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Integrating AI into the Front End of New Product Development

A Case Comparison of Traditional and Augmented Processes

Companies can use AI tools to streamline NPD workflows, reduce development time, and increase the likelihood of successful product launches by rooting design in customer needs drawn from larger, more diverse data.

Tucker Marion, Chelsea Yuan, and Mohsen Moghaddam

OVERVIEW: This study explores the integration of artificial intelligence (AI) into the fuzzy front end (FFE) of new product development (NPD). Using the AI-augmented LUCID platform, we demonstrate how large-scale customer data can be synthesized to enhance decision-making, accelerate concept development, and improve product evaluation efficiency. While traditional NPD methods are time-intensive and rely heavily on subjective expertise, AI streamlines the process by generating and evaluating thousands of design options in real time. Our findings show that AI augments human expertise by identifying critical insights within vast datasets, uncovering previously overlooked opportunities. Adopting AI to optimize NPD workflows can help companies improve both precision and speed in product development. We offer practical guidance for innovation practitioners looking to integrate AI into NPD processes.

PRACTITIONER TAKEAWAYS

- AI tools can drastically reduce NPD timelines by automating data analysis, concept generation, and evaluation, enabling faster iteration and market responsiveness.
- By leveraging AI-driven sentiment analysis and feature prioritization, firms can align product attributes more closely with genuine customer needs, minimizing reliance on subjective decision-making and improving product–market fit.
- AI shifts NPD personnel from creators to curators, focusing on refining AI-generated concepts. This transformation requires upskilling teams to interpret AI insights and optimize workflows for a data-driven development process.

KEYWORDS: Product development, Artificial intelligence, Conceptual design, New product development

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This article has been republished with minor changes. These changes do not impact the academic content of the article.

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Given artificial intelligence's (AI's) ability to process, analyze, and make predictions with large amounts of data, it naturally lends itself to benefit the front end of new product development (NPD), where data on markets and users are integrated into early design efforts (Patnaik and Becker 1999; Schaffhausen and Kowalewski 2016; Ulrich, Eppinger, and Yang 2020). Researchers have observed that AI deeply enacts several popular design principles that could benefit NPD. For example, AI may reinforce the principles of concept development through the interlacing of human and machine data collection and analysis (Verganti, Vendraminelli, and Iansiti 2020). Recent research has shown AI to dramatically increase creativity, improve success rates, and increase decision-making and organizational efficiency (Zhang, Song, and He 2020; Bouschery, Blazevic, and Piller 2023; Marion, Srour, and Piller 2024). Even though these initial studies highlight the potential benefit of AI for NPD and R&D, research on how such AI tools can impact project workflows is limited. In this article, we investigate the implications of AI integration within the front end of NPD using a novel suite of tools that builds on state-of-the-art AI techniques such as natural language processing (NLP), computer vision, and multimodal data fusion. Our research is focused on an overall question related to AI and its potential integration into the NPD process: *Does integrating AI into the front end of the NPD process significantly enhance the speed and ability to synthesize data to inform decisions compared to traditional methods?*

This research offers one of the first perspectives on how companies can incorporate AI into the NPD process and represents an initial exploration of how dramatically it can influence process efficiency and effectiveness. We follow calls for further research into how AI can be applied to innovation systems (Verganti, Vendraminelli, and Iansiti 2020; Zhang et al. 2021) and contribute to the literature by highlighting the opportunities and challenges of integrating AI into the front end of the innovation process. While researchers have conducted many initial AI studies regarding creativity in a classroom setting (Bouschery, Blazevic, and Piller 2023; Girotra et al. 2023), this study illustrates how multimodal AI, trained in a specific industry with customer data, has the potential to radically optimize the workflow in the front end of product design in real-world applications. It also shows that AI-augmented systems may dramatically improve how customer and user data are collected, analyzed, and integrated to develop and optimize new product concepts (Demirel et al. 2024; Delgado et al. 2023; Kim and Maher 2023; Liu et al. 2023; He et al. 2023).

This article describes a prototype compound AI platform called LUCID, which is designed to enhance the front end of NPD. Compound AI combines multiple models and solutions—for example, machine learning (ML), natural language processing (NLP), large language models (LLMs), and generative AI (Gen AI)—designed to enhance the front end of NPD. The LUCID prototype system shows the potential of combining multimodal data with compound AI, allowing for a higher level of task augmentation, such as assessing product concepts nearly instantaneously instead of the lengthier time required by human-driven analysis. Hence, there is the potential for a step function improvement in efficiency concurrently with improving the number of high-quality concepts evaluated. We also illustrate that having AI trained and optimized within a segment or category can significantly impact tasks requiring expertise and greater trust in the outputs. Our research is the first to illustrate that decisions made in the front end of NPD—which significantly influences downstream activities and outcomes—must be guided by AI beyond general models such as public LLMs. While we are still in the infancy of AI deployment, our research points to a future where AI will play a significant role in the deeper, more challenging tasks within NPD and R&D, far beyond ideation.

Literature Review of AI and NPD

The growing adoption of AI has spawned new value creation across various industries and is beginning to change the product development processes radically (Marion, Srour, and Piller 2024; Bouschery, Blazevic, and Piller 2023; Zhang, Song, and He 2020; Davenport and Ronanki 2018; Nambisan et al. 2017). AI exploits the strengths of large-scale information and digital operating models and creates opportunities and challenges for those seeking to leverage its benefits (Iansiti and Lakhani 2020; Verganti, Vendraminelli, and Iansiti 2020). While companies and researchers have integrated new tools continually into the NPD process over the past five decades (Marion and Fixson 2021), NPD activities are still highly human-centric, from idea generation and evaluation to business analysis, testing, and commercialization.

