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From Users to Innovators: Making the Case for Lead UX in IS

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Abstract

This viewpoint article argues that Information Systems (IS) professionals must evolve their design practices to effectively harness insights from user-generated content (UGC). While participatory and user-centered design remain foundational, they struggle to scale and anticipate emerging needs in today's dynamic digital ecosystems. We introduce the Lead UX framework, which integrates von Hippel's lead user theory with data-analytic approaches to systematically identify both innovation-driving lead users and key emergent lead topics within large-scale user discussions. By combining automated topic modeling and related natural language processing techniques with expert human review, Lead UX enables IS professionals to transform overwhelming volumes of UGC into actionable intelligence for proactive, innovation-driven design. We outline a hybrid workflow for operationalizing Lead UX, address challenges such as data quality and analytic bias, and propose future research directions, including comparative case studies, practitioner assessments, and algorithmic benchmarking. Finally, we offer actionable recommendations for educators and practitioners on embedding Lead UX into curricula and development processes, positioning users as co-designers in continuous IS innovation.

Keywords: Lead UX, user-generated content, information systems design, innovation analytics.

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1. Introduction

Information Systems (IS) design must adapt to harness the innovative potential of user-generated content (UGC). This paper argues that IS professionals can enhance design processes by adopting Lead UX analytics, a data-analytic practice grounded in von Hippel's (2005) lead user innovation theory. Lead UX systematically identifies (1) lead users, individuals whose advanced needs and solutions anticipate broader markets, and (2) emergent lead topics, recurring themes in user discourse that point to high-impact design opportunities. This approach complements established methods as users have shifted from passive recipients to active content creators.

The proliferation of UGC across digital platforms has fundamentally reshaped user–system interactions. Millions of reviews, forum posts, and social media comments now reveal system performance, unmet needs, and creative workarounds (Kitchin, 2014). Traditional IS methods, such as user-centered design (UCD; Abras et al., 2004) and participatory design (PD; Muller, 2007), remain valuable for deep, contextual understanding but struggle with the volume, speed, and diversity of contemporary UGC. These approaches are resource-intensive (Schuler & Namioka, 1993), sensitive to power dynamics that may limit open participation (Bratteteig & Wagner, 2014) and often focus on current or average users rather than emerging behaviors and disruptive use cases (Koskinen et al., 2011). In contrast, integrating UGC into UX work can provide richer context than structured interviews (Schäfer, 2011), support tracking of evolving needs (Krumm, 2018), and inspire the development of new features (von Hippel, 2005).

Lead UX extends von Hippel's (2005) lead user theory, which posits that some users experience needs and devise solutions that later diffuse to the broader market. These users frequently encounter challenges that later become mainstream and possess both the incentive and capability to innovate (von Hippel, 2005). Classic examples include Chris Messina's (2007) proposal of the hashtag (#) on Twitter, which evolved into a core platform convention (Huddleston, 2020), and 1970s mountain biking enthusiasts in Marin County, California, who modified bicycles with oversized tires and reinforced frames to create "clunkers," anticipating a new market category years before manufacturers such as Specialized and Trek responded (von Hippel, 2006). Another example would be 3M products, developed through systematic lead-user engagement, which achieved annual sales of approximately $146 million after five years, about eight times those of products developed through traditional approaches (Lilien et al., 2002).

Lead UX adapts this perspective to large-scale digital environments. Rather than relying on small, curated samples, it employs computational tools to identify both individual- and collective-level signals. Lead topics, persistent recurring themes in user discussions, reveal emergent needs that may not be visible in traditional studies of average users. Analyses of social media interactions, for instance, show how early adopters introduce practices (such as hashtags) ahead of official platform support, shaping collective behavior and core functionalities (Zappavigna, 2015; Dvir et al., 2019). Lead UX seeks to detect these signals systematically.

The advent of big data analytics has expanded possibilities for understanding user needs at scale (Chen et al., 2015; Goes, 2014). Techniques such as topic modeling and sentiment analysis can reveal patterns in large text corpora that would be infeasible to analyze manually. These computational approaches augment, rather than replace, established user research methods by distilling actionable insights from large volumes of user comments and informing more targeted design decisions.

Accordingly, this paper addresses two central questions for IS design in the UGC era: (1) How can IS professionals systematically identify and amplify the perspectives of lead users whose insights may signal emergent needs yet are often overlooked in traditional large-scale analyses? (2) What analytic strategies facilitate the scalable extraction of actionable findings from large volumes of unsolicited user content? While Lead UX cannot capture all user perspectives, it aims to surface insights that drive innovation and shape future design directions.

