Creativity and Innovation Management

WILEY

RESEARCH ARTICLE OPEN ACCESS

Measuring Lead Userness: Development and Validation of a Hierarchical Scale

Moritz Paulus[1] | Slawka Jordanow[2] | Sven Heidenreich[2] | Franziska Janz[2]

[1]August-Wilhelm Scheer Institute, Saarbrücken, Germany | [2]Chair of Technology and Innovation Management, Saarland University, Saarbrücken, Germany

Correspondence: Sven Heidenreich (sven.heidenreich@uni-saarland.de)

Received: 10 September 2024 | **Revised:** 15 June 2025 | **Accepted:** 23 June 2025

Funding: Open-access funding was enabled and organized by Projekt DEAL (WOA Institution: Universität des Saarlandes; Consortia Name: Projekt DEAL).

Keywords: adoption | innovation | lead user | literature review | new product development | scale development

ABSTRACT

Lead user theory has gained traction in both academia and practice, given that involving lead users (LUs) can yield more innovative and commercially successful products. Yet, measurement inconsistencies have hindered consensus on how to reliably assess lead userness. This paper develops and validates a new 30-item scale that conceptualizes lead userness as a hierarchical construct with two second-order dimensions: ahead of trend (AoT) and high benefit expectation (HBE). Each dimension is further subdivided into three first-order subdimensions, capturing facets such as ideas, information and experience (AoT) or problems, needs and gains (HBE). In multiple studies, the scale demonstrated robust reliability and convergent, discriminant and nomological validity, correlating as expected with key antecedents (e.g., divergent thinking, product knowledge, innate innovativeness and risk aversion) and outcomes (e.g., social innovativeness, opinion leadership, innovation experience and innovation intention). Additionally, a separate predictive and explanatory power study comparing the new scale with seven established measures underscored its superior capacity to account for both past and future user-driven innovation activities. Moreover, a market test across smartphones, e-bikes and refrigerators confirmed that product concepts developed by identified LUs commanded higher willingness to pay than those from regular consumers, reinforcing the scale's practical relevance. Finally, a short-scale variant with six items is introduced as a viable alternative when item minimization is crucial. Taken together, these findings provide a comprehensive inventory for measuring lead userness, laying the foundation for deeper theoretical insights into user-driven innovation and more targeted managerial strategies for collaborating with LUs across diverse product categories.

1 | Introduction

Nowadays, many companies face rapidly evolving consumer demands and increasing competition, making product innovation a key driver of sustainable growth and financial success (Cooper and Kleinschmidt 1987; Nylén and Holmström 2015). At the same time, rapid advancements in AI-based analytics and digital technologies have reshaped how firms gather and interpret consumer insights (Gupta et al. 2020; Khatri 2021), accelerating the pace of product innovation. Yet, a substantial number of newly introduced products fail to achieve their expected market success (Heidenreich and Kraemer 2016; Lee and Markham 2016), highlighting how crucial it is to identify and address real consumer needs in new product development (Globocnik and Faullant 2021; Gruner and Homburg 2000; von Hippel 1986). Prior studies have demonstrated that integrating consumers in the innovation process holds immense potential to address these needs and thereby can significantly enhance a product's commercial viability and innovativeness (Blazevic and Lievens 2008; Carbonell et al. 2012; Gupta et al. 2021;

Lüthje 2004). However, consumer heterogeneity remains pronounced: Not every individual exhibits the same aptitude or motivation to generate commercially valuable ideas (Gruner and Homburg 2000; Lüthje 2004; Gemser and Perks 2015). Against this backdrop, one of the most pressing questions regarding customer integration in innovation is: which consumers show the 'right' characteristics for effectively contributing to new product development (Hamdi-Kidar et al. 2019; Hoffman et al. 2010; Hyysalo et al. 2015)?

A compelling answer to this question stems from von Hippel's (1986) concept of lead users (LUs), who are characterized by two defining attributes: (1) They sense needs earlier than the majority of the market (ahead of trend, AoT), and (2) they expect to benefit substantially from solutions to those emergent needs (high benefit expectation, HBE). Their practical importance has been repeatedly demonstrated (Carbonell et al. 2012; Lilien et al. 2002; Schreier and Prügl 2008; Ye and Kankanhalli 2018), with evidence showing that these individuals generate superior and more commercially appealing product ideas than regular users (Franke et al. 2006; Lilien et al. 2002; Urban and von Hippel 1988). LUs thus constitute a major source of innovative potential (Carbonell et al. 2012; Morrison et al. 2000), not only producing high financial benefits (Lilien et al. 2002) and successful products (Schreier et al. 2007; Gruner and Homburg 2000) but also enhancing broader adoption and diffusion (Schreier et al. 2007).

Despite widespread interest in the LU phenomenon (e.g., Kratzer et al. 2016; Kratzer and Lettl 2009; Morrison et al. 2000; Schweisfurth and Dharmawan 2019), the underlying characteristics that set LUs apart remain subject to considerable debate (Faullant et al. 2012; Schreier and Prügl 2008). Different authors have introduced disparate conceptualizations and measurement approaches for the LU construct (Hienerth and Lettl 2017). More specifically, some authors limit their operationalization of LUs to one of the two original components, AoT and HBE (e.g., Jahanmir and Cavadas 2018; Schweisfurth and Herstatt 2015), whereas others consider both (e.g., Franke et al. 2006; Wellner and Herstatt 2014; Ye and Kankanhalli 2018), and still, others combine them with further characteristics such as likeliness to innovate (e.g., Kratzer and Lettl 2009; Morrison et al. 2000; Morrison et al. 2004), opinion leadership (Spann et al. 2009), knowledge (Belz and Baumbach 2010) or experience (Schuhmacher and Kuester 2012). Moreover, various subfacets of AoT and HBE have been empirically identified yet remain scattered across different studies without being integrated into a cohesive framework. As a result, the literature suffers from conceptual fragmentation and inconsistent operational definitions, creating barriers to a cumulative understanding of the lead-user construct (Hienerth and Lettl 2017). Although existing measurement inventories and identification methods have made important strides, there is no consensus on how best to tap a consumer's lead userness reliably (Hienerth and Lettl 2017).

To address these gaps, this study investigates the root causes of AoT and HBE to develop a comprehensive reconceptualization of the LU phenomenon at a lower level of abstraction. By parsing AoT and HBE into more granular subdimensions, the proposed approach aims to provide clearer insights into how some users detect and respond to emerging trends ahead of others and why they derive such strong personal benefit expectations from doing so. Hence, this paper not only offers a fresh theoretical perspective and an empirically validated measurement instrument but also contributes to the field in several ways: It integrates previously fragmented conceptualizations of lead userness into a cohesive framework; it empirically demonstrates the hierarchical nature of AoT and HBE through a comprehensive scale development and validation process; it tests the instrument across multiple product categories to underscore its applicability and robustness; and it lays the groundwork for more targeted managerial strategies that leverage LUs' unique capabilities. By synthesizing these elements, this research aspires to bring the field closer to an integrated, multidimensional view of lead userness, thereby facilitating both deeper empirical inquiry and more strategic, evidence-based engagement with LUs in practice.

The remainder of this paper is organized as follows. First, we review the current state of research by synthesizing the findings of a systematic literature review on LUs. Building on these insights, we then propose a new theoretical framework for the LU construct, which underpins the development of a comprehensive scale to measure individual degrees of lead userness in a hierarchical manner. Next, we detail the scale development process, including an exploratory factor analysis (EFA) and a confirmatory factor analysis (CFA) to validate the instrument. We further establish nomological validity by linking lead userness to several constructs from innovation and consumer research that are expected to correlate significantly with the LU construct. Finally, we demonstrate the instrument's capacity to pinpoint individuals (LUs) who generate commercially more successful product concepts than regular users. The paper concludes with a discussion of the findings, including theoretical and managerial implications, before suggesting avenues for future research and highlighting limitations of the study.

2 | Current State of Research

To ensure that the conceptualization and scale development were grounded in a robust and comprehensive literature base, a systematic literature review was conducted following the approach outlined by Bartels and Reinders (2011). The search was conducted on the EBSCOHost (Business Source Premier) and ScienceDirect databases and included all articles available through January 2021. As the review is primarily focused on the LU phenomenon, the search terms 'lead user' and 'lead users' were included. Because some studies refer to the individual characteristic by using the label 'lead userness' (e.g., Schreier and Prügl 2008; Schweisfurth 2017; Wu et al. 2020), this term was also added. The three focal search terms were combined using the 'OR' condition. Within the database search, the search terms needed to occur in the abstracts, title or author-specified keywords of the articles retrieved. In addition, only peer-reviewed articles in English were considered. Table 1 provides a detailed overview of the results and further illustrates the procedure of the systematic literature review. As shown in Table 1, 284 articles could be identified (191 from EBSCOHost and 93 from ScienceDirect) within the first stage of the review process. To ensure a high quality of the literature base, the articles were then categorized according to the Academic Journal Guide (AJG) 2021 rating for

TABLE 1 | Results of the database search.

Search term	Databases: EBSCOHost number of articles	ScienceDirect number of articles	Methodical approach
'lead user' OR 'lead users' OR 'lead userness'	191	93	Search within abstract, title or author-supplied keywords
	Total:	284	
		200	AJG 2021 ranking from 2 to 4*
		168	Removing duplicates
	Final relevant set:	41	Abstract and full-text analysis

scientific journals. During this procedure, 200 articles could be assigned to categories ranging from '2' to '4*'. Because this work aims to consider only highly prestigious journals, 23 '1' ranked articles and 61 articles that were not ranked or listed were rejected.

After removing the duplicates, 168 articles remained, which were then assessed for eligibility by conducting a detailed abstract and full-text analysis. Within this stage, articles that did not include a measurement inventory to empirically assess the LU construct or LU components were discarded. As a result, 41 articles (eight articles from journals with a '4*' rating, 14 with a '4' rating, seven from '3' ranked and 12 from '2' ranked journals) were identified to exhibit the potential to contribute purposefully to this work. Table A1 provides a comprehensive overview of the final 41 articles encompassing information about the construct definitions, measured components, original sources of the measurement inventories and research contexts of the identified LU studies. It is worth noting that LU components were only considered when they were clearly addressed in the measurement or when the authors explicitly stated that certain items reflect a specific facet of the construct.

As a result of the literature review, pertinent LU-related research streams could be observed. First, some of the identified articles are intended to test the LU theory by comparing LUs with other consumer types, such as emergent nature consumers (Hamdi-Kidar et al. 2019; Hoffman et al. 2010), opinion leaders (Kratzer and Lettl 2009), experts (Ozer 2009) or problem solvers from analogues markets (Franke et al. 2014). Second, a number of studies rather focused on examining the commercial potential of LU generated products or services (e.g., Carbonell et al. 2012; Herstatt and von Hippel 1992; Urban and von Hippel 1988; Ye and Kankanhalli 2018). Third, a substantial number of articles were intended to amplify the LU theory by reconceptualizing lead userness or by examining determinants and consequences of the construct (Faullant et al. 2012; Hau and Kang 2016; Morrison et al. 2000; Morrison et al. 2004; Schreier and Prügl 2008; Schreier and Prügl 2008; Wellner and Herstatt 2014). Fourth, several studies could be found that developed context-specific methods for LU identification (Belz and Baumbach 2010; Hyysalo et al. 2015; Spann et al. 2009). Finally, because LUs can also be identified among employees, some articles concentrate on internal LUs (e.g., Schweisfurth 2017; Schweisfurth and Herstatt 2015; Wu et al. 2020) or investigate their roles and communication activities within social groups and organizations (e.g., Jeppesen and Laursen 2009; Kratzer and Lettl 2008; Kratzer et al. 2016; Nørskov et al. 2016). Although prior research and the original concept of LUs (von Hippel 1986) show that both consumers and firms can be LUs (e.g., Urban and von Hippel 1988; Morrison et al. 2000), the vast majority of articles in this review focused on consumers' lead userness. Even though organizational lead userness is undeniably important and can be captured by surveying firm representatives (Morrison et al. 2004), we maintain this consumer-centric approach in developing our instrument to provide clearer theoretical underpinnings and ensure precision in capturing personal (rather than organizational) characteristics. More specifically, focusing on consumers allows us to isolate individual-level drivers of lead userness, such as personal need recognition and direct usage experiences, which may be confounded in an organizational setting by structural factors (e.g., formalized R&D processes and hierarchical decision making).