With greater computational information processing ability and an analytical approach, AI can enhance human intuition and extend a human's cognition, thereby lending itself to many human-centered tasks within NPD (Jarrahi 2018; Dane, Rockmann, and Pratt 2012). AI may help promote better and more open knowledge searching and ideation, which have been shown to improve the efficacy of fuzzy front end (FFE) activities (Martini, Neirotti, and Appio 2017; Sukhov et al. 2021; Thanasopon, Papadopoulos, and Vidgen 2016; Nevo, Nevo, and Pinsonneault 2020). Research has also shown that information technology can stimulate employee creativity and collaboration (Nevo, Nevo, and Pinsonneault 2020) and that increased collaboration can positively influence innovation, particularly at the FFE (Thanasopon, Papadopoulos, and Vidgen 2016).

Koen, Bertels, and Kleinschmidt (2014) denote a five-step front-end activity called "front-end innovation," which includes opportunity identification and analysis, idea generation, idea selection, and concept definition. The front end of innovation is arguably the most significant area of weakness in the NPD process, mainly because the FFE is often chaotic, unpredictable, and unstructured (Koen 2004). The FFE is the set of activities employed before the more formal and well-defined requirements specifications are completed. Requirements speak to what the product should do or have, at varying degrees of specificity, and the ability to meet the perceived market or business need (Ulrich, Eppinger, and Yang 2019). Research suggests that the FFE of innovation is essential to positive outcomes (Cooper, Edgett, and

> **NPD decision-making is mainly based on novel and highly varying information, which provides potential for the use of AI.**

Kleinschmidt 2004). According to Smith and Reinertsen (1991), firms that concentrate on the FFE successfully improve their NPD process because of the lower cost of idea generation and greater time savings. A better understanding of the activities and decisions at the front end can ultimately bring competitive advantages (Reid and De Brentani 2004).

For example, design thinking requires the collection of rich and varied data (customer interviews, data of users in natural settings, videos of product use) and interpretation of these data to cull interesting insights about potentially valuable user needs that are often not explicitly expressed (Liedtka 2015; Fixson 2023). With its ability to synthesize data and identify patterns, design thinking tasks may be well-suited for AI. Because AI is highly effective in many of the front-loading activities such as data collection, pattern identification, and generating new data and analyses that comprise the FFE (Lee and Shin 2020), research for a better understanding of AI-driven FFE NPD processes is of great interest to academics and industry professionals alike.

Front-end NPD decision-making tasks such as defining opportunity spaces and categorizing latent user needs usually contain high complexity and uncertainty (Koen 2004). AI with higher levels of data-driven interpretations can achieve those tasks. The outputs of AI can be expressed as analyses of numbers, words, and images and as digital and physical task performance (Davenport and Kirby 2016), leading to outputs such as summaries of user needs, product requirements, documents, and new concepts. AI can assist decision makers by providing strategies that practitioners can adopt at any stage of the NPD process (Soltani-Fesaghandis and Pooya 2018). AI can also offer support with real-time information generation for human decision-making when faced with uncertain and unpredictable situations (Jarrahi 2018).

Some researchers argue that AI should augment human judgment by providing support rather than automating it (Miller 2019; Wilson and Daugherty 2018). They espouse that human intelligence can learn and adapt to new environments and challenges where AI tools cannot (Duan, Edwards, and Dwivedi 2019). By contrast, other researchers advocate for task dependency—that is, that AI can be used for structured decisions and is effective for operational and tactical decisions in a replacement role (Edwards, Duan, and Robins 2000). NPD decision-making is mainly based on novel and highly varying information, which provides potential for the use of AI. There are various interpretation tasks related to AI: support for humans, repetitive task automation, context awareness, learning, and self-awareness (Davenport and Ronanki 2018). To fit with various information contexts, AI techniques can learn data patterns and generate new data (Lee and Shin 2020). Recent research has shown the efficacy of AI in FFE tasks such as ideation (Bouschery, Blazevic, and Piller 2023; Girotra et al. 2023), but there is a gap in our understanding of how AI might benefit activities that require a higher level of data integration, analysis, and expertise—such as evaluation and optimization of design concepts.

In this article, we ask an overarching research question: *Does integrating AI into the front end of the NPD process significantly enhance the speed and ability to synthesize data to inform decisions compared to traditional methods?*

Research Methods and Data

Research at the intersection of AI and NPD is comparatively new, with limited studies examining AI's role during development and its impact on managing the NPD process. This study explores the role of AI in transforming NPD by integrating AI-enhanced concept development into the process. Given the complexity and novelty of this research topic, we used a qualitative case-based approach (Yin 1994; Barratt, Choi, and Li 2011), comparing a prototype AI-augmented system developed by the authors with a traditional NPD process. Case-based research is critical in innovation management for developing new concepts and theories (Goffin et al. 2019). This method has been used in various NPD contexts, including the study of digital design tools (Fixson and Marion 2012) and new ventures (Marion, Friar, and Simpson 2012).

Combining engineering systems prototype development and case research is an example of multi-method research (Bunduchi 2017; Woodside and Wilson 2003). This multi-method qualitative investigation benefits exploratory research and theoretical development (Eisenhardt 1989). This study calls for more research into knowledge management and the connection between new technology and NPD activities (Barley, Treem, and Kuhn 2018; Raghuram et al. 2019). To derive themes and insights in comparing the two cases, we followed an iterative and systematic approach to coding and analysis (Grodal, Anteby, and Holm 2021). We present data sources and details on the collection (Table 1).

Our coding and analysis involved cycles of comparison of results from the AI system and Firm A with notes, review of interviews, and discussions among the team members (Glaser and Strauss 1967; Grodal, Anteby, and Holm 2021). The LUCID development team met weekly to discuss and review research progress and the testing with Firm A, which resulted in multiple journal articles and conference papers. We show our coding details (Table 2).