We present Lead UX as both a conceptual framework and a practical methodology that synthesizes lead user theory with contemporary analytical tools. Unlike participatory approaches that broadly engage stakeholders, Lead UX targets participants whose authentic, unsolicited feedback indicates high innovation potential. Combining automated techniques with human interpretation enables IS professionals to turn significant data challenges into strategic opportunities for innovation.

The remainder of this viewpoint paper is structured as follows. Section 2 reviews the rise of UGC in IS and highlights the limitations of PD and UCD in scaling and anticipating emergent needs. Section 3 introduces the Lead UX framework, situates it among established design methodologies, defines lead user characteristics, explains their strategic importance, and outlines hybrid methods for identifying them. Section 4 discusses the operationalization of Lead UX in practice, including implementation challenges and directions for future research. Section 5 offers actionable recommendations for the IS community to adopt and refine this approach.

2. Related Work

2.1 The Rise of User-Generated Content in Information Systems

The arrival of user-generated content (UGC) has fundamentally reshaped interactions between users and digital systems. With billions of reviews, forum contributions, and social media messages submitted daily, users have transitioned from passive consumers to active participants in the evolution of products and services (Chen, Mao, & Liu, 2014; Ren et al., 2007). Within the IS community, research increasingly emphasizes the importance of analyzing large-scale user contributions to inform system design and enhance engagement (Mitchell, 2018; Lebens, 2021).

UGC provides continuous, large-scale, and authentic feedback on system performance and unmet needs, far surpassing the snapshot nature of traditional usability studies (Preece & Shneiderman, 2009). It enables users to appropriate and redefine technology, a dynamic characterized as “user innovation” (von Hippel, 2005), which blurs conventional boundaries between designers and users. Emerging analytical techniques now allow researchers to capture and interpret this feedback at unprecedented scales, strengthening the link between user participation and system improvement (Klein, 2017).

Capturing value from this “social big data” requires integrating automated analytical strategies such as sentiment mining and natural language processing (Schäfer, 2011). Advances in computational methods, including collaborative filtering and crowdsourced recommendations, enable IS professionals to systematically extract patterns and actionable insights from massive UGC datasets (Solachidis et al., 2009). Building on these developments, recent work has proposed frameworks for mining, analyzing, and applying large volumes of user feedback to guide iterative improvements in information systems (Mitchell, 2018; Lebens, 2021). In this context, UGC functions both as a critical data resource and as evidence of a participatory cultural shift in IS development (O’Reilly, 2007; Jenkins, 2006; Markus & Silver, 2008).

2.2 Limitations of Traditional Design Approaches

User-centered design (UCD) and participatory design (PD) have historically empowered users in system development (Simonsen & Robertson, 2013; Bratteteig & Wagner, 2014). However, in the context of massive, continuously flowing UGC, these approaches show important shortcomings.

UCD often privileges mainstream preferences and averages, overlooking heavy users or those with unconventional needs who may drive disruptive innovation (Nielsen, 2024; Koskinen et al., 2011; Norman, 2013; Schreier & Prügl, 2008; von Hippel, 2005). Lüthje, Herstatt, and von Hippel (2006) illustrate the scale of this issue in their study of mountain biking user-innovators: 38% of users reported having developed ideas for product modifications, yet traditional UCD is structurally unable to systematically identify and prioritize these distributed innovations, particularly when they originate from a minority of highly advanced users.

Common UCD techniques, such as interviews, surveys, and usability tests, are effective in controlled, small-scale settings (Kujala, 2003; Maguire, 2001; Kuutti, 2009) but lack scalability to address the volume and velocity of modern digital contributions. Conducting in-depth studies with large user bases is economically infeasible, forcing organizations to rely on small, potentially unrepresentative samples that may systematically exclude lead users whose insights signal emerging trends (Wu & Huberman, 2007). These methods excel at generating deep contextual understanding but require complementary techniques to analyze large-scale, diverse user discussions.

Similarly, PD’s collaborative workshops typically involve small groups and can reinforce the views of the average user while marginalizing outlier voices (Muller & Kuhn, 1993; Baldwin & von Hippel, 2011; Bødker, Kensing, & Simonsen, 2004). Wu and Huberman (2007) demonstrate that user contributions in online environments follow power-law distributions, with a small fraction of users generating a disproportionate share of content and innovation. Broad-sample PD may dilute or overshadow these minority perspectives, treating them as noise rather than as signals of innovation.

Both UCD and PD also tend to capture user needs at discrete points in time, making it difficult to adapt to rapidly changing requirements in dynamic digital ecosystems. In addition, they demand substantial investments of time and resources in recruitment, facilitation, and analysis, constraints that become prohibitive when organizations must monitor evolving user feedback across multiple platforms.