From a conceptual perspective, there is some consensus about the LU construct. Thus, all 41 articles based their conceptualization, at least to some extent, on the two definitional LU characteristics, AoT and HBE introduced by von Hippel (1986). Whereas a significant number of authors exclusively focused on AoT and HBE (Carbonell and Rodriguez-Escudero 2015; Franke et al. 2006; Globocnik and Faullant 2021; Hau and Kang 2016; Schweisfurth and Raasch 2015), nine articles were identified that explicitly considered further aspects of LUs in their conceptualization. Regarding the operationalization of the LU construct, inconsistencies could be identified. Twenty three of the 41 final articles measured lead userness as a unidimensional construct (e.g., Chou et al. 2015; Hamdi-Kidar et al. 2019; Hoffman et al. 2010; Morrison et al. 2000; Morrison et al. 2004; Ozer 2009). Correspondingly, these studies either integrated items for AoT and HBE together in one scale (e.g., Kratzer et al. 2016; Nijssen et al. 2012; Schreier and Prügl 2008; Schweisfurth and Raasch 2015) or applied measurement inventories for lead userness that do not explicitly specify which items reflect a specific component (e.g., Hamdi-Kidar et al. 2019; Hoffman et al. 2010; Jeppesen and Laursen 2009; Ozer 2009). Four articles measured only one of the two original dimensions sufficiently (Füller et al. 2009; Jahanmir and Cavadas 2018; Jahanmir and Lages 2016; Schweisfurth and Herstatt 2015). Despite this, 18 of the identified articles pursued a multidimensional approach (e.g., Spann et al. 2009; Wellner and Herstatt 2014; Ye and Kankanhalli 2018). These studies understand AoT and HBE as independent and distinct dimensions and thus consider lead userness as a second-order construct (e.g., Franke et al. 2006; Nørskov et al. 2016; Schweisfurth and Dharmawan 2019; Wellner and Herstatt 2014; Wu et al. 2020; Ye and Kankanhalli 2018). Specifically, Franke et al. (2006) found empirical support for AoT and HBE to be distinct dimensions of lead userness. They claim that AoT and HBE are conceptually different dimensions, which should be considered separately in the measurement (Franke et al. 2006). Across the 18 articles that employed a multidimensional approach, 16 exclusively focused on HBE and AoT, and only two articles were found that measured lead userness with more than two dimensions (Mütterlein et al. 2019; Spann et al. 2009). With respect to measurement specification, the studies that employed a second-order operationalization of lead userness (e.g., Franke et al. 2006; Ye and Kankanhalli 2018; Wu et al. 2020; Hau and Kang 2016) predominantly employed a formative approach for the higher order dimensions (AoT and HBE). Only Mütterlein et al. (2019) used a reflective operationalization at the second-order level. By contrast, the first-order items (reflecting measurements of AoT or HBE) have consistently been measured reflectively.

Overall, the evidence from prior research suggests that adopting a multidimensional conceptualization and operationalization of lead userness, which is in line with von Hippel's (1986) two core components (AoT and HBE), is both theoretically and empirically more robust than a unidimensional view. Multidimensional constructs are generally advantageous when key dimensions represent distinct but complementary facets of a broader conceptual domain (Jarvis et al. 2003). In this case, AoT and HBE tap different yet interrelated aspects of lead userness: AoT captures the ability to anticipate future needs, whereas HBE reflects the strength of personal benefits one expects from developing novel solutions. Treating these two facets as a single, unidimensional construct risks obscuring the unique contribution each dimension makes to lead-user behaviour, as well as overlooking users who excel in one dimension but not the other. Hence, the two-dimensional perspective provides a richer, more precise account of how 'leading-edge' behaviour emerges and is sustained (Franke et al. 2006). Accordingly, formatively specifying AoT and HBE at the second-order level, as done by most studies that adopt a second-order conceptualization (e.g., Franke et al. 2006; Ye and Kankanhalli 2018; Wu et al. 2020; Hau and Kang 2016), is theoretically justified because these dimensions collectively form lead userness, rather than merely reflecting it (Jarvis et al. 2003). In other words, each dimension (AoT vs. HBE) is viewed as a causal indicator that contributes uniquely to the higher order construct: A user can be AoT but have low benefit expectations, or vice versa, and still exhibit lead-user qualities in a particular context. If subdimensions can vary independently, and changes in one dimension do not necessarily imply proportional changes in the other, a formative approach is more appropriate (Diamantopoulos and Winklhofer 2001). Hence, approaching lead userness as multidimensional construct encompassing AoT and HBE as subdimensions increases content validity and theoretical clarity, ensuring that the conceptualization and subsequent operationalisation remain closely aligned with von Hippel's (1986) seminal idea that LUs are both 'ahead of trend' and 'positioned to benefit significantly' from solving their early-arising needs.

However, although early research showed consensus regarding the conceptualization of lead userness as a multidimensional construct, substantial inconsistencies were observed in the measurement of its subdimensions, namely, AoT and HBE. Although most of the identified studies targeted their measures to at least one of these components, the instruments used were found to differ significantly. This applies particularly to the AoT component, which five of the 41 articles covered via trend-specific performance measures (Franke et al. 2006; Schreier et al. 2007; Schreier and Prügl 2008; Schweisfurth and Raasch 2015; Urban and von Hippel 1988). Likewise, studies that employed direct questions to assess AoT (e.g., Faullant et al. 2012; Schweisfurth and Dharmawan 2019) varied in their focus on whether consumers perceive themselves, or are perceived by others, as leading edge (e.g., Faullant et al. 2012; Hung et al. 2011; Morrison et al. 2004), have earlier access to product information (e.g., Globocnik and Faullant 2021; Kratzer et al. 2016; Ye and Kankanhalli 2018) or engage in past product improvement activities (e.g., Hau and Kang 2016; Hyysalo et al. 2015). Concerning the HBE component, items referring to unsolved problems with the prevailing solution (e.g., Franke et al. 2014), unmet needs (e.g., Franke et al. 2006), dissatisfaction (e.g., Schweisfurth and Herstatt 2015) and awareness of personal benefits or rewards (e.g., Kratzer and Lettl 2008, 2009) were predominantly employed.

Conclusively, multiple subfacets of AoT and HBE have been empirically observed, but they remain scattered across different studies without converging on a unified framework. Although some authors measured one aspect of AoT or HBE, others highlighted entirely different domains, implying that each individual facet, for instance, information advantages or unmet needs, can be crucial for capturing lead userness, but none offers a complete picture in isolation. To our knowledge, however, no study has systematically integrated these diverse AoT and HBE subfacets into a coherent model of lead userness. Instead, previous research has largely treated lead userness unidimensionally or conceptualized AoT and HBE as first-order constructs. Against this background, a deeper understanding of how these scattered subfacets collectively shape AoT and HBE is needed. Such an endeavour would not only clarify what exactly makes a LU 'ahead of trend' and strongly motivated by personal benefits but also enable a more unified measurement approach that consolidates prior empirical insights (Hienerth and Lettl 2017). Accordingly, the following section proposes a hierarchical conceptualization of lead userness in which AoT and HBE each comprise multiple subdimensions, thereby accommodating the variety of facets identified in the literature and unifying disparate strands of research.

3 | Conceptual Development

In order to establish a common ground for an adequate specification of the LU construct (MacKenzie et al. 2011), this paper provides a comprehensive conceptualization of lead userness that focuses on its definitional origin (Hienerth and Lettl 2017). As already indicated, LUs are characterized by two definitional components, which von Hippel (1986) originally defined as follows: 'Lead users face needs that will be general in a marketplace—but face them months or years before the bulk of that marketplace encounters them', which represents the AoT component (von Hippel 1986, 796) and 'Lead users are positioned to benefit significantly by obtaining a solution to those needs', which mirrors the HBE component (von Hippel 1986, 796). Consistent with these foundational definitions, this paper conceptualizes AoT as the individual's capacity to sense, discover and act on emerging trends or needs in advance of others, not through deliberate foresight, but as a result of personally relevant activity that unintentionally anticipates broader market developments. HBE, in turn, refers to the individual's strong awareness of how solving those needs or problems can yield substantial personal benefit. Although AoT and HBE have long been recognized as the two fundamental dimensions of lead userness (Franke et al. 2006; von Hippel 1986), studies vary considerably in how they measure these constructs (see Table A1). This heterogeneous treatment suggests that each study has tapped into different segments of a broader conceptual domain, emphasizing certain facets over others. Table A2 provides an overview of how studies have captured each subdimension, illustrating the prevalence and theoretical relevance of each. A closer look at the full scope of prior operationalizations reveals six recurring yet sometimes inconsistently labelled subdimensions, i.e., three for AoT and three for HBE. By systematically integrating these subdimensions into a hierarchical conceptualization of lead userness, a more comprehensive basis for operationalizing and identifying LUs in future research can be provided.

3.1 | AoT

From the systematic literature review, three subdimensions, namely, ideas, information and experience, emerged as central to capturing the future-oriented nature of being 'ahead of trend'. 'Ideas' refers to the distinctive ability of LUs to generate novel solutions that are significantly ahead of current standards and earlier than the majority of the market (Kratzer and Lettl 2009; Schweisfurth 2017; Lilien et al. 2002). This involves not merely having creative capacity but developing solutions intended for personal use that unintentionally anticipate broader future developments. 'Information' encompasses a user's privileged access to cutting-edge product or market knowledge (Hau and Kang 2016; Jeppesen and Laursen 2009; Schuhmacher and Kuester 2012). Crucially, LUs seek out or discover 'future-shaping' information earlier than others (Globocnik and Faullant 2021; Ye and Kankanhalli 2018), such that this subdimension specifically pertains to privileged knowledge about upcoming trends, rather than simply having a broad overview of existing products. 'Experience' reflects direct involvement in modifying or developing products well before similar features become widespread (Urban and von Hippel 1988; Hyysalo et al. 2015). This subdimension emphasizes how hands-on product modifications anticipate future market demands, such that the user's solutions eventually become mainstream or otherwise prove to be 'leading edge'. Taken together, ideas, information and experience form a robust composite of what it means to be 'ahead of trend'. They capture the breadth of future-oriented activities and cognitions, ranging from conceptual ideation to practical, foresighted modifications, and clearly distinguish AoT from mere expertise or innovativeness that is anchored in the present. This conceptualization thereby aligns with von Hippel's (1986) notion that LUs face needs 'months or years' before others and helps ensure that AoT truly reflects being at the forefront of an emerging market direction.