Prototype AI System (LUCID)

The LUCID prototype, developed at Northeastern University in collaboration with researchers at the University of Michigan, is an AI-augmented tool suite designed to predict a product's desirability at both the overall and attribute levels

TABLE 1. Data sources and collection details

Data source	Details
Number of interviews, methods, and duration	• 20 interviews with Firm A executives and employees • Semi-structured interviews via Microsoft Teams, Zoom, and in-person meetings • Each meeting, which included semi-structured interviews, lasted approximately 2 hours; conducted over 18 months
Participant roles	• Vice president of sales • Vice president of strategy • Product line managers • Product designers
External data sources	LUCID platform analysis of 1 million product reviews across 6,000 SKUs. System trained on 8 million data points.
Key data metrics	Sentiment analysis on product attributes, customer feedback

TABLE 2. Coding details

Data type	Coding method	Thematic analysis	Themes/categories
Interview responses	Manual coding and thematic analysis conducted by the research team; weekly review meetings (2021–2024).	Identified challenges and opportunities in traditional vs. AI-augmented NPD.	Product development challenges, evolving user needs, capturing emerging market trends, decision-making based on limited data and intuition.
Product reviews	Sentiment analysis using ML and AI-powered methods; validation in team meetings to align coding with outputs.	Synthesized explicit and implicit user sentiment on product features/attributes.	Sentiments on attributes like "fit," "design," and "comfort," identifying explicit and latent user needs, data-driven decision-making.
Quantitative data	Multimodal data analysis using LUCID; Validation with f-scores and presented in academic forums.	Analysis of product evaluation metrics to derive actionable insights.	Customer satisfaction scores, feature-specific concept evaluation, efficiency of AI-driven NPD insights, data-driven decision-making.

based on frequently mentioned product features (Marion et al. 2023). The system automates design evaluation, embeds learnings into new AI-generated concepts, and evaluates these concepts before prototyping. This end-to-end system analyzes images, natural language, and structured data to inform design decisions and optimize product concepts. We illustrate the suite of AI tools used in the LUCID prototype during the FFE of the development process (Figure 1). Training LUCID for a new product type can take up to four weeks using graphical processing units (GPUs). However, once fully trained, the outputs are derived in seconds.

Traditional Development Case (Firm A)

Firm A is an established German-based footwear manufacturer with more than 14,000 employees. They approach traditional development by relying on a human-driven, time-intensive process. It begins with internal brainstorming and market exploration, followed by manual concept development based on the expertise and intuition of design teams. The company gathers customer feedback through focus groups and surveys, which take months to organize, and evaluates product concepts manually using small expert teams. This iterative process includes developing and refining sketches and designs over several rounds of feedback. We benchmarked the traditional process at Firm A against the AI-augmented LUCID prototype for comparison.

Results

We describe the process characteristics to explore the distinction between an AI-augmented NPD process and a traditional NPD process, with a summary comparison (Table 3). This comparison highlights stark differences between the two approaches in development time, data volume, analysis capabilities, and concept evaluation efficiency.

The AI-augmented LUCID process drastically reduces the time needed for customer insight identification and concept evaluation. LUCID's platform (Figure 2) includes a dataset of nearly 6,000 SKUs and over 1 million product reviews. The analysis of customer sentiment and opinions on specific product features can be processed in under a minute, using more than 8 million data points. As a product line manager at Firm A highlighted, "We want faster, broader, early feedback," which reflects the need for more agile insight gathering that AI can deliver. In contrast, Firm A's traditional process for discovering user insights is significantly slower, often taking several months to synthesize. Firm A's VP of design noted, "The challenge is not a simple process . . . it is a long process with a lot of internal discussions." This reliance on manual input, including feedback from retail partners and focus groups, introduces delays and restricts the depth of insights derived. For the traditional firm, the data gathered in these sessions often comes from less than 10 individuals, limiting the robustness of insights. We illustrate a sampling

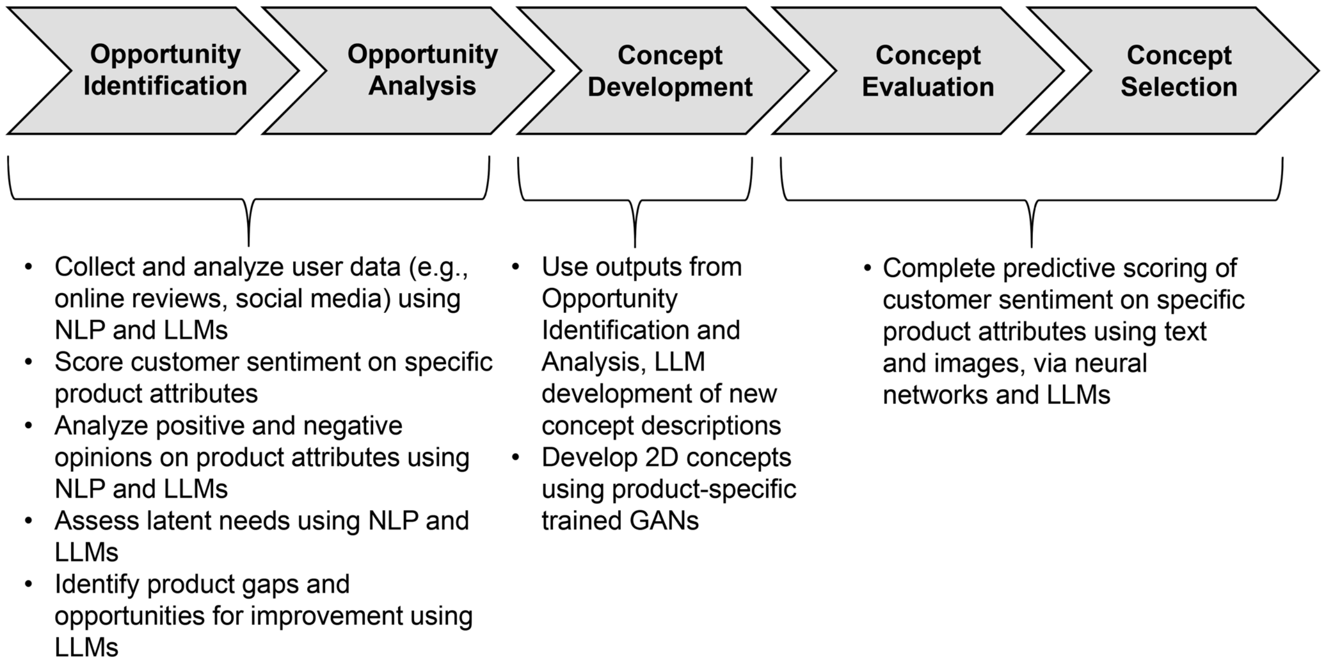

FIGURE 1. AI-augmented tools used on the LUCID process

of the SKUs and data for casual footwear, such as Croc's Women's Classic in white, with 747 customer reviews used in the analysis (Figure 2).