Taken together, these limitations reveal a gap between the capabilities of established user research methods and the demands of the contemporary UGC landscape. Neither UCD nor PD fully leverages the scale, diversity, or velocity of user-generated data, nor do they systematically surface the most innovative insights, which typically originate from a small minority of highly engaged users (Wu & Huberman, 2007). The underdevelopment of analytic strategies for extracting, synthesizing, and applying these innovation-driving signals motivates the need for new frameworks that combine design principles with computational analysis. The following section introduces the Lead UX framework.

3. The Lead UX Framework: Harnessing Innovation from User-Generated Content

The Lead UX framework addresses gaps left by participatory design (PD), user-centered design (UCD), and conventional user-generated content (UGC) analytics in identifying and leveraging innovation-driving insights. By focusing on advanced, future-oriented users and emergent needs surfaced in digital contexts, Lead UX integrates the voices and foresight of strategically important contributors into information systems (IS) design (Baldwin & von Hippel, 2011; Schreier & Prügl, 2008).

This section positions Lead UX among established design approaches, defines the characteristics and strategic value of lead users, and outlines methods for identifying both lead users and lead topics.

3.1 Positioning Lead UX Among Design Approaches

Traditional PD distinguishes itself by directly involving a broad range of stakeholders through collaborative tools and workshops (Muller & Kuhn, 1993; Bratteteig & Wagner, 2014). UCD centers on usability and satisfaction, typically assessed through interviews, surveys, and usability tests, with an emphasis on the average end-user (Nielsen, 2024; Norman, 2013; Kujala, 2003). UGC analytics broadens this focus to capture input from a wide spectrum of everyday users via online platforms, employing both quantitative (e.g., engagement metrics) and qualitative (e.g., topic or sentiment analysis) techniques to reveal consumer attitudes, pain points, and shifting expectations (Wu & Huberman, 2007; Goes, 2014). The comparative matrix, presented below as Table 1, demonstrates how Lead UX uniquely centers advanced, future-oriented users and hybrid analytic workflows, filling significant gaps left by traditional PD and UCD approaches in the context of large-scale digital ecosystems.

Factor	Participatory Design (PD)	User-Centered Design (UCD)	User-Generated Contents (UGC) Analytics	Lead User Experience (Lead UX)
Involvement	Involves all stakeholders directly in the design process.	Focuses on understanding and meeting the needs of end-users.	Everyday users are central including anyone who voluntarily shares their experiences online	Involves advanced users who are ahead of market trends. Investigates user leads in data.
Users	All stakeholders, including all end-users, are involved.	End-users are involved through interviews, surveys, and testing.	Broad range of users, including customers and fans, who share authentic experiences or	Advanced users with strong innovation needs. Users who express their ideas in online contexts.

			feedback in digital public forums or branded spaces	
Focus	Collaboration and democratization of the design process.	Usability and user satisfaction.	Mining insights about attitudes, pain points, satisfaction, and emerging needs	Future-oriented innovation. Emergent needs in online forums.
Execution Method	Ongoing collaboration with a broad range of stakeholders using tools such as workshops and brainstorming sessions	Iterative testing and refinement based on user feedback. User interviews, surveys, personas, and usability testing	Both quantitative (such as engagement, reach) and qualitative (such as theme, sentiment) approaches	Engagement with a small group of lead users and identifying leads, e.g. common user issues.
Tools to Identify User	Workshops, surveys, interviews, observations	User studies, surveys, interviews, observations	Social media listening platforms, AI-driven analytics, hashtag tracking, content management systems	Data analytic tools to identify lead users and common user issues to innovate
Related References	Muller & Kuhn (1993); Bratteteig & Wagner (2014)	Nielsen (2024); Norman (2013); Kujala (2003)	Wu & Huberman (2007); Goes (2014)	Baldwin & Von Hippel (2011); Schreier & Prügl (2008)

Table 1. Comparison of PD, UCD, UGC Analytics, and Lead UX: Key Factors, User Roles, and Distinctive Features.

Lead UX integrates the advantages of PD, UCD, and UGC analytics, as summarized in Figure 1. This framework advances beyond these established practices in two fundamental ways. First, it explicitly seeks out lead users, those whose needs, capabilities, and motivations are ahead of contemporary market trends. Second, it leverages scalable analytics to identify not only individual insights but also emergent collective concerns (lead topics) that signal future innovation opportunities. Figure 1 illustrates how Lead UX synthesizes and builds on the strengths of PD, UCD, and UGC analytics to offer a more comprehensive and forward-looking design framework.