3.2 | HBE

Multiple strands of research have approached HBE from distinct angles, and our literature review revealed three recurring subdimensions, i.e., problems, needs and gains, that collectively reflect why and how LUs anticipate high benefits. 'Problems' refers to the pressing or extreme difficulties LUs often face with existing solutions, spurring them to innovate (Schweisfurth and Raasch 2015; Faullant et al. 2012). Because LUs push product limits or identify shortcomings in ways that others do not yet experience, they stand to gain substantial personal value if a novel solution emerges. This dimension taps whether individuals perceive and struggle with problems in currently available products, highlighting that the root of these high benefits lies in dissatisfaction with prevailing solutions (Hienerth and Lettl 2017). 'Needs' captures forward-looking demands or preferences that are not yet met by the market (Franke et al. 2006; Carbonell et al. 2012), highlighting users whose expectations stem from a perceived gap in future product functionality rather than a concrete shortcoming in current offerings. Users whose expectations stem from a perceived future gap in product performance have reason to believe they can benefit significantly from a solution, even if they are not currently 'suffering' from an immediate shortcoming, placing the dimension of 'needs' firmly in the context of personal benefit expectations. 'Gains' denotes users' awareness of the tangible or anticipated rewards they might derive from an early fix (Morrison et al. 2000, 2004; Kratzer and Lettl 2008, 2009). Here, the focus is on the user's conscious perception and anticipation of a payoff, whether in the form of usability advantages, functional enhancements or any kind of personal reward. It refers to whether individuals foresee that their own lives would be improved or that they would 'somehow be rewarded' by contributing to new product developments (Kratzer and Lettl 2009). By integrating problems, needs and gains, HBE can account for multiple motivational pathways to HBEs, whether driven by immediate product deficiencies, unaddressed future demands or a heightened awareness of personal payoffs. This conceptualization thereby aligns with von Hippel's (1986) notion that LUs occupy a unique position of having needs (or encountering problems) and knowing that meeting these needs would confer substantial advantages.

Overall, the literature review underscores the importance of adopting a more holistic perspective when conceptualizing lead userness. Lead userness encompasses two overarching dimensions—AoT and HBE—each of which can be further refined into three subdimensions, thereby aligning with the diverse yet fragmented evidence reported in prior studies (Tables A1 and A2). We argue that integrating all six subdimensions is theoretically necessary to achieve a truly comprehensive understanding of lead userness, rather than omitting certain facets and potentially overlooking key aspects of what it means to be 'ahead of trend' and 'motivated by high benefits'. Critically, each subdimension captures a distinct manifestation of lead userness. In practice, for instance, one user might excel at generating trend-setting product modifications, whereas another might focus on identifying unmet needs. Failure to assess any of these facets can lead to underestimating who genuinely meets von Hippel's (1986) criteria for LUs (Franke et al. 2006). Hence, our hierarchical conceptualization of lead userness, and its established subdimensions of AoT and HBE, unifies disparate strands of existing research under one coherent framework, reducing measurement gaps. In line with calls for more observable and objective measurement approaches (Hienerth and Lettl 2017; Franke et al. 2006), this higher level of granularity ultimately enhances content validity by recognizing the varied ways in which different individuals display lead-user qualities, whether through generating advanced ideas, leveraging specialized knowledge, anticipating future needs or realizing tangible benefits that flow from early problem-solving.

4 | Measuring Lead Userness

4.1 | Construct Specification and Item Generation

For the development of the new lead userness scale, procedures suggested by Heidenreich and Handrich (2015), Rossiter (2002), Clark and Watson (1995), Baumgartner and Steenkamp (1996) and Moore and Benbasat (1991) were followed. In line with previous LU research, the category of technological (consumer) products was chosen as a research context (e.g., Jahanmir and Cavadas 2018; Ozer 2009; Schreier et al. 2007) as it is highly innovative (Rogers 2003) and generally accessible to a broad range of consumers (Mütterlein et al. 2019). Since LUs are AoTs and expect high benefits from a particular trend or domain (Hienerth and Lettl 2017), we specifically selected smartphones to reflect this domain specificity. Smartphones were chosen not only because of their relevance but also because they are frequently used in studies on innovative consumer behaviour (Heidenreich et al. 2024). The proposed instrument entails measures that tap individual differences in a consumer's lead userness arising from their AoT position, which can only persist temporarily, and the situation-specific state in which they exhibit HBE. Therefore, the scale is developed to measure an intrinsic consumer characteristic that can arise and disappear over time (Hienerth and Lettl 2017), rather than an innate or permanent trait.

For item generation, several steps were followed. At first, the final set of relevant sources identified through the systematic literature review was analysed to identify existing scales suitable for adaptation. Following the approach of Moore and Benbasat (1991), items from the identified instruments were clustered according to the components they were originally designed to capture. Ambiguous items and those deemed insufficiently representative of the construct's dimensions were subsequently removed. The remaining items were refined to ensure their appropriateness for adaptation. This process resulted in an initial pool of items representing the various elements of the construct. To maintain conciseness, the number of items per facet was limited to 10 (Moore and Benbasat 1991). Consequently, the initial scale development process comprised 60 items, 10 for each of the three facets of AoT and HBE (see Table A3).

4.2 | Scale Development

As already indicated, lead userness is conceptualized as a third-order construct with AoT and HBE as second-order dimensions. AoT is composed of three first-order dimensions, namely, (1) *ideas*, (2) *experience* and (3) *information*, and HBE consists of the three first-order dimensions, namely, (1) *problems*, (2) *needs* and (3) *gains*. In order to establish content validity, i.e., a priori evidence that the items sufficiently represent the construct (Rossiter 2002) and factor structure, two initial steps were carried out. In the first stage, the 60 potential items were randomly ordered and presented to a panel of eight expert judges (professors and doctoral students in innovation and marketing research). Similar to Moore and Benbasat (1991), the judges were asked to cluster the items into logical categories (i.e., dimensions) and then label those categories. To prevent 'interpretational confounding', the number of possible dimensions was neither limited nor were construct definitions provided (Moore and Benbasat 1991). As a result of the first stage, eight of the nine experts assigned the 60 items to six distinct dimensions and thus initially supported the proposed factor structure at the first-order level. Furthermore, the expert labelling indicated whether the items corresponded to the scale's intent (Moore and Benbasat 1991). Overall, the labelling task showed satisfactory results across all dimensions, providing additional support for content validity. Examples of the expert labelling for needs were 'uncovered needs', 'unmet needs with available smartphones', 'need for special functions' or 'unfulfilled needs'. Subsequently, a second expert survey was conducted to establish discriminant validity and identify confusing or redundant items (Bassellier and Benbasat 2004). The 60 items (again randomly ordered) were presented to eight expert judges in this stage. Based on previously provided definitions, the experts were asked to assign each item to one of the six facets of AoT and HBE (Heidenreich and Handrich 2015). During this procedure, only items that were categorized correctly by at least seven expert judges were further considered. As a result, seven items of the AoT elements (three for ideas and four for experience) were excluded. Regarding HBE, all 10 items could be retained for each element (i.e., problems, needs and gains).

Afterwards, an online questionnaire containing the AoT and HBE items was administered to a sample of participants recruited through an online panel of a German market research institute, using 7-point rating scales anchored by '*completely disagree*' (1) and '*completely agree*' (7). In total, 199 usable responses could be obtained. The descriptive analysis shows that 23.1% of participants held a high-school diploma, whereas 8.5% had a secondary school certificate and 13.1% had completed vocational training. Additionally, 53.3% reported having a university degree or another form of higher education. The sample consisted of 41.2% female participants, with an average age of 40.9 years, and 57.3% male participants, with an average age of 42.6 years. Furthermore, 44.7% of respondents reported an annual income exceeding €35,000, indicating a balanced income distribution. Afterwards, the corrected item-to-total correlation was determined for each of the remaining 53 items. As a result, all items scored above 0.4 on the hypothesized dimension (Baumgartner and Steenkamp 1996). In order to make the measurement inventory as concise as possible, only the five items with the highest item-to-total correlations were preserved for each facet. Hence, the final 30-item lead userness scale contains five items for each first-order dimension of AoT (ideas, information and experience) and HBE (problems, needs and gains). Table A3 shows which items were considered for the final scale and which were discarded based on the expert rating and item-to-total correlation.

4.3 | Scale Validation

As suggested by Clark and Watson (1995), an EFA and a large-scale CFA were conducted for the validation of the proposed scale. At first, EFA was conducted to examine whether the LU construct indeed consists of six distinct dimensions at the first-order level. Hence, an online questionnaire containing the final lead userness items, again using 7-point scales, ranging from '*completely disagree*' (1) to '*completely agree*' (7), and further demographic variables, was administered to an online panel of respondents, provided by a German market research institute. After excluding participants who failed the integrated attention check, 148 usable responses could be obtained for EFA. The descriptive analysis displays that 26.4% of the participants had a high-school diploma, 5.4% had a secondary school certificate and 13.5% reported a completed vocational training. Another 35.7% had a university or some other graduate degree. Furthermore, 42.6% of the respondents are female, with an average age of 42.1, whereas 55.4% are male, with an average age of 42.8. Moreover, 44.6% of the respondents reported having an annual income of more than €35,000, indicating a normal income distribution. Following the Kaiser–Meyer–Olkin criterion (0.929), it can be inferred that the data are well-suited for factor analysis. The results confirmed the proposed factor structure by showing six dimensions for the 30 items, which can explain 86.13% of the variance after rotation. All 30 items were retained for further analysis, as the factor loadings ranged from 0.721 to 0.874, far above the suggested threshold value (see Table A4; Homburg and Giering 2001).

Although the EFA has produced satisfactory results, there may still be a concern that these results are context or sample specific (Heidenreich and Handrich 2015). In order to further validate these findings and thus rule out this possibility, a CFA was performed using a fresh sample (Dabholkar 1994). The respondents for the CFA were again recruited via an online panel of a German market research institute. Furthermore, the same questionnaire was utilized as for the previous factor analysis. After excluding participants who had not passed the attention check, 149 usable responses could be obtained. Regarding the descriptive analysis, 24.2% of the respondents had a high-school diploma, 3.4% had a secondary school certificate and 9.4% had completed vocational training. Moreover, 59.7% had a university or some other graduate degree. Most participants are male (55.0%), with an average age of 43.5, whereas 43.0% of the participants are female, with an average age of 40.7. Concerning the income category, 45.6% of the participants reported an annual income above €35,000.