In the traditional process, customer insights are gathered through focus groups, channel partner feedback, and internal evaluations. However, these insights are often incomplete and anecdotal. As Firm A's head of customer insights shared, "We have skepticism when listening to customers," indicating a cautious approach to interpreting consumer feedback. In contrast, LUCID uses ML, NLP, and LLM tools to analyze thousands of reviews and extract detailed customer sentiments on specific product attributes, such as fit and traction (Figure 3). This allows the AI-augmented platform to perform detailed analyses across brands, product categories, and individual SKUs. Additionally, LUCID can uncover latent needs, providing a more comprehensive view of user preferences in seconds (Han and Moghaddam 2021; Bruggeman, Ciliotta, and Ciuccarelli 2023). We present the customer opinions on specific product attributes for the women's white Croc (Figure 3).

The AI-augmented LUCID prototype can uncover latent needs, providing a more comprehensive view of user preferences in seconds.

Firm A's traditional concept development process relies heavily on internal brainstorming and manual sketching, taking months to develop a refined prototype. According to a product line manager, "We focus on silhouette, proportion, and size . . . We want a cool factor and the design to be visually appealing," underscoring the importance of aesthetics. However, this process can be slow, as designers must also "sell their ideas internally" to gain buy-in, lengthening development timelines. In contrast, LUCID automates concept generation using Gen AI specifically trained in the industry segment, presenting designers with thousands of Gen AI-generated options, each scored based on customer feedback (Ghasemi et al. 2023, 2024). This enables designers to select the most promising concepts quickly (see Figure 4, which displays AI-developed sneaker concepts). LUCID's LLM also uses opportunity identification and analysis outputs to create concept descriptions that address specific pain points. For instance, we show a concept focusing on workplace comfort and heel support (Figure 5), derived directly from latent needs identified in user reviews, integrating a design-thinking approach into AI outputs (Bruggeman, Ciliotta, and Ciuccarelli 2023).

The AI-augmented LUCID process also enables rapid concept evaluation. Using images, concept descriptions, and textual analysis, LUCID Gen AI scores customer sentiment on potential designs across 10 attributes, with results available in seconds (Yuan, Marion, and Moghaddam 2023). We show a concept evaluation with scores ranging from −1 to 1, with 1 indicating the highest predicted customer satisfaction. This speed and accuracy contrast with Firm A's traditional approach, which often depends on "informal channels, like ad hoc in-store interviews with random consumers," as the head of customer insights noted. The LUCID system, powered by neural networks, uses

TABLE 3. Comparison summary between conventional NPD and AI-augmented development

PDD step	Conventional development	AI-augmented development
Opportunity investigation	• Discussion with channel partners • Internal research on market and style trends • Multiple in-person store visits	• Fast natural language processing (NLP) analysis of 1 M + customer reviews • System retrieves a large amount of new customer information • Data-driven trend forecasting
Development time:	3 months	3 seconds
Opportunity analysis	• Input from channel partners • Internal designer ideation of new features • Internal designer ranking of attributes • Product manager writes product brief	• Attribute-level sentiment analysis • Automated analysis and categorization using machine learning (ML) • List of top needs compiled and synthesized into a large language model (LLM)-derived concept description
Development time:	3 months	Instantaneous
Concept development	• Designer ideation and sketching of several concepts • Collaborative software assists designer interaction and output	• AI simulates concept development with thousands of generated images • Connects multiple features based on user satisfaction and sentiment analysis
Development time:	3 months	2 seconds
Concept evaluation	• Discussions with channel partners • Limited focus groups with users • Socialization with product influencers • After human review and internal sales pitch, a prototype is constructed	• AI prediction of customer sentiment • Specific feature and attribute prediction of new concept potential using text and images
Development time:	4 months	2 seconds
Concept selection	• Design team ranking • Contains uncertainty factors • Subjective decision-making with some use of focus groups, channel feedback, and "merchandizing art"	• Automated design ranking with user-oriented evaluation based on concept scores
Development time:	3 months	Instantaneous
Total:	16 months	< 1 minute