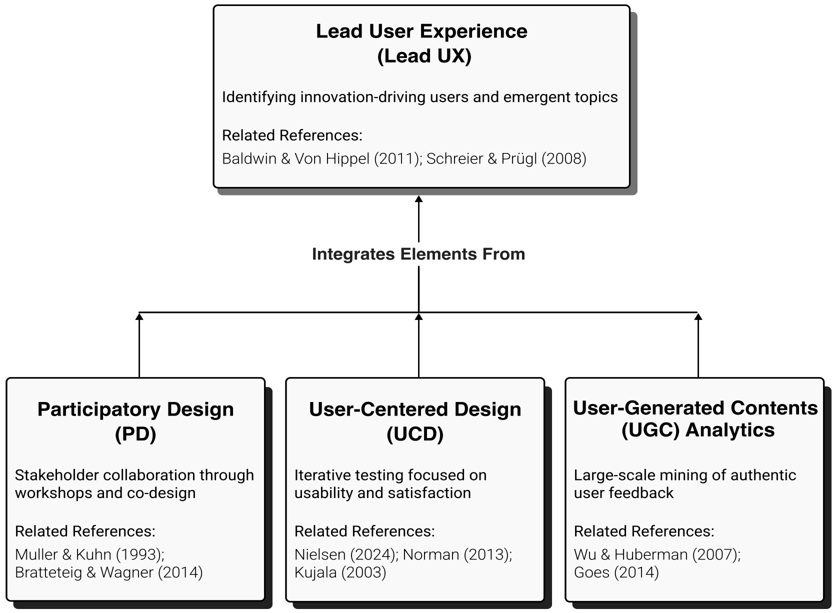

Figure 1. Relationship of PD, UCD, UGC Analytics, and Lead UX: Overlapping roles and strengths in IS design

3.1.1 Theoretical Propositions for Lead UX

While this viewpoint article presents Lead UX as a conceptual framework, the following propositions outline testable claims that future empirical research should investigate. These propositions clarify the theoretical contributions of Lead UX and set benchmarks for future validation studies. Since the main goal of developing the Lead UX framework is to create accurate, timely, relevant, and scalable interfaces unified in function and appearance, our propositions focus on these three aspects. As we conduct future research, validating these propositions against existing approaches will help develop cost-effective, scalable interfaces and market-aligned user experiences.

Proposition 1 (Early Detection): Lead UX will identify innovation opportunities earlier in the product development lifecycle than traditional PD or UCD methods, enabling proactive design decisions rather than reactive adaptations to already-established user demands.

Proposition 2 (Market Alignment): Design decisions informed by lead-user insights identified through Lead UX will demonstrate higher market acceptance and commercial relevance than those based solely on average-user feedback, because lead users' needs anticipate mainstream market trends.

Proposition 3 (Scalable Rigor): The hybrid automated-human workflow of Lead UX will enable systematic analysis of user-generated content at scale without sacrificing contextual validity, by leveraging computational efficiency for initial clustering while preserving human interpretive rigor for validation and labeling.

These propositions are not tested in this article but serve to guide future empirical efforts and to position Lead UX within a broader research agenda for IS design innovation.

3.2 Characteristics of Lead Users

Lead UX centers on advanced users whose contributions anticipate future mainstream demand. Drawing on Lüthje and Herstatt (2004) and Schreier and Prügl (2008), lead users are characterized by:

1. High product knowledge: deep familiarity with system features and technical nuances, enabling specific and technically informed feedback.

2. Strong locus of control: a proactive stance toward shaping outcomes, reflected in proposing remedies or alternatives rather than only reporting problems.

3. Innovativeness: willingness to experiment with, repurpose, or extend existing features, often revealing novel use cases.

4. Superior UX awareness: heightened sensitivity to usability and workflow issues and the ability to clearly articulate these concerns for designers and peers. These traits make lead users especially valuable in digital environments in which innovation-relevant content is concentrated among a small subset of highly engaged contributors.

3.3 Strategic Importance of Lead Users

Lead users are more than early adopters; they detect needs, performance gaps, and opportunities well before they are visible to the broader market (von Hippel, 2005). Their intensive, advanced use allows them to identify subtle friction points and envision breakthrough features.

Empirical studies demonstrate the commercial value of systematically engaging lead users. Urban and von Hippel (1988) found that innovations guided by lead-user insights were significantly more likely to succeed commercially. Lüthje and Herstatt (2004) showed that 38% of mountain biking users had developed product modifications, illustrating the prevalence of user-generated innovations that traditional methods often miss. Enthusiasts in Marin County, California, for example, created off-road “clunker” bicycles years before manufacturers recognized and served this market (von Hippel, 2006).

Digital platforms offer parallel cases. Chris Messina’s (2007) proposal of the hashtag (#) on Twitter, later documented by Huddleston (2020), illustrates how a lead user introduced a practice that became central to platform functionality. Such contributions show how lead users can shape core system features and social conventions.