The CFA was performed by using the previously developed lead userness scale and the Basic CB-SEM algorithm of SmartPLS 4.0 (Hair et al. 2022). The goal was to assess the psychometric properties of our six first-order constructs (ideas, information, experience, problems, needs and gains), each representing a subdimension of the two higher order factors AoT and HBE (see Table A5). Because these items correlated highly, suggesting they capture the same underlying dimension, each construct was specified reflectively (Gefen et al. 2000). All standardized loadings exceeded 0.70 (see Table A6), indicating strong item reliability (Homburg and Giering 2001). Composite reliabilities ranged from 0.925 to 0.974, whereas average variance extracted (AVE) values ranged from 0.709 to 0.882 (see Table A7), collectively supporting convergent validity (Hair et al. 2022). Discriminant validity was assessed using both the Heterotrait–Monotrait (HTMT) ratio and the Fornell–Larcker criterion. In the HTMT matrix, all interconstruct ratios fell below 0.85, satisfying the threshold for adequate discriminant validity (Henseler et al. 2015). Likewise, in the Fornell–Larcker criterion, each construct's square root of the AVE exceeded the correlations with other constructs, further confirming discriminant validity (Fornell and Larcker 1981). The second- and third-order measurement models performed exceptionally well, with all second- and third-order weights being significant (t-value > 1.98) and all VIFs remaining well below the critical threshold of 10 (Henseler et al. 2009; see Table A8). Regarding model fit, an RMSEA of 0.073 indicated no severe model misspecification, whereas an SRMR of 0.032 and a CFI of 0.946 both pointed to an adequate global fit (Hair et al. 2022; Hu and Bentler 1999). Overall, these findings offer robust support for the six first-order constructs as reliable, distinct dimensions of lead userness. High factor loadings confirm that items converge well on their respective subdimensions, and the evidence for discriminant validity indicates that each dimension captures unique variance. The favourable global fit indices further validate the hypothesized measurement model, reinforcing the idea that AoT (formed by ideas, information and experience) and HBE (formed by problems, needs and gains) serve as coherent higher order constructs constituting lead userness.

5 | Nomological Validity

In order to test the nomological validity of the construct, the upcoming section identifies and describes essential constructs that are assumed to show significant relationships with lead userness, either as antecedent or as outcome. Because lead userness differs from these constructs, it is expected that there is a satisfactory degree of discriminant validity (Bruner and Kumar 2007), which will be examined after clarifying the theoretical rationale for the potential relationships of these constructs with lead userness.

5.1 | Antecedents of Lead Userness

Innate innovativeness is defined as a 'predisposition to buy new and different products and brands rather than remain with previous choices and consumption patterns' (Steenkamp et al. 1999, 56). As a predisposition, it covers the aspect of individuals' attraction to novelty (Roehrich 2004), and their cognitive style of interpreting and processing information in new ways, generating new solutions that deviate from prevailing conventions (Im et al. 2007). Because LUs were found to create highly novel ideas (Lilien et al. 2002) and often produce especially radical product innovations (Lettl et al. 2008), innate innovativeness should act as antecedent and correlate positively with the lead userness construct.

Divergent thinking refers to the ability to explore multiple approaches to problem-solving and break away from established thought and problem-solving patterns (Wigert et al. 2022). It is characterized by cognitive processes such as fluency, originality, flexibility and elaboration, which collectively enhance creative potential (Runco and Acar 2012). As such, divergent thinking represents a fundamental cognitive ability essential for identifying and developing innovative solutions. As LUs tend to be highly innovative individuals (Hienerth and Lettl 2017; Matthing et al. 2006), divergent thinking enhances this capability by fostering creative and unconventional problem-solving, which is a crucial driver of originality and breakthrough innovations (Runco and Acar 2012). Accordingly, previous research demonstrated that a stronger predisposition to divergent thinking is associated with a higher leading-edge status (Faullant et al. 2012). Against this background, it is assumed that divergent thinking is positively correlated with lead userness.

Product-related knowledge refers to the understanding and expertise users gain about a product's design, materials and technology (Lüthje 2004). Experienced consumers develop deeper insights into how products work, their technical features and functional connections (Mitchell and Dacin 1996). This knowledge helps bridge the gap between customer needs and technical specifications, driving innovation and product development (Lüthje et al. 2003). Thus, within LU theory, product-related knowledge is seen as a fundamental enabler of lead userness (Faullant et al. 2012; Schreier and Prügl 2008; Wellner and Herstatt 2014). To innovate beyond existing market solutions, users must first master conventional products. As their expertise expands, they are able to anticipate emerging needs, identify market gaps and drive product development AoTs (Mahr and Lievens 2012; Spann et al. 2009). Therefore, product-related knowledge as antecedent should be positively correlated with lead userness.

Risk aversion describes the tendency to prefer low-risk alternatives and avoid uncertainty (Taylor 1974). In innovation contexts, risk-averse individuals are more likely to adhere to established solutions rather than challenge existing products or usage patterns (Talke and Heidenreich 2014). In contrast, LUs are often the first to adopt new products (Morrison et al. 2004; Schreier et al. 2007). Their willingness to innovate, and thus cope with uncertainty, is driven by their experience of unmet needs, which could lead to the expected benefits of innovation outweighing the perceived risks (Hienerth and Lettl 2017; Schweisfurth and Herstatt 2015). Supporting this, research on the antecedents of LU behaviour shows that individuals with a high internal locus of control—who believe they can actively shape their environment and tend to be more risk tolerant and open to uncertainty—are more likely to exhibit LU characteristics (Schreier and Prügl 2008). Consequently, risk aversion is expected to be negatively correlated with lead userness.

5.2 | Outcomes of Lead Userness

Social innovativeness refers to the 'extent to which a consumer is motivated to be the first to adopt new technology-based goods and services' (Bruner and Kumar 2007, 331). Accordingly, individuals high on this behavioural tendency tend to buy innovative products more often than others (Heidenreich and Kraemer 2015). Because LUs embrace new products earlier than regular users (Schreier et al. 2007; Schreier and Prügl 2008; Urban and von Hippel 1988) and are often considered to be a source of information regarding any kind of innovation issues (Morrison et al. 2004), social innovativeness should be an outcome of lead userness and thus correlate positively with the respective scale.

Opinion leadership refers to an individual's ability to influence others' purchasing and consumption decisions by sharing expertise, serving as role models and shaping the diffusion of innovations within a specific product domain (Van Eck et al. 2011). LUs, who stay ahead of market trends (von Hippel 1986) and possess deep knowledge (Schreier and Prügl 2008), are particularly valuable sources of information. Research confirms this connection, showing that individuals with a leading-edge status are more likely to influence peers by endorsing or discouraging innovations (Morrison et al. 2000; Schreier et al. 2007; Schweisfurth and Herstatt 2015). Given LUs' involvement in communities (Han and Yang 2019), their central role within social networks (Kratzer et al. 2016) and their ability to shape market perceptions (Schreier et al. 2007), lead userness should lead to higher levels of opinion leadership and thus correlate positively with this construct.

Innovation Experience and Intention Lead users are inherently inclined to innovate within their respective domains. This characteristic has been examined in the literature from different perspectives. One approach considers the *intention to innovate* as a direct outcome of LU traits, reflecting an individual's anticipated willingness to engage in the development of new applications, create novel solutions or enhance existing products (Kankanhalli et al. 2015). Another perspective, explored by Franke et al. (2006), investigates the *innovation experience* among LUs. This concept captures actual past behaviour, assessing whether an individual has previously proposed improvements, developed new functionalities or actively sought solutions to existing challenges within a relevant product domain. Thus, although innovation intention represents cognitive and motivational readiness, innovation experience reflects the tangible realization of past innovative activities. Crucially, the AoT-Experience subdimension in our LU scale only records modifications carried out before comparable solutions became available, thereby tracing the ahead-of-trend state (Franke et al. 2014; Hoffman et al. 2010), whereas innovation experience and intention capture any innovation activity irrespective of timing. Both constructs can be seen as natural outcomes of lead userness, as LUs, driven by their advanced needs and personal experience, are intrinsically motivated to seek and develop new solutions (Lüthje et al. 2003). Confirming this, a growing body of research identifies LUs as key drivers of innovation—including both *innovation intention* (Kankanhalli et al. 2015; Olson and Bakke 2001) and actual *innovation experience* (Franke et al. 2006; Schweisfurth 2017; Ye and Kankanhalli 2018), indicating that the developed LU scale should positively correlate with both constructs.

5.3 | Data and Measurements

For the process of data collection, again, an online survey was administered to a consumer panel via a German market research institute. The same research context, i.e., smartphones, was applied as in the previous studies. In total, 198 respondents produced usable outcomes. The descriptive analysis displayed that most respondents reported holding a university or some other graduate degree (51.5%), whereas 25.8% had a high school diploma, 5.1% a secondary school certificate and 15.2% reported a completed vocational training. In addition, 38.4% of the participants are female, with an average age of 41.7, and 60.1% are male, with an average age of 42.7. Regarding the income category, 39.9% of the participants declared to have an annual income above €35,000.

To measure lead userness, the previously developed measurement inventory was used. Based on the theoretical considerations and empirical results above, lead userness was operationalized as a third-order construct of Type II (Sarstedt et al. 2019). More specifically, the first-order constructs (ideas, information, experience, problems, needs and gains) were modelled reflectively because high interitem correlations in the preceding studies, along with the strong convergent and discriminant validity revealed by the CFA, indicated that each set of items captures a common underlying dimension (Gefen et al. 2000). By contrast, the second- and third-order constructs were modelled formatively, reflecting the idea that these higher level factors are 'formed by' the first-order dimensions (Bassellier and Benbasat 2004). In other words, AoT (formed by ideas, information and experience) and HBE (formed by problems, needs and gains) emerged as distinct and discriminant clusters of subdimensions in the CFA, each contributing independently to the meaning of its respective higher order factor. Because changes in any single subdimension (e.g., information or needs) can alter the conceptual domain of AoT and HBE, respectively, without necessarily implying changes in the other subdimensions, treating them as formative subconstructs is theoretically more appropriate (MacKenzie et al. 2011). This choice of operationalization is supported by the satisfactory fit indices and discriminant validity at the first-order level, which confirm that the six reflective first-order constructs capture unique facets of lead userness. Subsequently, combining those facets under AoT and HBE in a formative manner acknowledges that these subdimensions can vary independently while still 'forming' the broader constructs. Extending this logic to the third-order factor (lead userness) allows us to integrate AoT and HBE as the fundamental building blocks, as suggested by von Hippel (1986). Hence, each of the higher order constructs, at both the second and third levels, represents a defining set of formative suborder constructs whose sum uniquely shapes lead userness (Sarstedt et al. 2019). The remaining constructs pertaining to antecedents and outcomes of lead userness were measured as reflective, unidimensional constructs using established measurement inventories. More specifically, divergent thinking was measured using three items from Faullant et al. (2012), product knowledge was measured using three items from Wellner and Herstatt (2014), innate innovativeness was assessed by five items from Hurt et al. (1977) and risk aversion was operationalized using three items from Mandrik and Bao (2005). With regard to the outcome variables, social innovativeness was measured with Bruner and Kumar's (2007) measurement inventory, which consists of five items. Opinion leadership was assessed with three items from Schreier et al. (2007). Finally, innovation intention and experience were measured using three items from Kankanhalli et al. (2015) and Franke et al. (2006), respectively. All constructs were assessed on 7-point rating scales, ranging from '*completely disagree*' (1) to '*completely agree*' (7). Age, gender, education and income were included as control variables.