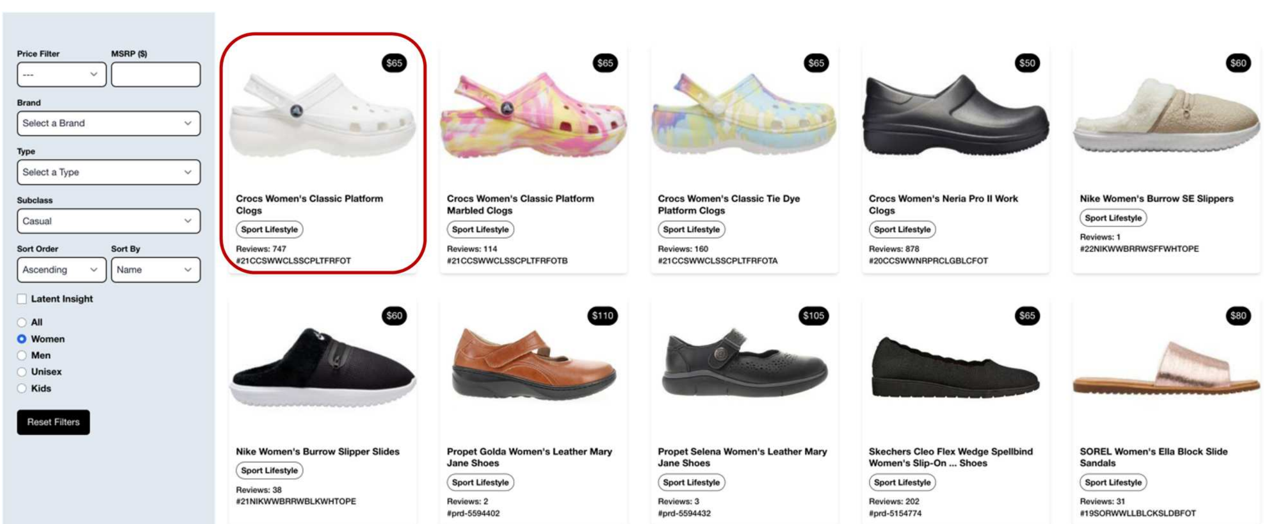

FIGURE 2. Casual shoe sort of SKUs in the LUCID platform

eight million data points to generate these predictions, representing a transformative shift in concept assessment. In early validation tests, LUCID's predictions proved to be highly accurate in estimating market performance. For example, we highlight high predicted scores for stability, heel support, and durability, with the Gen AI-generated design concept selected based on

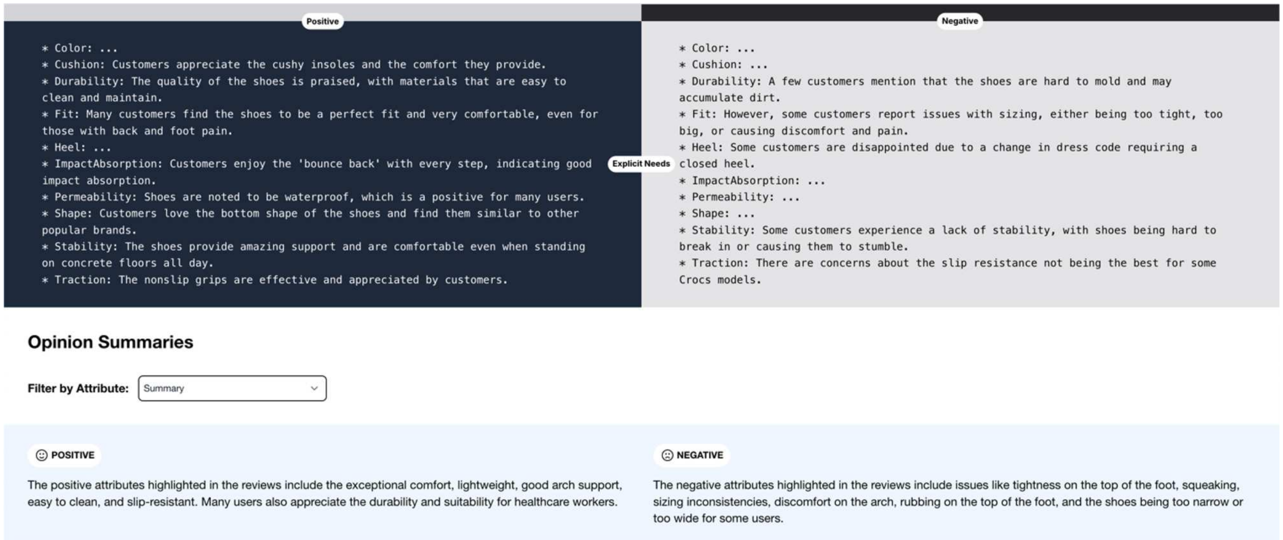

FIGURE 3. Croc Woman's Classic Casual shoe SKU customer opinion detail in the LUCID platform

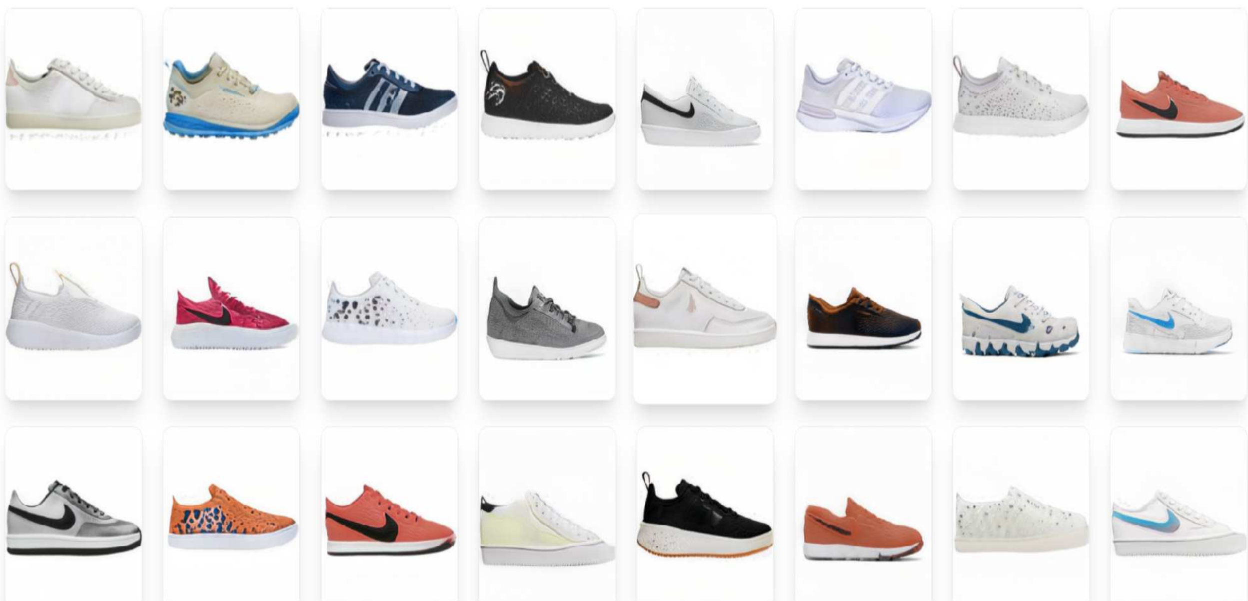

FIGURE 4. Examples of LUCID AI-developed casual sneaker concepts

LUCID offers significant advantages in terms of development time (minutes versus months), scalability, and the ability to derive actionable insights from large datasets.

shape, heel design, and upper lacing (Yuan, Marion, and Moghaddam 2021). Future iterations of the platform could include automated design selection.

