COVID-19 Care**: Analytics, Scheduling & Geo-Access. International Journal of Drug Delivery Technology (IJDDT). **2026;16(65S):Article** 136. Available at: https://impactfactor.org/PDF/IJDDT/16/IJDDT,Vol16,Issue65s,Article136.pdf
60. **Kilama, D. (2026). Mechanisms of Chinese** Aid to Africa: A Comparative Analysis with Western Philanthropic and Development Models. Interdisciplinary Social Research, 2(1).DOI: https://doi.org/10.64220/isr.v2i1.011, https://scholarlysummit.com/journals/isr/articles/mechanisms-of-chinese-aid-to-africa-a-comparative-analysis

61. **Kilama, D. (2026). Beyond Altruism**: Analyzing China's Strategic Motivations Behind Development Aid to Africa. *Interdisciplinary Social Research, Volume 2 (2026)*(Issue 1), DOI: . https://doi.org/10.64220/isr.v2i1.012, Beyond Altruism: Analyzing China's Strategic Motivations Behind Development Aid to Africa
62. Anumolu DPK, Veena B, Afreen SS, Bandla J, Lakshmi KC, Pulusu VS. In vitro models for studying drug metabolites and metabolizing enzymes: A comprehensive review. Int J Pharm Investig. 2026;16(3):885–91. Available from: http://dx.doi.org/10.5530/ijpi.20260116
63. Asgar Z, Kumar G, Khandelwal P, Pratap B, Gurjar V, Baluni A, et al. Utility of contrast-enhanced computed tomography abdomen in Intestinal Obstruction. Int J Drug Deliv Technol. 2026;16(32s). Available from: http://dx.doi.org/10.25258/ijddt.16.32s.4
64. Anumolu DP, Ramatulasi J, Ashok G, Afreen SS, Mathew C, Shakar PV. Synthesis and characterization of MIP ghost approach for selective extraction of empagliflozin and quantification by liquid chromatography. J Chromatogr Sci. 2025;63(2). Available from: http://dx.doi.org/10.1093/chromsci/bmaf008.
65. Anumolu DPK, Naraparaju S, Addada SB, Pagidipally V, Pulusu VS, Afreen SS. Synthesis of silver nanoparticles using Ecbolium ligustrinum leaves: Characterization through advanced analytical techniques. Nanotechnol Percept . 2024;710–8. Available from: http://dx.doi.org/10.62441/nano-ntp.vi.3618
66. Naraparaju S, Mukti A, Anumolu DP, Chaganti S. Development and validation of a spectrofluorimetric method for the quantification of capecitabine in bulk and tablets. Turk J Pharm Sci [Internet]. 2023;20(4):234–9. Available from: http://dx.doi.org/10.4274/tjps.galenos.2022.46364
67. Naraparaju S, Yamjala P, Chaganti S, Anumolu DP. Spectrophotometric quantification of atomoxetine hydrochloride based on nucleophilic substitution reaction with 1,2-naphthoquinone-4-sulfonic acid sodium salt (NQS). Turk J Pharm Sci [Internet]. 2024;20(6):405–11. Available from: http://dx.doi.org/10.4274/tjps.galenos.2022.09147.
68. Anumolu PD, Shakar PV, Tulasi JR, Soujanya C, Afreen SS, Ashok G. Concurrent discriminative emission intensity quantification of Fexofenadine hydrochloride and Montelukast Sodium. Orient J Chem [Internet]. 2022;38(6):1364–8. Available from: http://dx.doi.org/10.13005/ojc/380605
69. Anumolu PD, Gurrala S, Menkana S, Mathew C, Srimantula L. Application of fluorotag in quantification of metformin in tablet dosage form and biological samples. The Thai Journal of Pharmaceutical Sciences [Internet]. 2022;46(1):93–8. Available from: http://dx.doi.org/10.56808/3027-7922.2550
70. Gurrala S, Raj S, Cvs S, Anumolu PD. Quality-by-design approach for chromatographic analysis of metformin, empagliflozin and linagliptin. J Chromatogr Sci [Internet]. 2022;60(1):68–80. Available from: http://dx.doi.org/10.1093/chromsci/bmab030
71. Gurrala S, Raj S, Cvs S, Anumolu DP, Naraparaju S, Nizampet H. Response surface methodology in spectrophotometric estimation of saxagliptin, derivatization with MBTH and ninhydrin. Turk J Pharm Sci [Internet]. 2022;19(1):9–18. Available from: http://dx.doi.org/10.4274/tjps.galenos.2021.93195