5.4 | Analysis and Results

SmartPLS 4.0 (Hair et al. 2022) was used to estimate the parameters of both the outer and inner models, applying PLS path modelling with a path weighting scheme for the inner approximation (Chin 1998; Tenenhaus et al. 2005). For the standard errors of the estimates, nonparametric bootstrapping (Chin 1998; Tenenhaus et al. 2005) with 5000 replications and individual-level change preprocessing was conducted (Heidenreich and Handrich 2015; Wetzels et al. 2009). In order to implement lead userness, the hierarchical component model approach was used (Lohmöller 1989; Tenenhaus et al. 2005). As an initial step, a null model of lead userness was specified and estimated using the repeated indicator approach, without incorporating structural relationships (Wetzels et al. 2009). All indicator loadings, composite reliabilities, and AVEs exceeded common cut-off values (see Table A6; Chin 2009). Moreover, discriminant validity was supported, as the AVE of each first-order variable was higher than the common variances of the variable with any other variable (see Table A9; Fornell and Larcker 1981). Regarding the model fit of the formative second- and third-order constructs, the second-order outer weights showed that information, experience and ideas (ordered from highest to lowest) contribute significantly to AoT and gains, needs and problems contribute significantly to HBE, respectively (significance threshold t-value > 1.98). The third-order weights likewise indicated a significant contribution of AoT (0.53) and HBE (0.47) to the lead userness construct (see Figure 1). The VIFs of the second- and third-order constructs were far below the critical value of 10 (Henseler et al. 2009). Hence, it can be assumed that no multicollinearity exists. Conclusively, these results are in line with the findings derived from the CFA, supporting the good psychometric properties of the lead userness scale.

After having evaluated the hierarchical measurement model of lead userness in a null model, a structural model was set up operationalizing lead userness by employing the two-stage approach (Hair et al. 2022) and including all antecedents as independent constructs of lead userness and all outcomes as dependent constructs. The employed scales for divergent thinking, product knowledge, innate innovativeness and risk aversion, as well as for social innovativeness, opinion leadership, innovation intent and likelihood, also showed satisfactory psychometric properties. All indicator loadings, CRs and AVEs were above common thresholds (see Table A10). Because the AVE of each variable was higher than the variable's squared correlation with any other variable in the model, lead userness showed a satisfactory level

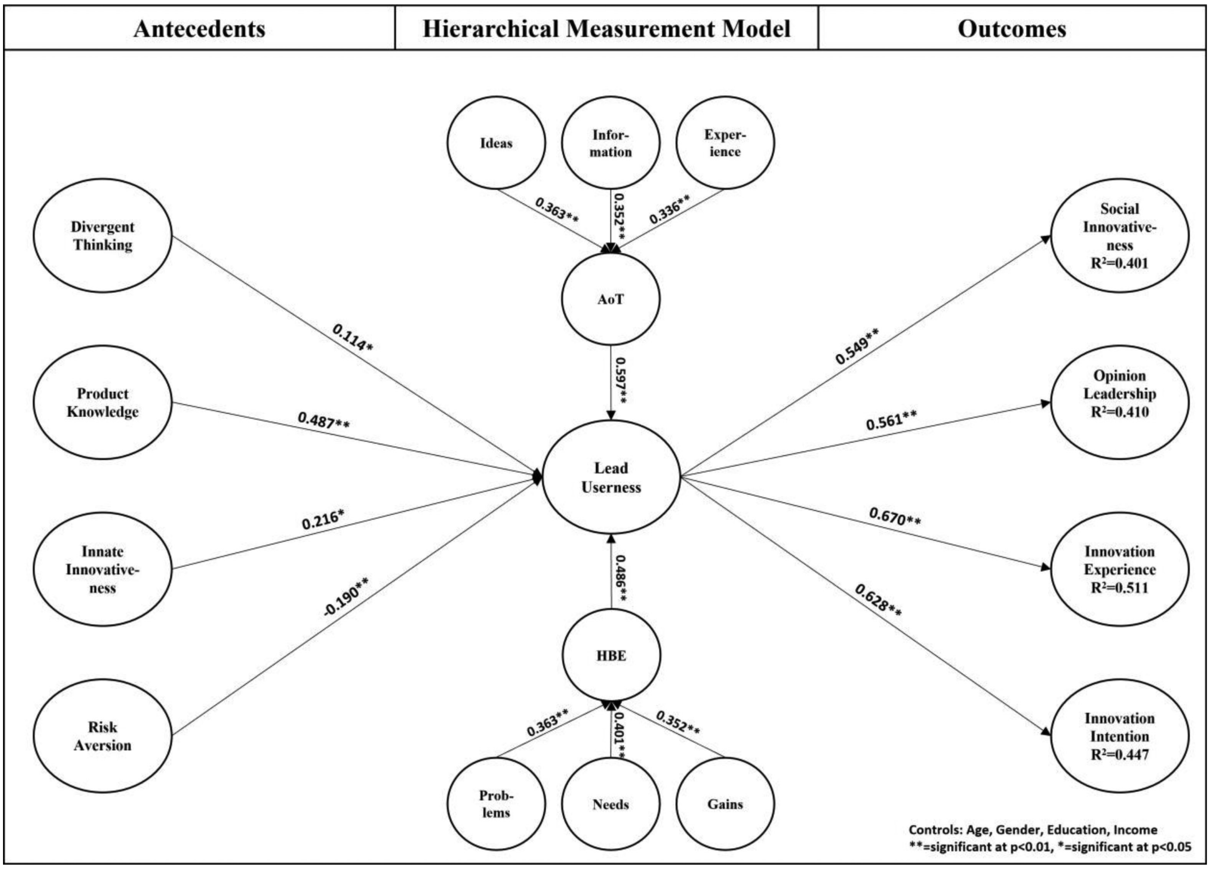

FIGURE 1 | Empirical test on nomological validity.

of discriminant validity with all constructs in the nomological network (Fornell and Larcker 1981). Finally, the results of the structural analyses confirmed the hypothesized relationships (see Figure 1). More specifically, with respect to the antecedents, lead userness had a positive relationship with divergent thinking ($\beta = 0.114$, $p < 0.05$), product knowledge ($\beta = 0.487$, $p < 0.01$) and innate innovativeness ($\beta = 0.216$, $p < 0.05$), while being negatively related to risk aversion ($\beta = -0.190$, $p < 0.01$). With respect to the outcomes, lead userness exhibited a positive effect on social innovativeness ($\beta = 0.549$, $p < 0.01$), opinion leadership ($\beta = 0.561$, $p < 0.01$), innovation experience ($\beta = 0.670$, $p < 0.01$) and innovation intention ($\beta = 0.628$, $p < 0.01$). Overall, these findings confirm that the lead userness construct exhibits the expected relationships with established constructs from the innovation adoption literature, thereby demonstrating the high nomological validity of the proposed measurement instrument.

5.5 | Additional Analysis: Short Scale

Although the full 30-item lead userness scale exhibits robust psychometric properties, practitioners and researchers often seek shorter measurement tools for large-scale surveys or where respondent time is at a premium. Consequently, this section proposes a short scale for lead userness that relies on a second-order construct specification (Jarvis et al. 2003) rather than the original third-order model. Specifically, each of the six subdimensions (ideas, information and experience for AoT; problems, needs and gains for HBE) is measured by only one formative indicator chosen from the original five reflective items (see Table A3). The selection process hinges on the highest item-to-total correlation per subdimension, ensuring that the single strongest item for each facet is retained. This resulted in six indicators (one per subdimension), each now treated as a formative indicator directly composing AoT and HBE as second-order constructs. Forming a Type IV hierarchical component model (Jarvis et al. 2003) means that AoT and HBE themselves become first-order latent variables (each measured by three single indicators), which in turn form the second-order factor (lead userness).

The goal of this section is to test whether this parsimonious operationalization can still capture most of the explanatory power of the full scale regarding (a) the overall lead userness construct and (b) key outcome variables (i.e., social innovativeness, opinion leadership and innovation experience and intention). As a first step, a null model was set up in SmartPLS 4.0 to assess the viability of lead userness as a second-order formative construct, capturing AoT and HBE as first-order latent factors using the repeated indicator approach (Hair et al. 2022). Results show that the outer weights for each single formative indicator were significant and that variance inflation factors remained well below the common threshold of 10, indicating no serious collinearity problems (see Table A11). This initial test suggests that reducing each subdimension to one formative item still yields a coherent second-order measurement structure. The next step was to determine whether the short scale predicts key outcome variables, namely, innovation experience, innovation intention, opinion leadership and social innovativeness, at a level comparable with the full scale. Results indicate that the short scale exhibited slightly lower R^2-values (ranging from 6% to 11% less variance explained), but in all cases, the path coefficients remained highly significant ($p < 0.01$). In particular, innovation intention was predicted by the short scale with $\beta = 0.55$ and $R^2 = 0.40$ compared with $\beta = 0.67$ and $R^2 = 0.51$ for the full scale. For innovation experience, the short-scale relationship reached $\beta = 0.52$ and $R^2 = 0.35$ compared with $\beta = 0.63$ and $R^2 = 0.45$ for the full scale. Opinion leadership was explained with $\beta = 0.49$ and $R^2 = 0.35$ under the short scale, as opposed to $\beta = 0.56$ and $R^2 = 0.41$ under the full scale. Finally, social innovativeness was predicted at $\beta = 0.44$ and $R^2 = 0.32$ by the short scale versus $\beta = 0.55$ and $R^2 = 0.40$ by the full scale. Although the short scale loses a small measure of explanatory nuance, it still accounts for a substantial share of variance in these innovation-related behaviours, suggesting that it can serve as a practical alternative when item minimization is paramount. That said, investigators who aim to maximize explanatory power or require full diagnostic detail on each subdimension may still benefit from the original, more comprehensive instrument. The short scale's single formative indicators per subdimension also limit reliability checks and prevent deeper analyses of the internal structure within AoT and HBE.

6 | Explanatory and Predictive Power

Following a procedure similar to Heidenreich and Handrich (2015), we conducted an additional study to compare the explanatory and predictive capabilities of our newly developed hierarchical lead userness (HLU) scale with seven established lead userness measurement inventories. Specifically, we benchmarked our HLU scale against measurement inventories employed by Faullant et al. (2012), Franke et al. (2014), Jahanmir and Cavadas (2018), Hamdi-Kidar et al. (2019), Kratzer and Lettl (2008), Schweisfurth (2017) and Ye and Kankanhalli (2018).

For this purpose, we recruited a new sample of 196 participants from a consumer panel, using the same online questionnaire previously employed in the nomological validity study. However, this questionnaire was extended to include items capturing the seven established measurement inventories. In this sample, educational backgrounds varied: 25.0% of participants held a high school diploma, 6.1% had a secondary school certificate, 18.4% reported completion of vocational training, and 48.5% had attained a university degree or higher. The gender distribution included 40.8% female and 56.6% male participants, with average ages of 43.33 and 43.27 years, respectively. Additionally, 39.2% of participants reported an annual income exceeding €35,000.

Following the methodological approach of Heidenreich and Handrich (2015), we utilized SmartPLS 4.0 in a two-step procedure to evaluate each measurement inventory's explanatory and predictive capabilities regarding innovation experience (Franke et al. 2006), which captures past user-driven innovation activities, and innovation intention (Kankanhalli et al. 2015), representing the likelihood of future user-driven innovation activities, as dependent variables. Step 1 individually examined the impact of each lead userness scale on innovation experience and innovation intention, controlling for age, gender, education and income. This step allowed us to determine the explanatory power (R^2), effect sizes (f^2) and path coefficients of each scale concerning past and future user-driven innovation activities. Step 2 involved creating separate models pairing our HLU scale with each established measurement inventory, again including the same control variables, enabling direct comparative analyses of their explanatory and predictive strengths.