Organizational examples underscore similar dynamics. At 3M, products developed through systematic lead-user engagement achieved annual sales of approximately $146 million after five years, about eight times those of products developed through traditional approaches (Lilien et al., 2002). LEGO Ideas enables advanced fans to submit and refine new set concepts; selected fan-designed sets have become bestsellers, demonstrating how structured lead user engagement can reduce market risk and strengthen community ties (King & Lakhani, 2013). Similar effects can be seen in the information domain when we observe “power editors” set the agenda on user-generated content pages (Panciera et al., 2009)

Lead users also serve as valuable partners for iterative prototyping and co-design. Their willingness to experiment, test new workflows, and provide detailed feedback creates a living laboratory effect, enabling organizations to validate hypotheses, refine features, and develop solutions with those most invested in system advancement. By systematically surfacing and analyzing lead user contributions, organizations tap into innovation signals that inform both immediate feature improvements and broader strategic directions. Recognizing and leveraging lead user insights is thus central to the Lead UX approach, transforming overlooked feedback into sustained innovation.

3.4 Identifying Lead Users: From Manual Coding to Human-Guided Automated Analytics

Traditionally, lead users have been identified through manual coding of qualitative data, an approach suitable for small-scale PD or UCD but not for the volume and diversity of contemporary UGC (Krippendorff, 2018). Lead UX instead adopts a hybrid strategy that combines automated analysis with expert human interpretation.

Computational tools such as topic modeling and other natural language processing (NLP) techniques first cluster large text corpora around salient themes (Wu & Huberman, 2007; Goes, 2014). These clusters may involve repeated complaints, detailed feature suggestions, or advanced workarounds. Human analysts then review and label the clusters, applying the four lead-user characteristics—high product knowledge, strong locus of control, innovativeness, and superior UX awareness—to identify which contributors are likely lead users.

This workflow enables IS professionals to efficiently identify both pervasive concerns and high-potential lead users, without manually inspecting all UGC. Future research can refine this process by developing automated lead-user scoring models and comparing alternative NLP and classification techniques across platforms and domains.

3.5 Lead Topics: Signal Amidst the Noise

Lead UX detects innovation signals at both the individual (lead user) and community (lead topic) levels. This builds on work on collective intelligence, which shows that large-scale user input can reveal opportunities and risks not visible from isolated observations (Surowiecki, 2004; Ickler & Baumöl, 2012).

Lead topics are recurring, persistent themes in UGC that point to high-impact opportunities for system improvement. They are typically discovered through automated clustering of user comments and posts into thematic groups. Human analysts then assess which clusters represent genuine innovation signals, drawing on lead-user traits (e.g., technical depth, solution focus) and considering the novelty and practical relevance of the ideas expressed.

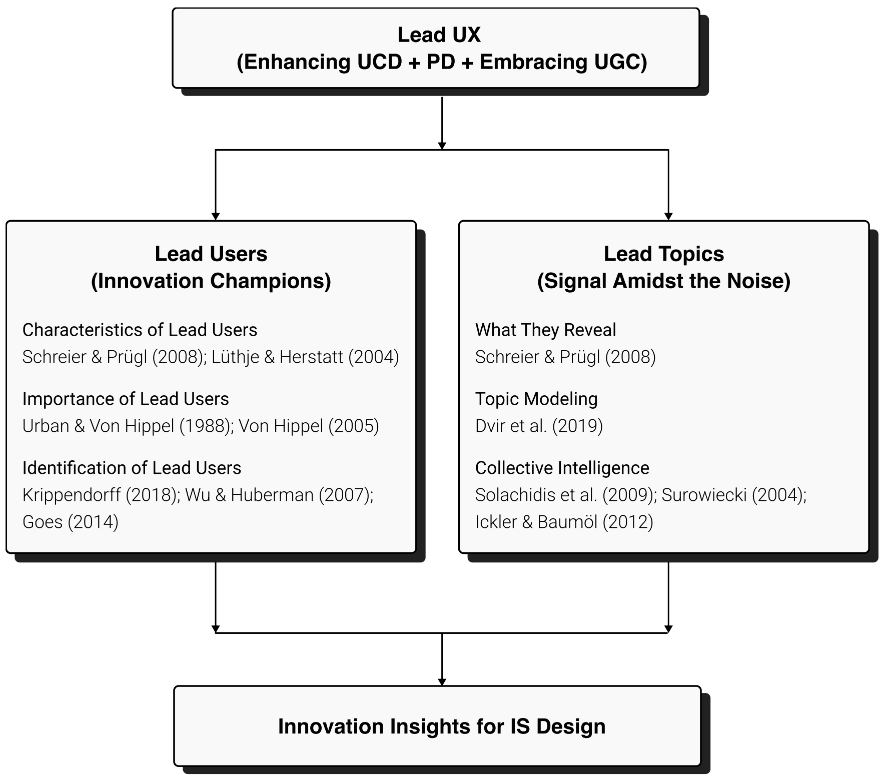

Figure 2. Identifying Lead Users and Topics: Workflow for extracting innovation from user-generated content

By combining lead user identification with lead topic analysis, as illustrated in Figure 2, Lead UX helps IS professionals shift from reactive adaptation, responding to well-established demands, to proactive innovation guided by early signals from user communities. The following section explains how these concepts can be operationalized in practice, translating the framework into concrete workflows for research and development.