The AI-augmented LUCID platform offers significant advantages in terms of development time (minutes versus months), scalability, and the ability to derive actionable insights from large datasets. We show this improvement (Figure 6), comparing development times across Firm A and LUCID's processes. Even when accounting for organizational delays, such as scheduling focus groups and arranging internal meetings, the time savings are substantial—translating to a potential 40,000× reduction in development cycles.

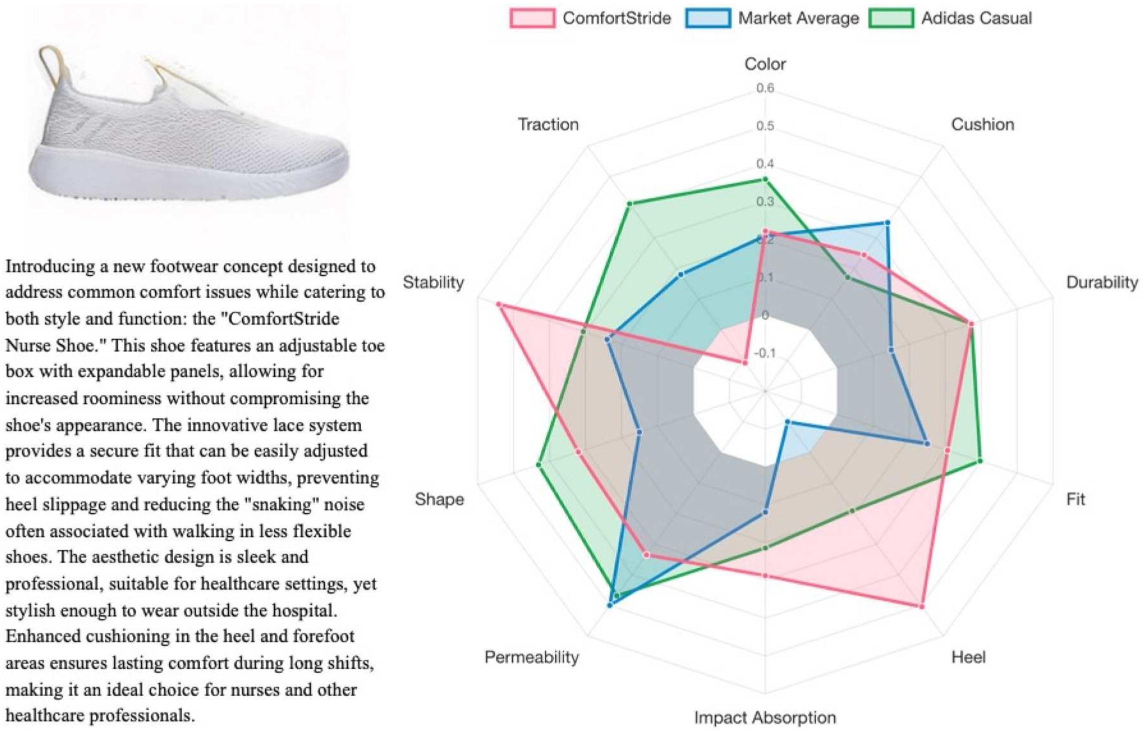

FIGURE 5. LUCID concept evaluation scoring

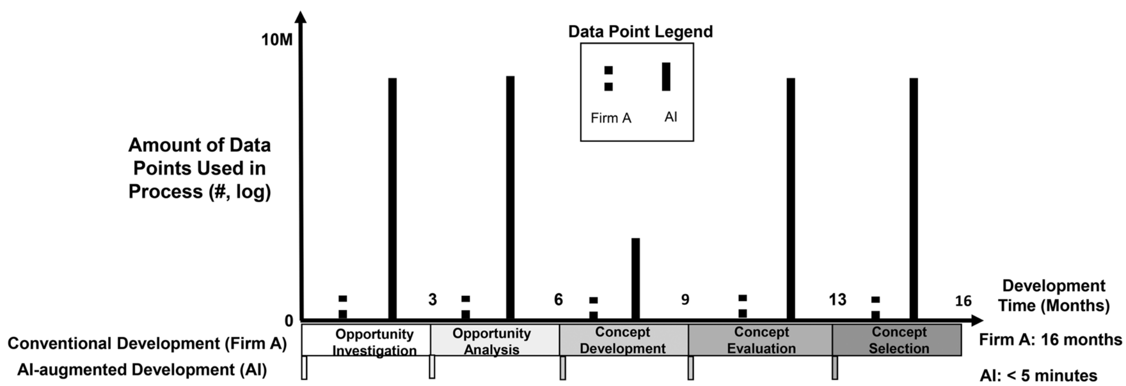

FIGURE 6. Chart of development time and amount of data used

While Firm A's traditional process remains effective in maintaining close relationships with key retail partners, it lacks the speed and data-driven depth of LUCID's AI-enhanced approach. As summarized, the interviews reveal skepticism toward customer input, reliance on limited data for decisions, and the need for "curb appeal" in product design (Table 4). The AI-augmented approach, in contrast, provides exponential improvements in iteration speed, market alignment, and real-time evaluation capabilities. These findings suggest that integrating AI into NPD could fundamentally reshape how firms gather, analyze, and act upon customer insights.

Discussion

The AI-augmented process demonstrated in this study presents a transformative shift in how NPD activities, particularly in the FFE, are managed. By integrating AI, firms can process vast datasets to extract actionable customer insights and predict product success with unprecedented speed compared to traditional methods. For instance, Firm A's conventional process required several months for in-store visits, internal brainstorming, and customer interviews. In contrast, LUCID's AI-augmented process completed similar tasks in minutes. A stark difference exists in the potential to radically reduce development time while dramatically increasing the amount of data used to inform the process.