Across all individual comparisons in Step 1 (see Table 2), the HLU scale consistently outperformed established scales, exhibiting higher path coefficients and R^2-values for both innovation experience and innovation intention. Additionally, the HLU scale demonstrated generally larger effect sizes (f^2), highlighting its superior unique contribution to explaining and predicting past and future user-driven innovation activities. In combined models from Step 2 (see Table 2), where the HLU scale was tested alongside each competing measure, the HLU scale continued to demonstrate stronger path coefficients and effect sizes, reinforcing its enhanced explanatory and predictive capability. Overall, these findings indicate that capturing multiple subfacets of lead userness (i.e., AoT and HBE, each with three distinct elements) offers a more robust assessment of who engaged in past user-driven innovation activities and who is likely to innovate in the future, compared with existing single- or two-dimensional scales.

7 | Application and Market Test

7.1 | Procedure

Since the scale aims to capture individual differences in lead userness, the next section assesses whether the instrument can effectively identify individuals who develop commercially more successful product concepts than regular users, as suggested by prior research (Franke et al. 2006; Lilien et al. 2002; Morrison et al. 2000). Specifically, it is hypothesized that product concepts created by LUs exhibit higher market potential and thus receive more favourable evaluations from independent consumers. The methodological approach follows established procedures by Hoffman et al. (2010) and Hamdi-Kidar et al. (2019). More specifically, new product concepts are first generated by both LUs and regular consumers during an idea contest. Subsequently, these concepts are evaluated by a panel of independent consumers. The present study again focused on the development of mobile phone concepts but also incorporated two additional product categories, namely, e-bikes and refrigerators, to reduce potential category-specific bias and enhance external validity. Moreover, examining three distinct product categories tests whether the measurement inventory, originally developed for the smartphone context, can be effectively applied elsewhere, thus reinforcing the generalizability of the instrument for future research.

7.2 | Concept Development

For concept development, three separate idea competitions—one each for a smartphone, an e-bike and a refrigerator—were conducted on the crowdworking platform Clickworker. Participants were compensated for creating innovative product concepts and were informed about the opportunity to win one of three €50 Amazon gift vouchers for the top submissions,

TABLE 2 | Explanatory and predictive power.

	Measurement inventory		Innovation experience				Innovation intention			
			β	t	R^2	f^2	β	t	R^2	f^2
Step 1	HLU		0.834	24.763	0.683	1.801	0.754	18.052	0.659	1.339
	LU_SC		0.775	18.879	0.638	1.452	0.623	13.203	0.537	0.723
	LU_YE		0.736	14.434	0.584	1.132	0.579	10.514	0.490	0.565
	LU_FR		0.776	16.860	0.627	1.378	0.613	12.341	0.520	0.662
	LU_JA		0.541	8.674	0.379	0.428	0.618	11.315	0.548	0.767
	LU_KR		0.621	12.824	0.446	0.602	0.649	13.850	0.569	0.851
	LU_FA		0.744	16.709	0.595	1.192	0.589	11.644	0.502	0.601
	LU_HA		0.774	19.271	0.657	1.587	0.587	10.513	0.515	0.646
Step 2	LU_SC & HLU	HLU	0.542	5.909	0.718	0.286	0.647	7.424	0.645	0.318
		LU_SC	0.347	3.811		0.125	0.105	1.256		0.009
	LU_YE & HLU	HLU	0.623	7.792	0.707	0.421	0.721	10.003	0.665	0.533
		LU_YE	0.262	3.095		0.079	0.049	0.665		0.003
	LU_FR & HLU	HLU	0.484	6.075	0.710	0.289	0.666	9.197	0.663	0.429
		LU_FR	0.426	5.105		0.238	0.111	1.510		0.013
	LU_JA & HLU	HLU	0.752	13.988	0.660	0.829	0.567	8.874	0.701	0.530
		LU_JA	0.102	1.567		0.021	0.280	4.436		0.146
	LU_KR & HLU	HLU	0.728	12.203	0.671	0.688	0.545	8.146	0.706	0.463
		LU_KR	0.137	2.263		0.026	0.306	4.787		0.158
	LU_FA & HLU	HLU	0.556	6.160	0.686	0.293	0.759	9.984	0.660	0.484
		LU_FA	0.317	3.705		0.103	−0.004	0.056		0.000
	LU_HA & HLU	HLU	0.462	4.505	0.728	0.266	0.669	7.877	0.666	0.455
		LU_HA	0.440	5.085		0.261	0.108	1.288		0.013

Abbreviations: HLU: Proposed Hierarchical Lead User Measurement Inventory; LU_FA: Faullant et al. (2012); LU_FR: Franke et al. (2014); LU_HA: Hamdi-Kidar et al. (2019); LU_JA: Jahanmir and Cavadas (2018); LU_KR: Kratzer and Lettl (2008); LU_SC: Schweisfurth (2017); LU_YE: Ye and Kankanhalli (2018).

in addition to their standard Clickworker compensation (Boss et al. 2017). Data were collected through an online questionnaire integrated into the idea contest, which included the new lead userness scale as well as additional control and demographic variables. To ensure applicability across product categories, we adapted the scale items by replacing 'smartphone' with 'e-bike' and 'refrigerator' in the respective contests. The final samples comprised 99 participants for the smartphone contest, 100 for the e-bike contest and 100 for the refrigerator contest. Further details on participant sociodemographics for each contest can be found in Table A12. Within each idea contest, participants were instructed to develop a new product concept that would be highly successful in the market, specifying four expressive and innovative features to illustrate the concept's novelty. For each participant, we calculated a latent variable score for lead userness. The average lead userness scores were 3.42 for the smartphone contest, 3.15 for the e-bike contest and 2.99 for the refrigerator contest. For the subsequent market test, we selected 10 concepts per contest from participants with the highest lead userness scores (average scores: smartphone = 5.34, e-bike = 5.74, refrigerator = 5.21), thereby representing 'lead user' concepts. In the smartphone contest, for instance, one identified LU proposed a holographic display projecting interactive 3D content into space, enabling touch-free control via gesture recognition. Another suggested a smartphone that can convert body heat into energy to autonomously recharge its battery. To serve as a comparison group, we also selected 10 concepts per contest from participants with the lowest lead userness scores (average scores: smartphone = 1.29, e-bike = 1.09, refrigerator = 1.07) representing the 'regular consumer' concepts.

7.3 | Market Test

In order to assess whether there are differences between the concepts of LUs and regular consumers regarding their potential for commercial success, a representative online consumer panel was recruited via a German market research institute. Ultimately, a total of 300 usable responses could be obtained. Concerning the descriptive analysis, 40.0% of the respondents are female, with an average age of 43.4, and 59.0% are male, with an average age of 41.8. In addition, 4.3% of the respondents had a secondary school certificate, 23.7% reported having a high school diploma and 18.3% a completed vocational training. Another 50.7% had a university or some other graduate degree. Regarding the income category, 47.7% of the participants reported an annual income above €35,000. At the beginning of the online questionnaire, each respondent was randomly assigned one of the 20 concepts from each product category, resulting in the evaluation of one smartphone, one e-bike and one refrigerator concept. For the statistical analysis, two groups were formed, one for the respondents who evaluated one of the LU concepts ($N_{\text{Smartphone}} = 151$; $N_{\text{E-Bike}} = 141$; $N_{\text{Refrigerator}} = 156$) and one for those who evaluated one of the regular consumer concepts ($N_{\text{Smartphone}} = 149$; $N_{\text{E-Bike}} = 159$; $N_{\text{Refrigerator}} = 144$). Although the dichotomous variable 'new product concept' (0 = regular consumer concept and 1 = lead user concept) was implemented as the independent variable, the online questionnaire further assessed the consumers' willingness to pay (WTP) in order to explore the commercial success potential of the concepts by means of a highly market-oriented variable. Consequently, WTP was set up as the dependent variable and measured by using the contingent valuation method, where respondents are directly asked how much they would be willing to pay for a specific product (Franke and Piller 2004; Mitchell and Carson 1989).

To assess whether product concepts developed by LUs were perceived as superior in terms of WTP, multiple ANOVAs were conducted, controlling for age, gender, education and income. For the smartphone category, a significant main effect of concept type on WTP was observed ($F(5,\ 294) = 9.99$, $p < 0.01$). Specifically, participants indicated a higher WTP for LU concepts ($M = €620.60$) compared with concepts developed by regular consumers ($M = €508.13$). A similar pattern emerged for the e-bike category, where the effect of concept type on WTP was also significant ($F(5,\ 294) = 8.72$, $p < 0.01$). Participants reported a higher WTP for LU concepts ($M = €1851.99$) than for concepts created by regular consumers ($M = €1406.40$). Finally, for the refrigerator category, a significant main effect of concept type on WTP was found as well ($F(5,\ 294) = 6.61$, $p < 0.05$). Here, too, participants indicated a higher WTP for LU concepts ($M = €927.79$) compared with concepts from regular consumers ($M = €749.99$). In summary, these results not only corroborate previous findings on the commercial appeal and financial potential of concepts developed by LUs but also underscore the effectiveness of the proposed scale in reliably identifying these individuals. Furthermore, its successful application beyond the smartphone domain, covering e-bikes and refrigerators, underscores the instrument's broader transferability and bolsters its generalizability for future research contexts.

8 | General Discussion

This research aimed to develop a comprehensive measurement inventory to capture individual differences in lead userness using a hierarchical approach. The process of scale development, validation and testing yielded encouraging results regarding reliability, convergent and discriminant validity and nomological validity across multiple studies. Aligned with previous research (e.g., Franke et al. 2006; Hau and Kang 2016), the findings confirm that lead userness is indeed a hierarchical construct composed of AoT (ideas, information and experience) and HBE (problems, needs and gains). Applying this hierarchical structure ensures that neither of the core dimensions is omitted, thereby preventing substantial information loss (Franke et al. 2006) and enabling a more holistic representation of how LUs detect emerging trends and foresee substantial personal benefits from innovative solutions. Importantly, and in line with Hienerth and Lettl (2017), lead userness is conceptualized not as a stable trait but as a situational state that arises in specific problem contexts. Accordingly, the scale is designed to capture a current, context-specific user state rather than a fixed identity. Both AoT and HBE are regarded as temporary user characteristics, which fluctuate with changing individual needs and market conditions.

Furthermore, the results from the nomological validity test demonstrated that the new scale exhibited theoretically consistent relationships with key antecedents and outcomes. More precisely, lead userness correlated positively with divergent thinking, product knowledge, and innate innovativeness, and negatively with risk aversion, showing that a user's capacity for generating unusual solutions, their expertise and their willingness to depart from established norms are central drivers of lead-user behaviour (Hienerth and Lettl 2017; Schweisfurth and Herstatt 2015). In terms of outcomes, lead userness predicted social innovativeness, opinion leadership, as well as innovation experience and intention, reinforcing the notion that LUs often act as key influencers and active innovators in their respective domains (Franke et al. 2006; Schreier et al. 2007).

In addition, a follow-up study comparing our HLU scale with seven established measurement inventories (Faullant et al. 2012; Franke et al. 2014; Hamdi-Kidar et al. 2019; Jahanmir and Cavadas 2018; Kratzer and Lettl 2008; Schweisfurth 2017; Ye and Kankanhalli 2018) confirmed its superior explanatory and predictive power for innovation experience (past innovative behaviour) and innovation intention (future innovative behaviour). When tested individually, our scale showed higher path coefficients and effect sizes (f^2) than each of the competing measures. Even in direct comparisons where both scales were included in the same model, the hierarchical approach outperformed existing single- or two-dimensional constructs. These findings reinforce the value of capturing multiple subfacets of lead userness, namely, AoT and HBE, each with three distinct elements, to provide a more comprehensive understanding of who has innovated in the past and who is likely to innovate going forward.