4. Operationalizing Lead UX in Information Systems

To move Lead UX from concept to practice, information systems researchers and practitioners need a hybrid workflow that combines computational analytics with expert human interpretation. The process starts with the systematic collection and cleaning of user-generated content from relevant digital platforms, ensuring data quality and integrity. Prior work outlines protocols for managing unstructured user comments and extracting actionable insights, including best practices for preprocessing and analytic rigor (Mitchell, 2018; Lebens, 2021). Natural language processing techniques, such as topic modeling, then organize this content into thematic clusters that reflect recurring concerns, emerging needs, or innovative suggestions. Human analysts review these clusters and apply established lead user criteria—high product knowledge, strong locus of control, innovativeness, and superior UX awareness—to identify those most likely to yield forward-looking insights. These high-potential clusters inform system enhancements, help prioritize development efforts, and guide ongoing user engagement strategies.

Lead UX improves scalability and supports early identification of innovation opportunities, but it also faces limitations in data quality and analytic rigor. Large volumes of user-generated content increase the risk of including fake or bot-generated reviews, which can distort findings if not properly filtered. Robust data quality procedures, including automated detection and removal of suspicious or non-human entries, are therefore essential preprocessing steps.

Analytic rigor presents a second challenge. Any workflow involving human coding or interpretation, manual or hybrid, is vulnerable to bias. In manual coding, different raters may classify the same reviews differently; accordingly, inter-rater reliability measures, such as the intraclass correlation coefficient (ICC), are used to establish consensus and build confidence in the coded results. In topic modeling and other semi-automated approaches, algorithms first cluster themes from large text corpora and humans then label the output. Because grouping is performed automatically, this interpretive stage does not readily lend itself to ICC-style metrics. Instead, analysts should emphasize clear documentation of labeling criteria and periodic validation exercises to minimize interpretive bias. In practice, both human coding and automated clustering contribute to data integrity and analytical rigor. Used together, they complement each other in extracting information and reducing noise in user-generated comments, thereby advancing the development of the Lead UX paradigm. Continued improvements in data quality management and analytic transparency are essential to strengthen the rigor and trustworthiness of Lead UX implementations, regardless of the specific workflow adopted.

4.1 Future Research Directions and Proposed Evaluation Approaches

As a viewpoint article, this paper offers a theoretical and practical foundation for Lead UX rather than empirically testing the framework. Although the core methodology and conceptual claims are grounded in prior literature, empirical research is needed to assess the effectiveness of Lead UX across organizational contexts, platforms, and user populations.

Future work should pursue three complementary validation approaches. First, comparative case studies can examine how Lead UX identifies innovation opportunities relative to traditional design methods (Yin, 2009; Eisenhardt & Graebner, 2007), documenting both timing and commercial relevance. Second, expert practitioner assessments can evaluate feasibility, scalability, and implementation requirements across organizational settings (Wandersman et al., 2012; Slaghuis et al., 2011). Third, algorithmic benchmarking can compare automated lead user–topic identification against manual expert coding (Hripcsak & Rothschild, 2005), using metrics such as precision, recall, and F1-score across platforms. Prior work suggests that hybrid automated–manual approaches often outperform single methods in classification accuracy and interpretability, a claim that future Lead UX studies can test explicitly. Together, these investigations will clarify the conditions under which Lead UX delivers the most significant strategic value and inform the implementation of best practices.

5. Call to Action: Transforming IS Practice Through Lead UX

The volume and velocity of user-generated content (UGC) are reshaping IS design. Slow responses to emerging user signals can lead to costly redesigns, reduced satisfaction, and missed opportunities for innovation. Lead UX offers a disciplined, scalable path for shifting from reactive adaptation to proactive innovation.

Evidence from established lead user practices underscores this potential. At 3M, products developed through systematic lead-user engagement achieved annual sales of about $146 million after five years, eight times those of products developed through traditional methods (Lilien et al., 2002). LEGO's crowdsourced innovation platform, LEGO Ideas, likewise transforms fan submissions into best-selling products by systematically identifying and amplifying advanced users' ideas, demonstrating that organizations can scale lead user engagement while maintaining community connection (King &

Lakhani, 2013).