The results demonstrate that AI enhances decision-making by enabling the system to analyze and rank product attributes based on customer sentiment, a task traditionally handled by domain experts whose knowledge and input can be subjective and limited in scope (Iansiti and Lakhani 2020). By processing large-scale data, AI overcomes these limitations and ensures a more data-driven approach to identifying product features. AI's strength lies in its ability to process vast amounts of user data and efficiently extract valuable insights, helping designers

TABLE 4. Relevant quotes and connections to themes and results

Theme/category (from coding analysis)	Supporting interview quotation	Summary/connection to results
Market trends and innovation	"It's a challenge to lead the market…. The shoe industry is mostly incremental innovation."—VP, Sales	Emphasizes the constant challenge of staying competitive, linking to the use of AI for real-time trend analysis in the Results section, and supporting AI's role in enabling faster and more targeted iterations.
Aesthetic appeal and design	"We want a cool factor and the design to be visually appealing."—Product Line Manager	Reflects the need for strong visual appeal, supporting findings on the significance of aesthetic attributes in product desirability.
Data-driven skepticism	"We have skepticism when listening to customers."—Head of Customer Insights	Illustrates a cautious approach to consumer data, highlighting AI's role in distinguishing genuine needs from perceived preferences.
Data-driven decision-making	"We need to see metrics and trends. We need to improve knowing the difference between perception and reality."—Head of Customer Insights	Supports the desire for metrics-backed decisions, showing how AI provides clarity between consumer perception and actual behavior.
Structured development process	"The product brief includes needed $$$, demographics, description of the shoe, job to be done."—Product Line Manager	Reflects a clear, metrics-based approach in product development, aligned with AI's capacity to generate structured insights.
Development timeline constraints	"The development process takes about 18 months, from initial concept to final delivery."—Product Line Manager	Underscores the lengthy timeline of traditional development, contrasting with the reduced time frames enabled by AI.
Visual and in-store appeal	"I need curb appeal in design."—Design Lead	Emphasizes initial visual attraction as critical to consumer interest, reinforcing AI's role in optimizing aesthetics for immediate impact.
Consumer feedback integration	"They show prototypes to their most important accounts to get feedback . . . sometimes the product needs to be adjusted based on what key accounts say."—Product Line Manager	Shows reliance on key account feedback, linking to AI's role in swiftly incorporating broader consumer insights.
Need for speed and early feedback	"We need to accelerate—faster, broader, early feedback."—Product Line Manager	Reflects the necessity of rapid, expansive feedback to guide development, highlighting AI's efficiency in delivering this insight.

find the "needle in the haystack" that traditional methods might miss. By leveraging large datasets, AI enhances efficiency and the ability to identify outliers that might be critical in identifying new, unexpected pain points to solve.

In the LUCID models, this led to the identification of product features and attributes that resonated most with consumers, offering significantly more granularity than conventional observation methods, focus groups, or surveys (Rylander Eklund, Navarro Aguiar, and Amacker 2022). This is illustrated by the focus on the pain points of hospital work, long-term comfort, and noise reduction identified by AI during opportunity analysis. While human design thinking experts could identify those elements, they could not perform those tasks in minutes or seconds using millions of diverse data points.

The results further highlight how AI can transform the concept development phase. While traditional methods involve manual sketching and extensive approval cycles, AI-augmented systems like LUCID use deep learning and neural networks to generate thousands of concept options, which can be evaluated almost instantly. This rapid iteration process enables more diverse and novel design outputs, reducing the time and resources typically associated with concept development (Wierenga and Van Bruggen 1998; Norman 2017). Finally, the AI-augmented process significantly improves concept evaluation by leveraging compound AI models to predict real-time customer sentiment, offering immediate feedback on product attributes and potential market success. Traditional methods involving focus groups and expert panels introduce high costs and inherent bias. AI's ability to automate this step provides an objective, data-driven approach, enabling firms to optimize their designs based on empirical evidence rather than on subjective intuition (Verganti, Vendraminelli, and Iansiti 2020; Bouschery, Blazevic, and Piller 2023; Marion, Srour, and Piller 2024).

Managerial Implications

This study's findings have several important implications for NPD practitioners and R&D managers seeking to integrate AI into their development processes. These include dramatically accelerating development, data-driven feature identification, shifting roles of NPD personnel, and transforming NPD workflows.

Dramatically Accelerating Development

By automating the FFE, AI tools allow firms to front-load the NPD process, reducing the reliance on time-consuming methods such as focus groups and market research firms. This shift enables more efficient resource allocation and allows companies to focus on high-value activities within the NPD process (Barley, Treem, and Kuhn 2018; Piller, Srour, and Marion 2024). AI tools like LUCID also drastically reduce the time required for concept development and evaluation, allowing companies to iterate faster and respond quickly to market demands. Practitioners who currently rely on conventional methods such as focus groups or in-store visits should consider adopting AI to enhance the efficiency of their design processes. The LUCID example demonstrates that AI can provide real-time customer feedback and design evaluations, significantly shortening development timelines and reducing product failure risk (Iansiti and Lakhani 2020; Bouschery, Blazevic, and Piller 2023).

Data-Driven Feature Identification

AI enables a data-driven approach to feature identification by analyzing large volumes of customer data and extracting key insights. Traditional NPD methods often rely on internal expertise, which can be limiting in scope and subject to bias. AI tools, however, rank product attributes based on actual customer feedback, leading to better alignment between product features and consumer needs (Rylander Eklund, Navarro Aguiar, and Amacker 2022; Verganti, Vendraminelli, and Iansiti 2020).

Shifting Roles of NPD Personnel

AI is transforming the role of NPD teams from creators to curators of AI-generated concepts. As AI tools automate much of the ideation and evaluation process, NPD personnel must shift their focus to selecting and refining the most promising designs, ensuring they meet market needs and corporate objectives. Companies will need to invest in training to help NPD teams interpret and use the insights provided by AI systems (Norman 2017; Verganti, Vendraminelli, and Iansiti 2020; Piller, Srour, and Marion 2024).