Finally, the market test results showed that product concepts developed by LUs elicited higher WTP compared with those created by regular consumers, across three product categories (smartphones, e-bikes and refrigerators). These findings extend prior evidence of LUs' capacity to generate commercially appealing innovations (Lilien et al. 2002; Morrison et al. 2000), not necessarily because LUs predict future preferences, but because their self-motivated solutions address needs that later resonate with a broader audience. Moreover, the successful application of the measurement inventory beyond the smartphone domain underscores its robustness and broader transferability, highlighting the scale's potential for future research and practical innovation management in various consumer product contexts.

8.1 | Theoretical Implications

The findings of this study advance research on lead userness in several ways. First, by returning to von Hippel's (1986) original conceptualization of LUs as those who sense needs early (AoT) and benefit significantly from addressing them (HBE), this work offers a more unified understanding of the construct. Recent years have witnessed fragmentation in the literature, with some studies focusing exclusively on AoT (e.g., Hamdi-Kidar et al. 2019), others emphasizing HBE (e.g., Schweisfurth and Herstatt 2015), and still others using multidimensional measures with AoT and HBE as independent and distinct dimensions of lead userness as a second-order construct (e.g., Franke et al. 2006). Additionally, various subfacets of AoT and HBE have been empirically identified; however, they remain dispersed across different studies, with no integration into a cohesive framework. By proposing a hierarchical model that subdivides AoT (ideas, information and experience) and HBE (problems, needs and gains) into six first-order subdimensions, this study resolves inconsistencies in prior research and consolidates these subfacets into a coherent framework (Franke et al. 2006; Hienerth and Lettl 2017).

Second, in line with Gemser and Perks (2015) and Hoyer et al. (2010), scholars have emphasized the importance of identifying and characterizing the 'right' users for co-creation in new product development. Although LUs have been highlighted as a particularly promising segment (Hienerth and Lettl 2017; Lüthje and Herstatt 2004), the divergent conceptualizations and measures have hindered a shared understanding of how to systematically locate and engage these individuals. By clarifying the root causes of AoT and HBE, showing that each dimension comprises multiple, more observable elements, this study bridges the gap between the theoretical definition of lead userness and practical consumer characteristics driving successful new product development. Furthermore, this approach holds the potential not only to facilitate the identification of LUs (Franke et al. 2006) but also to determine individual differences in consumers' lead userness more accurately. In past research, many scales relied on self-assessment items asking whether respondents consider themselves at the leading edge of a trend (e.g., Hoffman et al. 2010; Morrison et al. 2000; Wellner and Herstatt 2014), yet individuals have been found to have limited ability to self-evaluate their 'leading-edge' status (Hienerth and Lettl 2017). By contrast, the third-order hierarchical conceptualization, with subdimensions such as ideas, information and experience, enables a more objective measure of AoT that may be better suited to self-assessment contexts. Consequently, the third-order hierarchical approach not only enriches our theoretical grasp on how an individual becomes a LU but also provides a straightforward scale for research in domain-specific settings.

Third, this work expands the theoretical scope of user-driven innovation by empirically testing the nomological network around lead userness. Specifically, we show that user characteristics like divergent thinking, product knowledge and innate innovativeness each contribute to lead userness, whereas risk aversion impedes it. This finding supports the argument that cognitive, experiential and motivational variables play distinct roles in fostering or hindering 'leading-edge' tendencies (Faullant et al. 2012; Schreier and Prügl 2008; Wellner and Herstatt 2014). Moreover, the positive associations with social innovativeness, opinion leadership and innovation experience/intention provide robust empirical support for the downstream influence of lead userness on broader innovation behaviours (Franke et al. 2006; Schreier et al. 2007). In doing so, the study extends prior theoretical models of how lead users shape market adoption and product success (Lilien et al. 2002; Morrison et al. 2000).

Fourth, the market test results offer new theoretical insights into the commercial significance of lead userness. By showing that product concepts generated by lead users consistently command a higher WTP than those from regular consumers, across multiple product categories (smartphones, e-bikes and refrigerators), this study links the micro-level psychology of lead userness to tangible market outcomes (Lilien et al. 2002). This underscores the economic rationale for focusing on 'leading-edge' consumers within innovation processes, as their forward-thinking ideas appear to align closely with market desires, thereby enhancing the broader theoretical argument that user innovativeness correlates with commercial success (Franke et al. 2006; Morrison et al. 2000).

Finally, by replicating the effectiveness of the scale in identifying LUs in multiple product categories, we demonstrate the transferability of the measure across varied consumer contexts. This cross-domain utility is crucial for generalizing LU theory beyond certain product categories, indicating that AoT and HBE retain explanatory power even when products vary considerably in complexity and consumer involvement. Moreover, the short-scale development indicates that practitioners can exploit this flexibility with even fewer items, thereby reducing respondent burden in contexts where multiple product categories are surveyed simultaneously. Preliminary findings suggest that the short scale, like the original instrument, retains enough diagnostic capability to pinpoint LUs across different domains, helping researchers and managers isolate individuals who consistently exhibit strong tendencies in AoT and HBE.

8.2 | Managerial Implications

Based on this paper's findings, several practical implications emerge. First, because innovative users often develop novel ideas for personal use rather than for commercial gain (Lüthje 2004), firms seeking to benefit from such user innovation must proactively identify these individuals. However, pinpointing LUs has traditionally presented a major challenge for service companies and manufacturers (Matthing et al. 2006; Schreier and Prügl 2008), in large part due to limited insight into who they are and why they emerge (Schreier and Prügl 2008). By examining the root causes of AoT and HBE at a third-order hierarchical level, the measurement instrument developed here provides crucial insight into the emergence of LU characteristics, thus facilitating the LU search process. Although methods such as screening (Urban and von Hippel 1988) or networking pyramiding (Lilien et al. 2002) have long been used to identify LUs (Hyysalo et al. 2015; Lüthje and Herstatt 2004), they have faced criticism regarding their effectiveness and efficiency (Kratzer et al. 2016; Lüthje and Herstatt 2004). Indeed, previous practical applications of the LU concept often involved high costs and extensive effort (Schreier and Prügl 2008). Given that digital technologies (e.g., social networks) can substantially improve the LU search (Kratzer et al. 2016), companies can seamlessly integrate the proposed measurement inventory into online community platforms (Belz and Baumbach 2010; Hau and Kang 2016; Hienerth et al. 2014) and social media (Kratzer et al. 2016). Consequently, using this comprehensive self-reported scale in combination with digital survey tools appears to be a cost-effective and efficient way for organizations to pinpoint LUs in large consumer populations.

Second, the newly developed lead userness scale emerges as a particularly effective tool in business-to-consumer contexts, where the sheer size of user populations (Schreier and Prügl 2008; Spann et al. 2009) and the relatively small proportion of LUs (e.g., Belz and Baumbach 2010; Hamdi-Kidar et al. 2019) pose significant challenges (Schreier and Prügl 2008; Spann et al. 2009). In large consumer markets, where users constitute a vast pool and LUs make up only a small fraction, leveraging a self-report scale is not only more efficient than traditional methods (e.g., expert assessment and time-intensive peer referral) but also highly cost-effective. Managers can quickly screen thousands of potential contributors online, directing resources toward those most likely to contribute breakthrough concepts (Schuhmacher and Kuester 2012).

Third, integrating AI-driven approaches with the lead userness scale could further enhance the efficiency of LU identification. For instance, machine-learning algorithms might pre-screen large consumer datasets to detect patterns in user behaviour or online engagement, which could then be cross-validated with our scale to pinpoint those individuals who exhibit strong AoT and HBE traits. This synergy between advanced analytics and the self-reported lead userness inventory would help practitioners focus their resources on the most promising consumer segments while maintaining the depth of insight afforded by the hierarchical model.

Fourth, as digitalization continues to evolve, companies increasingly leverage online tools to engage and empower consumers in new product development (Chou et al. 2015; Füller et al. 2009). Popular approaches include online idea competitions (Schuhmacher and Kuester 2012) and virtual integration (Füller et al. 2009, 2010; Hienerth et al. 2014), which tap into consumers' diverse knowledge and creativity (Füller et al. 2009, 2010; Schuhmacher and Kuester 2012). However, although these methods yield large volumes of user-generated ideas (Chou et al. 2015; Füller et al. 2009), firms still struggle to identify the highest quality concepts (Schuhmacher and Kuester 2012). In this regard, the lead userness scale can guide practitioners by pinpointing participants most likely to contribute groundbreaking solutions. Consequently, when faced with a flood of ideas, the scale acts as a filtering mechanism, spotlighting individuals who truly exhibit 'leading-edge' behaviours and maximizing the chances of discovering groundbreaking concepts. This heightened efficiency and clarity in user selection are particularly beneficial for firms under intense innovation pressure, confirming that the third-order LU scale is not only academically robust but also strategically valuable in practice.

8.3 | Limitations and Future Research

As with any other study, it is important to bear in mind some limitations when interpreting the results of this research. First, the hierarchical conceptualization of lead userness, as well as the corresponding instrument to measure an individual's lead userness, represents an initial step in the continuous evolution of the LU theory. Therefore, the newly developed measurement inventory should be further examined and refined in future research. Although the application of the developed lead userness scale and the subsequent market test underlined the applicability and practical relevance of the instrument, the results regarding the commercial potential of the LU concepts are confined to specific consumer products (smartphones, e-bikes and refrigerators). Yet, previous research has shown that LUs can next to various product categories (e.g., Morrison et al. 2000; Morrison et al. 2004; Urban and von Hippel 1988) also be employed in new service development (e.g., Matthing et al. 2006; Ye and Kankanhalli 2018). In order to enhance the external validity of the scale, future research should apply the measurement inventory in other research contexts, such as services.

Second, another limitation of this study lies in its consumer-centric focus. Although this approach enabled us to develop and validate our measurement instrument at the individual consumer level, it leaves open the question of how lead userness might manifest in organizational contexts. However, we acknowledge that the conceptualization and scale developed in this paper can, in principle, be adapted for organizational contexts by surveying employees rather than consumers (see, e.g., Schweisfurth 2017; Wu et al. 2020). In such an adaptation, items would be reworded to capture organizational need recognition and benefit expectations at the firm level, preserving the fundamental essence of AoT and HBE. Comparative studies across consumer and firm-level samples would thereby offer a valuable avenue for investigating whether, and how, structural factors, such as corporate strategies, formal innovation processes or resource constraints, moderate or reshape lead userness. This line of inquiry would not only broaden the applicability of our scale but also enrich the theoretical understanding of how individual- and organization-level LU characteristics emerge and interact in the pursuit of innovation.

Third, our study employed self-reports to capture lead userness. Yet, we acknowledge that this approach may introduce biases such as social desirability or limited self-awareness. Some studies have successfully used other ratings or independent indicators (e.g., third-party evaluations, peer nominations and objective performance measures) to gauge how 'ahead of trend' and 'highly motivated by benefits' a user actually is (Franke et al. 2006; Morrison et al. 2000, 2004). Incorporating such external assessments could provide stronger convergent validity for the lead userness construct. However, gathering these additional data can be resource-intensive, and the feasibility depends on the specific domain and sample. Future research might compare self-ratings with other-ratings or objective proxies to ascertain whether they converge on the same 'leading-edge' individuals. Doing so would help confirm whether LUs identified by the hierarchical measurement inventory based on self-reports remain robust when triangulated with multiple data sources, thereby further enhancing their practical relevance and theoretical soundness.