IS professionals and educators can operationalize Lead UX through the following steps:

- **Integrate into curricula:** Use community-based service-learning to have students apply Lead UX analytics to real small-business challenges, enhancing both learning and local innovation capacity (Mitchell, 2018).
- **Design interactive classwork:** Employ prototyping assignments in asynchronous online courses, so students iterate on system designs informed by Lead UX signals (Mitchell, 2018).
- **Blend computational and interpretive analysis:** Combine topic modeling and other NLP tools with expert review to identify lead users and emerging topics at scale, augmenting rather than replacing qualitative methods.
- **Embed lead-topic monitoring in development:** Build regular cadences (e.g., within Agile sprints) for reviewing and prioritizing emergent user signals, turning high-potential findings into hypotheses for rapid prototyping and testing.
- **Cultivate lead user engagement channels:** Establish sustained mechanisms, such as advisory panels, beta communities, or dedicated feedback spaces, that systematically involve advanced users in design decisions and treat them as partners in innovation.

By adopting Lead UX, IS professionals can redefine user feedback from a retrospective evaluation tool into a real-time driver of innovation. Automated topic detection and human interpretation become integral to iterative development, enabling teams to detect friction points and opportunities earlier than competitors. Treating users as co-designers promotes continuous, participatory innovation, systematically surfacing breakthrough ideas from user communities and reducing risk in development cycles.

6. Conclusion

This viewpoint article has addressed two central research questions: (1) How can IS professionals systematically identify and amplify the perspectives of lead users whose insights may signal emergent needs but are often overlooked in traditional large-scale analyses? (2) What analytic strategies enable the scalable extraction of actionable findings from large volumes of unsolicited user content?

We introduced Lead UX, a framework that integrates von Hippel's lead-user innovation theory with scalable computational analytics and human interpretive rigor. Lead UX positions advanced, innovation-driving users and emergent collective concerns (lead topics) as focal points for user research, complementing rather than replacing participatory design and user-centered design. By combining automated clustering techniques with expert interpretation grounded in established lead-user characteristics, Lead UX enables organizations to convert big data challenges into strategic opportunities for sustained innovation.

The framework has implications for both research and practice. For researchers, Lead UX offers avenues for empirical validation through comparative case studies, expert practitioner assessments, and algorithmic benchmarking, which can clarify when and why Lead UX outperforms traditional design approaches. For practitioners, Lead UX provides implementable workflows for monitoring UGC, identifying high-potential innovations, and prioritizing design decisions, which can accelerate time-to-market and reduce innovation risk.

Limitations remain. Empirical effectiveness across different organizational contexts, platforms, and user populations is still to be tested. Optimal tuning of the hybrid workflow, balancing automated efficiency with human interpretive accuracy, requires further investigation, as do potential biases introduced by algorithmic clustering or analyst interpretation.

The next era of IS design depends less on isolated genius than on combining analytics with community-driven creativity. By systematically revealing, interpreting, and acting on latent innovation within user communities, IS professionals can transform design from a reactive, inward-facing discipline into a proactive, collaborative partnership with users. The call to action is to activate Lead UX now: use it to unlock strategic foresight, refine analytic practices through rigorous testing, and position users as central co-creators in sustainable innovation.

7. References

Abras, C., Maloney-Krichmar, D., & Preece, J. (2004). User-centered design. In W. Bainbridge (Ed.), *Berkshire encyclopedia of human-computer interaction* (pp. 763-768). Berkshire Publishing Group.

Baldwin, C., & von Hippel, E. (2011). Modeling a paradigm shift: From producer innovation to user and open collaborative innovation. *Organization Science*, 22(6), 1399-1417.

Bratteteig, T., & Wagner, I. (2014). *Disentangling participation: Power and decision-making in participatory design*. Springer.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly*, 36(4), 1165-1188.

Dvir, N., & Gafni, R. (2019). Systematic improvement of user engagement with academic titles using computational linguistics. *arXiv preprint arXiv:1906.09569*.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. *Academy of Management Journal*, 50(1), 25–32.

Goes, P. B. (2014). Editor's comments: Big data and IS research. *MIS Quarterly*, 38(3), iii-viii.
Hripcsak, G., & Rothschild, A. S. (2005). Agreement, the F-measure, and reliability in information retrieval. *Journal of the American Medical Informatics Association*, 12(3), 296–298.

Ickler, H., & Baumöl, U. (2012). Adding value with collective intelligence: A reference framework for business models for user-generated content. In J. Altmann, U. Baumöl, & B. Krämer (Eds.), *Advances in collective intelligence 2011* (pp. 41-50). Springer.

King, A., & Lakhani, K. R. (2013). Using open innovation to identify the best ideas. *MIT Sloan Management Review*, 55(1), 41.