Transforming NPD Workflows

The adoption of AI represents a fundamental shift in NPD workflows. As traditional roles in design and marketing evolve, companies must reorganize teams and centralize digital expertise. This transition from generating ideas to selecting AI-derived concepts offers the potential for improved product success rates and design efficiency, making AI adoption a top priority for forward-thinking firms (Marion, Fixson, and Brown 2020; Wu and Wang 2020).

Limitations and Future Research

This study has limitations. While the efficacy of the LUCID designs has been validated in academic studies, thus far no LUCID designs have been implemented beyond the conceptual design phase. Future research must investigate the real-world performance of AI-augmented output gains in terms of sales, profitability, market share gain or loss, and consumer satisfaction. This study also represents a single case study. Future research should focus on understanding the influence of AI on many projects, especially concerning the overall project outcome metrics such as market performance and product margins. Future research should explore how AI can be further integrated into later stages of NPD and should examine its long-term impact on decision-making, team dynamics, and organizational strategies. Finally, training time and associated costs for compound AI systems like LUCID are significant, and future research and technology development needs to focus on improving the efficiency of setup, training, and real-time operation of these systems and models.

Conclusion

This research contributes to the growing body of knowledge on AI in NPD by providing a model for integrating AI into the FFE. The shift from conventional NPD methods to AI-driven processes can increase the quantity and diversity of design outputs and reshape NPD personnel's role, focusing more on selecting and refining AI-generated concepts. As AI technology advances, firms must embrace new roles and workflows to fully leverage AI's transformative potential (Zhang, Song, and He 2020; Brundage et al. 2020; Piller, Srour, and Marion 2024).

Although the potential benefits of AI in NPD are substantial, companies must also address challenges such as data collection, data cleanliness, and the cost of developing AI systems. R&D managers must weigh the cost–benefit of building AI tools in-house versus partnering with external firms that specialize in AI development (Chui and Malhotra 2018; Piller, Srour, and Marion 2024). Despite these challenges, firms that successfully implement AI in NPD have reported efficiency gains of up to 50 percent (Marion, Srour, and Piller 2024), underscoring the value of implementing AI-augmented systems. An AI-augmented process reduces reliance on time-intensive traditional methods, such as focus groups and manual sketching, allowing for more accurate and data-driven design decisions. The practical value of this approach lies in its ability to streamline NPD workflows, reduce development time, and increase the likelihood of successful product launches by rooting design in customer needs drawn from larger amounts of more diverse data.

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CALL FOR PAPERS: Special Issue: Platforms as a Catalyst for Innovation

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***Research-Technology Management (RTM)* welcomes research articles that explore how platforms act as driving forces for innovation.**

Platforms have redefined industries by orchestrating ecosystems with multiple customer groups and leveraging cross-side network effects to create value dynamically. Transactional platforms like Uber in mobility and Airbnb in hospitality—where users and providers meet in a shared marketplace—or orthogonal platforms such as Google and Facebook, are examples that demonstrate how cross-side interactions drive value in unique ways. Google's search platform, for instance, connects two customer groups: users seeking information and advertisers targeting those users. As more users adopt Google's search engine, it becomes increasingly valuable to advertisers, whose spending, in turn, supports the free service Google offers users. Facebook follows a similar orthogonal model, gathering large user bases who generate data, which becomes valuable to advertisers aiming to reach targeted audiences.

Platforms have transitioned from being innovative business models to now acting as innovation engines across an array of contexts. As innovation engines platforms transform traditional industries, enable innovation within established firms, and form the backbone of emerging technologies.

1. **Platforms Reshaping Traditional Industries**
Platforms like Uber, Airbnb, Grab, and Bolt have demonstrated how platform business models can disrupt established sectors like transportation and hospitality. By creating ecosystems that connect demand and supply directly, these platforms facilitate interactions that traditional business models couldn't support. This shift allows for flexibility, scalability, and customer-centric experiences, offering lessons for firms in various industries looking to embrace platform thinking.

2. **Platforms Driving Innovation in Established Firms**
Established firms also are increasingly integrating platform models into their innovation strategies to stay competitive. For example, Telepass, originally designed as a toll payment system, has transformed into a comprehensive mobility platform in Italy, connecting drivers with services like parking, fuel, and insurance. Similarly, John Deere has built an agricultural platform that allows farmers to integrate data from their equipment, enhancing efficiency and enabling precision farming. By embedding platform models into their core operations, these firms leverage new data flows and services, creating value for both the company and its users.

3. **Platforms as Foundations of Emerging Technologies**
Platforms are foundational to emerging technologies, particularly in decentralized and data-driven spaces. Ethereum, a blockchain platform, empowers developers to build decentralized applications (dApps), facilitating innovations in finance, media, and supply chain without a central authority. Another example is MyGPTS, a generative AI platform that enables developers and companies to integrate advanced AI capabilities, from language generation to data analysis, into their solutions. Both Ethereum and MyGPTS underscore how platform structures support continuous innovation and adaptability, laying the groundwork for a new generation of digital ecosystems.

This special issue seeks submissions that examine the intricate relationship between platforms and innovation management to support scholars and practitioners in fostering innovation through platforms. We invite contributions on the following topics:

- Exemplar cases of established firms that have adopted platform thinking, including their key learnings and examination of the benefits and risks involved.
- Platform-based technologies and their role in fostering innovation within new and established companies.
- How subject matter experts are leveraging platform models to drive innovation and achieve competitive advantages.
- Tools and frameworks that support organizations in cultivating innovation through platforms.
- How innovation leaders guide transformative projects based on platforms models.
- Other perspectives exploring the practical nexus between platforms and innovation.

We invite papers that explore how platforms act as driving forces for innovation. This special issue aims to advance understanding of how platform-based strategies can reshape businesses, influence markets, and inspire sustainable innovation pathways in a platform-centric world.

RTM articles are concise and practice oriented. Submissions can be motivated by practice but must be grounded in relevant contemporary academic research. They should demonstrate more than just practical implications, but also the strategies, practices, and actions that practitioners can use from the research findings. Ideal submissions offer concrete examples and data to support their findings.

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