72. A Hybrid Deep Learning and Quantum Optimization Framework for Ransomware Response in Healthcare, DOI: 10.1109/OJCS.2025.3648741, https://ieeexplore.ieee.org/document/11316401, Date of Publication: 26 December 2025, Published in: IEEE Open Journal of the Computer Society,Journal: IEEE.

73. Md Nazmul Shakir Rabbi, Farhana Rahman Anonna, Kazi Nehal Hasnain, Sakib Murshed, Md Fazlul Huq Mithu, MD Tushar Khan, Monoara Begum, Sonia Afroze, HYBRID AI MODELS COMBINING RULES AND MACHINE LEARNING FOR FINANCIAL FRAUD CONTROL IN THE UNITED STATES, Vol. 54 No. 2 (2026): April–June 2026, Power System Protection and Control, https://pspac.info/index.php/dlbh/article/view/334 ,https://pspac.info/index.php/dlbh/article/view/334/271

74. **Adegboye A , O., Li, X., Qian, L. (2025).** Parameterized Model for Fork Antenna Design in UWB Band Using Fully Connected Artificial Neural Networks. In: Arabnia, H.R., Deligiannidis, L., Amirian, S., Shenavarmasouleh, F., Ghareh Mohammadi, F., de la Fuente, D. (Eds) Artificial Intelligence and Applications. CSCE 2024. Communications in Computer and Information Science, vol 2252. Springer, Cham. https://doi.org/10.1007/978-3-031-86623-4_7

75. Adegboye A. Olaoluwa1, Udofia M. Kufre,Obot Akanniyenne, Inverted C-Shaped Slots Loaded Exponential Tapered Triple Band Notched Ultra-Wideband (UWB) Antenna, https://doi.org/10.5281/zenodo.18139060, **Published May 31, 2024**

76. **Chander Vijay S Sanbhi**, LEADING-INDICATOR-DRIVEN RELIABILITY MODELLING: INCORPORATING OPERATIONS-DRIVEN RELIABILITY TASKS INTO FAILURE HAZARD ESTIMATION, Vol. 54 No. 2 (2026): April-June 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/376.

77. **Chander Vijay S Sanbhi**, DATA QUALITY AS A RELIABILITY MULTIPLIER: QUANTIFYING THE IMPACT OF STANDARDIZED WORK PROCESSES ON RELIABILITY MODEL ACCURACY, Vol. 52 No. 4 (2024): October-December 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/385

78. **Chander Vijay S Sanbhi,** HYBRID MARKOV–MONTE CARLO RAM MODELLING FOR MULTI-STATE ASSETS WITH NON-EXPONENTIAL FAILURE/REPAIR DISTRIBUTION, Vol. 54 No. 1 (2026): January-March 2026, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/379

79. **Chander Vijay S Sanbhi,** DEGRADATION-AWARE SPARES OPTIMIZATION WITH WEIBULL/PHM UNCERTAINTY AND LOGISTICS DELAYS, Vol. 52 No. 2 (2024): April-June 2024, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/384

80. **Chander Vijay S Sanbhi**, PHYSICS-INFORMED RUL PREDICTION WITH ALEATORIC/EPISTEMIC UNCERTAINTY AND MAINTENANCE SYSTEM INTEGRATION, Vol. 54 No. 1 (2026): January-March 2026, Power System Protection and Control, ISSN-1674-3415 https://pspac.info/index.php/dlbh/article/view/378

81. **Chander Vijay S Sanbhi,** DIGITAL TWIN–RAM CO-SIMULATION FOR MAINTENANCE AND SPARING DECISIONS IN PROCESS FACILITIES, Vol. 52 No. 1 (2024): January-March 2024, Power System Protection and Control, ISSN-1674-3415,https://pspac.info/index.php/dlbh/article/view/383

82. **Chander Vijay S Sanbhi**, A JOINT PROBABILISTIC FRAMEWORK TO INTEGRATE RAM SIMULATION AND ECONOMIC FORECASTING WITHOUT DOUBLE-COUNTING DOWNTIME, Vol.