Kitchin, R. (2014). *The data revolution: Big data, open data, data infrastructures and their consequences*. Sage Publications.

Klein, B. D. (2017). On the development and application of a framework for understanding the properties and information quality of online reputation systems. *Journal of the Midwest Association for Information Systems*, 2017(1), Article 3.

Koskinen, I., Zimmerman, J., Binder, T., Redström, J., & Wensveen, S. (2011). *Design research through practice: From the lab, field, and showroom*. Morgan Kaufmann.

Krippendorff, K. (2018). *Content analysis: An introduction to its methodology* (4th ed.). Sage Publications.

Krumm, J. (2018). *Ubiquitous computing fundamentals*. CRC Press.

Kujala, S. (2003). User involvement: A review of the benefits and challenges. *Behaviour & Information Technology*, 22(1), 1-16.

Kuutti, K. (2009). User-centered design and beyond: Towards more human-centered design. *Design Issues*, 25(3), 29-41.

Lebens, M. (2021). Using prototyping to teach the design thinking process in an asynchronous online course. *Journal of the Midwest Association for Information Systems*, 2021(2), Article 3.

Lilien, G. L., Morrison, P. D., Searls, K., Sonnack, M., & von Hippel, E. (2002). Performance assessment of the lead user idea-generation process for new product development. *Management Science*, 48(8), 1042-1059.

Lüthje, C., & Herstatt, C. (2004). The lead user method: An outline of empirical findings and issues for future research. *R&D Management*, 34(5), 553-568.

Maguire, M. (2001). Methods to support human-centred design. *International Journal of Human-Computer Studies*, 55(4), 587-634.

Messina, C. [@chrismessina]. (2007, August 23). How do you feel about using # (pound) for groups. As in #barcamp [Tweet]. *Twitter*. https://twitter.com/chrismessina/status/236136209

Mitchell, A. J. D. (2018). Small business website development: Enhancing the student experience through community-based service learning. *Journal of the Midwest Association for Information Systems*, 2018(2), Article 4.

Muller, M. J. (2007). Participatory design: The third space in HCI. In A. Sears & J. A. Jacko (Eds.), *Human-computer interaction handbook* (pp. 1051-1068). Lawrence Erlbaum Associates.

Muller, M. J., & Kuhn, S. (1993). Participatory design. *Communications of the ACM*, 36(6), 24-28.
Nielsen, J. (2024, January 30). 10 usability heuristics for user interface design. *Nielsen Norman Group*. https://www.nngroup.com/articles/ten-usability-heuristics/

Norman, D. A. (2013). *The design of everyday things* (Revised and expanded ed.). Basic Books.

Ren, Y., Harper, F. M., Drenner, S., Terveen, L., Kiesler, S., Riedl, J., & Kraut, R. E. (2012). Building member attachment in online communities: Applying theories of group identity and interpersonal bonds. *MIS Quarterly*, 36(3), 841-864.

Schreier, M., & Prügl, R. (2008). Extending lead-user theory: Antecedents and consequences of consumers' lead userness. *Journal of Product Innovation Management*, 25(4), 331-346.

Schuler, D., & Namioka, A. (Eds.). (1993). *Participatory design: Principles and practices*. Lawrence Erlbaum Associates.

Slaghuis, B., Steding-Jessen, M., Carvalho, S. W., Evers, W., & Ouwens, M. (2011). Framework and tools for evaluating scalability of health interventions. *Health Policy*, 105(2–3), 154–162.

Solachidis, V., Dimitriadis, S., Drosou, A., Tzovaras, D., & Konstantinidis, K. (2009). Collective intelligence generation from user contributed content. In A. Fink, B. Lausen, W. Seidel, & A. Ultsch (Eds.), *Advances in data analysis, data handling and business intelligence* (pp. 769-778). Springer.

Surowiecki, J. (2004). *The wisdom of crowds: Why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations*. Doubleday.

Urban, G. L., & von Hippel, E. (1988). Lead user analyses for the development of new industrial products. *Management Science*, 34(5), 569-582.

von Hippel, E. (2005). *Democratizing innovation*. MIT Press.

Wandersman, A., Duffy, J., Firebaugh, P., Noonan, R., Lubell, K., Malloy, P., ... & Saul, J. (2012). Bridging the gap between prevention research and practice: The interactive systems framework for dissemination and implementation. *American Journal of Community Psychology*, 50(3–4), 445–459.

Wu, F., & Huberman, B. A. (2007). Novelty and collective attention. *Proceedings of the National Academy of Sciences*, 104(45), 17599-17601.

Yin, R. K. (2009). Case study research: *Design and methods* (4th ed.). SAGE Publications.

Zappavigna, M. (2015). Searchable talk: The linguistic functions of hashtags. *Social Semiotics*, 25(3), 274-291.

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