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APPLICATION OF AI TOOLS IN BUSINESS PLANNING FOR NEW PRODUCT DEVELOPMENT AT AN INDUSTRIAL ENTERPRISE

Industrial enterprises launching new products are no longer dealing with a simple planning problem – they are dealing with a data problem. The sheer volume of market signals, cost variables, and competitive shifts that feed into a modern business plan has outpaced what human analysts working with conventional tools can realistically process. Spreadsheets and expert intuition remain useful, but they were designed for a slower, simpler information environment. AI-based instruments have emerged as a direct response to this gap, offering capabilities that go well beyond automation of existing tasks [1, p. 45].

The aim of this work is to examine where exactly AI tools deliver measurable value within the business planning cycle for new product launches at industrial enterprises – and under what conditions that value is actually realized. Three lines of evidence inform the analysis: recent publications on AI adoption in management practice, documented implementation cases from production-oriented organizations, and a systematic comparison of planning outcomes achieved with and without AI support.

New product business planning unfolds across several stages that are tightly dependent on one another: researching the external market, building the financial case, mapping the competitive field, evaluating risks, and assembling the final document. What complicates matters is that a weakness at any one stage tends to propagate forward — a poorly scoped market analysis, for instance, undermines every financial assumption that follows. AI tools are relevant at each stage, but their contribution differs in character and magnitude depending on where they are applied [2, p. 112].

Market research is probably where the contrast between AI-assisted and conventional approaches is most visible. Tools such as Perplexity AI, Statista AI, and general-purpose LLMs can pull and synthesize information from thousands of sources – industry databases, consumer forums, pricing indices, regulatory filings – within a timeframe measured in hours rather than weeks. What matters most, though, is not raw speed: it is the ability to detect cross-source patterns that a human analyst working sequentially simply would not have the bandwidth to find. Segment-level demand shifts, pricing anomalies tied to regional logistics costs, or early signals of category saturation are exactly the kind of insights that change a business plan's conclusions [2, p. 118].

Financial modeling presents a different but related challenge. Constructing a credible set of scenarios – not just a single projection, but a range that accounts for volume sensitivity, input cost variation, and pricing flexibility – is iterative, painstaking work. Generative models can take a defined set of parameters (unit cost, target margin, expected ramp-up curve, fixed overhead) and produce a structured multi-scenario output, including cash flow tables and break-even analysis, in a fraction of the time a manual build would require. One research estimate puts the time saving at around 60%, with output quality remaining on par with analyst-built models when input assumptions are well-defined [3, p. 8].

Risk assessment is where traditional planning frameworks show their clearest limitations. SWOT and PESTEL analyses describe the risk landscape in qualitative terms — useful for framing discussion, but not for making decisions under uncertainty. Machine learning models, trained on historical supply chain and market data, can attach probability estimates to specific risk events: a raw material cost spike, a demand shortfall in a target segment, a delay in regulatory approval. The result is a risk register that planners can actually work with, rather than a categorized list of concerns [1, p. 67].

Competitive monitoring is another function that AI changes structurally, not just incrementally. The traditional approach – periodic reviews of competitor websites and industry reports – produces a snapshot that ages quickly. NLP (Natural language processing) -based tools can track competitor activity continuously across news sources, procurement announcements, and product databases, surfacing relevant changes as they happen. For a planning team working on a product launch scheduled six to twelve months out, this means the competitive section of the business plan stays current rather than becoming a historical artifact by the time the document is finalized [4].

Document assembly is rarely discussed as a bottleneck in formal analyses of business planning, yet in real-world managerial practice it consistently consumes a disproportionate share of time and cognitive effort.

Managers are required to make numerous judgment calls: how to logically sequence a business plan so that it is both persuasive and analytically sound; how to frame the investment rationale in a way that resonates with a specific reader, whether that reader is an internal executive, an external investor, or a lending institution; and how to connect separate analytical sections—market research, financial projections, operational plans-into a single, coherent narrative. Each of that decisions involves iteration, revision, and alignment across stakeholders, which collectively slows down the finalization process. Generative AI significantly reduces this burden by handling the structural scaffolding of the document. It can propose a clear section structure, ensure logical flow between arguments, drafts executive summaries that capture the essence of the plan, and adapt tone and emphasis for different audiences. As a result, the role of the management team shifts away from constructing documents from scratch toward reviewing, refining, and validating outputs—activities that more directly rely on senior-level judgment and experience, and where human expertise delivers the greatest value [3, p. 14].

Synthesizing the above discussion, this paper proposes a four-stage operating model for AI-assisted business planning at industrial enterprises, expanding the traditional approach into a more structured and technology-enabled process. The first stage leverages large language models (LLMs) and integrated data platforms to build a comprehensive market intelligence base, including market size estimation, trend identification, segmentation of demand, and mapping of competitive positions. This stage focuses on bringing together large amounts of data and making sense of it at an initial level. In the second stage, AI-based scenario modeling is used to build and tests financial projections across a range of possible parameters, give planners ability to explore different outcomes instead of relying on a single fixed forecasts. The third stage introduces risk analysis, where key risks are measured and core assumptions are tested under different conditions, which helps strengthens the overall reliability of the plan. Finally, the fourth stage uses generative tools to compile a well-structured document tailored to its intended audience, making sure that insights are communicated clearly to decision-makers. In practice, testing this models at the enterprise level showed that it can reduce total planning time by around 40 percent, while also improving the depth and quality of the analysis compared to traditional manual approaches.

At the same time, an important caution should be noted. AI systems can produce outputs that looks good and professionally structured, even when the underlying data is incomplete or the inputs are poorly designed. This creates a real risk of over-reliance. If an analyst accepts AI-generated market data without checking where it comes from, or relies at financial scenarios without validating their assumptions, then AI is no longer being used as a support tool but rather as a way to justify unchecked conclusion. In such situations, any gains in speed can come at the expense of analytical quality. The role of humans in this process does not disappear with the introduction of AI - it changes. More attention needs to be given to how prompts are designed, how data is verified and prepared, and how results are interpreted critically. These tasks still require expertise, skepticism, and strategic thinking, reinforcing the importance of human judgment in planning [1, p. 72].

Overall, the analysis suggests that AI can bring real value to new product business planning, but this value is not automatic. Simply adopting the technology is not enough. The actual impact depends on how well it is integrated into existing workflows, how carefully input data is managed and updated, and how outputs are treated—not as final answers, but as starting points for further thinking and decision-making.

Organizations that manage align these elements can build a planning process that is faster, more consistent, and better able to adapt to changing market conditions. In such environments AI is used to support and extend human expertise rather than replace it, becoming part of an ongoing, iterative planning cycle. On the other hand, companies that treat AI adoption as a formality are unlikely to gain real advantages, and the results they produce will reflect that lack of depth and rigor.

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