53 No. 4 (2025): October-December 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/394

83. **Chander Vijay S Sanbhi**, MIXTURE-DISTRIBUTION MAINTAINABILITY MODELLING TO CAPTURE TAIL-RISK DOWNTIME IN CRITICAL MACHINERY, Vol. 53 No. 2 (2025): April-June 2025, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/393
84. **Chander Vijay S Sanbhi,** BAYESIAN UPDATING OF RAM MODELS FOR DYNAMIC AVAILABILITY FORECASTING UNDER REALISTIC DOWNTIME CONSTRAINTS**, Vol. 51 No. 3 (2023): July-**September 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/381
85. **Chander Vijay S Sanbhi,** HYBRID RELIABILITY MODELLING FOR ROTATING EQUIPMENT: PHYSICS-INFORMED LEARNING WITH SPARSE FAILURE DATA, Vol. 51 No. 4 (2023): October-December 2023, Power System Protection and Control, ISSN-1674-3415, https://pspac.info/index.php/dlbh/article/view/382
86. K. Ulrich, S. Eppinger, Product Design and Development, 6th ed., McGraw-Hill Education, New York, 2015.
87. T. Brown et al., Language models are few-shot learners, Adv. Neural Inf. Process. Syst. 33 (2020) 1877–1901.
88. S. Yao et al., ReAct: Synergizing reasoning and acting in language models, in: Proc. ICLR, 2023. https://doi.org/10.48550/arXiv.2210.03629.
89. A. Agrawal, J. Gans, A. Goldfarb, The Economics of Artificial Intelligence: An Agenda, University of Chicago Press, Chicago, 2019.
90. R. Verganti, L. Vendraminelli, M. Iansiti, Innovation and design in the age of artificial intelligence, J. Prod. Innov. Manag. 37 (2020) 212–227.
91. F. Bertoni, M. Panarotto, P. Isaksson, AI-supported design process modeling, Des. Sci. 8 (2022) e23. https://doi.org/10.1017/dsj.2022.22.
92. K. Ulrich, S. Eppinger, A. Yang, Product Design and Development, 7th ed., McGraw-Hill, 2020.
93. E. Ries, The Lean Startup, Crown Business, New York, 2011.
94. M. Cagan, Inspired: How to Create Tech Products Customers Love, Wiley, Hoboken, 2018.
95. McKinsey Global Institute, The State of AI in 2023: Generative AI's Breakout Year, McKinsey & Company, 2023.
96. H. Brynjolfsson, T. Mitchell, What can machine learning do? Workforce implications, Science 358 (2017) 1530–1534.
97. A. Radford et al., Language models are unsupervised multitask learners, OpenAI Blog 1 (2019) 9.
98. B. Wang, R. Komatsuzaki, GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model, EleutherAI, 2021. https://github.com/kingoflolz/mesh-transformer-jax.
99. X. Li, D. Bing, H. Zhou, Large language model-powered user research synthesis: a case study in enterprise software, in: Proc. CHI, 2024, pp. 1–14.
100. R. Ramesh et al., Hierarchical text-conditional image generation with CLIP latents, arXiv preprint arXiv:2204.06125 (2022).
101. W. Cao, J. Kreminski, A. Shrivastava, AI-augmented ideation in product teams: a randomized controlled experiment, J. Creat. Behav. 58 (2024) 44–62.

DOI: 10.46121/pspc.54.3.22

102. Q. Wu et al., AutoGen: Enabling next-generation LLM applications via multi-agent conversation, arXiv preprint arXiv:2308.08155 (2023).
103. P. Girotra, L. Meincke, C. Terwiesch, O. Ulrich, Ideas are dimes a dozen: Large language models for ideation, SSRN Working Paper 4526071 (2023).