Finally, future research could explore how AI-based user profiling and recommendation systems intersect with lead userness. For example, researchers might investigate whether automated data-mining techniques (e.g., text analytics of user reviews or social media posts) can serve as an initial filter for identifying potential LUs, which is then validated or enriched by our HLU scale. This hybrid approach could streamline large-scale LU searches and broaden the applicability of LU theory in increasingly digital and AI-driven marketplaces.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT and DeepL Write in order to improve language and readability. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Bartels, J., and M. J. Reinders. 2011. "Consumer Innovativeness and Its Correlates: A Propositional Inventory for Future Research." *Journal of Business Research* 64, no. 6: 601–609.

Bassellier, G., and I. Benbasat. 2004. "Business Competence of Information Technology Professionals: Conceptual Development and Influence on IT-Business Partnerships." *MIS Quarterly* 28, no. 4: 673–694.

Baumgartner, H., and J. B. E. Steenkamp. 1996. "Exploratory Consumer Buying Behavior: Conceptualization and Measurement." *International Journal of Research in Marketing* 13, no. 2: 121–137.

Belz, F. M., and W. Baumbach. 2010. "Netnography as a Method of Lead User Identification." *Creativity and Innovation Management* 19, no. 3: 304–313.

Blazevic, V., and A. Lievens. 2008. "Managing Innovation Through Customer Coproduced Knowledge in Electronic Services: An Exploratory Study." *Journal of the Academy of Marketing Science* 36: 138–151.

Boss, V., R. Kleer, and A. Vossen. 2017. "Walking Parallel Paths or Taking the Same Road? The Effect of Collaborative Incentives in Innovation Contests." *International Journal of Innovation Management* 21, no. 3: 1750024.

Bruner, G. C., and A. Kumar. 2007. "Gadget Lovers." *Journal of the Academy of Marketing Science* 35, no. 3: 329–339.

Carbonell, P., and A. I. Rodriguez-Escudero. 2015. "The Negative Effect of Team's Prior Experience and Technological Turbulence on New Service Development Projects With Customer Involvement." *European Journal of Marketing* 49, no. 3/4: 278–301.

Carbonell, P., A. I. Rodriguez-Escudero, and D. Pujari. 2012. "Performance Effects of Involving Lead Users and Close Customers in New Service Development." *Journal of Services Marketing* 26, no. 7: 497–509.

Chin, W. W. 1998. "The Partial Least Squares Approach for Structural Equation Modelling." In *Modern Methods for Business Research*, edited by G. A. Marcoulides, 295–336. Lawrence Erlbaum Associates.

Chin, W. W. 2009. "How to Write Up and Report PLS Analyses." In *Handbook of Partial Least Squares*, edited by V. E. Vinzi, W. W. Chin, J. Henseler, and H. Wang, 655–690. Springer.

Chou, C., K. P. Yang, and J. Jhan. 2015. "Empowerment Strategies for Ideation Through Online Communities." *Creativity and Innovation Management* 24, no. 1: 169–181.

Clark, L. A., and D. Watson. 1995. "Constructing Validity: Basic Issues in Objective Scale Development." *Psychological Assessment* 7, no. 3: 309–319.

Cooper, R. G., and E. J. Kleinschmidt. 1987. "Success Factors in Product Innovation." *Industrial Marketing Management* 16, no. 3: 215–223.

Dabholkar, P. A. 1994. "Incorporating Choice Into an Attitudinal Framework: Analyzing Models of Mental Comparison Processes." *Journal of Consumer Research* 21, no. 1: 100–118.

Diamantopoulos, A., and H. M. Winklhofer. 2001. "Index Construction With Formative Indicators: An Alternative to Scale Development." *Journal of Marketing Research* 38, no. 2: 269–277.

Faullant, R., E. J. Schwarz, I. Krajger, and R. J. Breitenecker. 2012. "Towards a Comprehensive Understanding of Lead Userness: The Search for Individual Creativity." *Creativity and Innovation Management* 21, no. 1: 76–92.

Fornell, C., and D. F. Larcker. 1981. "Evaluating Structural Equation Models With Unobservable Variables and Measurement Error." *Journal of Marketing Research* 18, no. 1: 39–50.

Franke, N., and F. Piller. 2004. "Value Creation by Toolkits for User Innovation and Design: The Case of the Watch Market." *Journal of Product Innovation Management* 21, no. 6: 401–415.

Franke, N., M. K. Poetz, and M. Schreier. 2014. "Integrating Problem Solvers From Analogous Markets in New Product Ideation." *Management Science* 60, no. 4: 1063–1081.

Franke, N., E. von Hippel, and M. Schreier. 2006. "Finding Commercially Attractive User Innovations: A Test of Lead-User Theory." *Journal of Product Innovation Management* 23, no. 4: 301–315.

Füller, J., R. Faullant, and K. Matzler. 2010. "Triggers for Virtual Customer Integration in the Development of Medical Equipment—From a Manufacturer and a User's Perspective." *Industrial Marketing Management* 39, no. 8: 1376–1383.

Füller, J., H. Mühlbacher, K. Matzler, and G. Jawecki. 2009. "Consumer Empowerment Through Internet-Based Co-Creation." *Journal of Management Information Systems* 26, no. 3: 71–102.

Gefen, D., D. W. Straub, and M. C. Boudreau. 2000. "Structural Equation Modeling and Regression: Guidelines for Research Practice." *Communications of the Association for Information Systems* 4, no. 7: 22–56.

Gemser, G., and H. Perks. 2015. "Co-Creation With Customers: An Evolving Innovation Research Field: Virtual Issue Editorial." *Journal of Product Innovation Management* 32, no. 5: 660–665.

Globocnik, D., and R. Faullant. 2021. "Do Lead Users Cooperate With Manufacturers in Innovation? Investigating the Missing Link Between Lead Userness and Cooperation Initiation With Manufacturers." *Technovation* 100: 102187 (14 pages).

Gruner, K. E., and C. Homburg. 2000. "Does Customer Interaction Enhance New Product Success?" *Journal of Business Research* 49, no. 1: 1–14.

Gupta, R., D. Gupta, K. Jain, and K. S. Momaya. 2021. "User Involvement in Technology-Based Service Innovations in Telecom: Cases From India." *IEEE Transactions on Engineering Management* 70, no. 12: 4287–4298.

Gupta, S., A. Leszkiewicz, V. Kumar, T. Bijmolt, and D. Potapov. 2020. "Digital Analytics: Modeling for Insights and New Methods." *Journal of Interactive Marketing* 51, no. 1: 26–43.

Hair, J. F., G. T. M. Hult, C. M. Ringle, and M. Sarstedt. 2022. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).* 3rd ed. Sage.

Hamdi-Kidar, L., P. Keinz, E. Le Nagard, and E. Vernette. 2019. "Comparing Lead Users to Emergent-Nature Consumers as Sources of Innovation at Early Stages of New Product Development." *Journal of Product Innovation Management* 36, no. 5: 616–631.

Han, C., and M. Yang, M. 2019. "Stimulating Innovation on Social Product Development: An Analysis of Social Behaviors in Online Innovation Communities." *IEEE Transactions on Engineering Management* 69, no. 2: 365–375.

Hau, Y. S., and M. Kang. 2016. "Extending Lead User Theory to Users' Innovation-Related Knowledge Sharing in the Online User Community: The Mediating Roles of Social Capital and Perceived Behavioral Control." *International Journal of Information Management* 36, no. 4: 520–530.

Heidenreich, S., and M. Handrich. 2015. "What About Passive Innovation Resistance? Investigating Adoption-Related Behavior From a Resistance Perspective." *Journal of Product Innovation Management* 32, no. 6: 878–903.

Heidenreich, S., S. Jordanow, T. Kraemer, and M. Obschonka. 2024. "Together Forever? How Customer Co-Creation Affects the Adoption of Digital Service Innovations Over Time." *Journal of Product Innovation Management* 41, no. 5: 1062–1090.

Heidenreich, S., and T. Kraemer. 2015. "Passive Innovation Resistance: The Curse of Innovation? Investigating Consequences for Innovative Consumer Behavior." *Journal of Economic Psychology* 51: 134–151.

Heidenreich, S., and T. Kraemer. 2016. "Innovations-Doomed to Fail? Investigating Strategies to Overcome Passive Innovation Resistance." *Journal of Product Innovation Management* 33, no. 3: 277–297.

Henseler, J., C. M. Ringle, and M. Sarstedt. 2015. "A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling." *Journal of the Academy of Marketing Science* 43: 115–135.

Henseler, J., C. M. Ringle, and R. R. Sinkovics. 2009. "The Use of Partial Least Squares Path Modeling in International Marketing." In *Advances in International Marketing*, edited by R. R. Sinkovics and P. N. Ghauri, 277–319. Emerald Group Publishing Limited.

Herstatt, C., and E. von Hippel. 1992. "From Experience: Developing New Product Concepts via the Lead User Method: A Case Study in a 'Low-Tech' Field." *Journal of Product Innovation Management* 9, no. 3: 213–221.

Hienerth, C., and C. Lettl. 2017. "Perspective: Understanding the Nature and Measurement of the Lead User Construct." *Journal of Product Innovation Management* 34, no. 1: 3–12.

Hienerth, C., C. Lettl, and P. Keinz. 2014. "Synergies Among Producer Firms, Lead Users, and User Communities: The Case of the LEGO Producer–User Ecosystem." *Journal of Product Innovation Management* 31, no. 4: 848–866.

Hoffman, D. L., P. K. Kopalle, and T. P. Novak. 2010. "The 'Right' Consumers for Better Concepts-Identifying Consumers High in Emergent Nature to Develop New Product Concepts." *Journal of Marketing Research* 47, no. 5: 854–865.

Homburg, C., and A. Giering. 2001. "Personal Characteristics as Moderators of the Relationship Between Customer Satisfaction and Loyalty?—An Empirical Analysis." *Psychology and Marketing* 18, no. 1: 43–66.

Hoyer, W. D., R. Chandy, M. Dorotic, M. Krafft, and S. S. Singh. 2010. "Consumer Cocreation in New Product Development." *Journal of Service Research* 13, no. 3: 283–296.

Hu, L. T., and P. M. Bentler. 1999. "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives." *Structural Equation Modeling: A Multidisciplinary Journal* 6, no. 1: 1–55.

Hung, C. L., J. C. L. Chou, and T. P. Dong. 2011. "Innovations and Communication Through Innovative Users: An Exploratory Mechanism of Social Networking Website." *International Journal of Information Management* 31, no. 4: 317–326.

Hurt, T. H., K. Joseph, and C. D. Cook. 1977. "Scales for the Measurement of Innovativeness." *Human Communication Research* 4, no. 1: 58–65.

Hyysalo, S., P. Helminen, S. Mäkinen, M. Johnson, J. K. Juntunen, and S. Freeman. 2015. "Intermediate Search Elements and Method Combination in Lead-User Searches." *International Journal of Innovation Management* 19, no. 1: 1550007.

Im, S., C. H. Mason, and M. B. Houston. 2007. "Does Innate Consumer Innovativeness Relate to New Product/Service Adoption Behavior? The Intervening Role of Social Learning via Vicarious Innovativeness." *Journal of the Academy of Marketing Science* 35, no. 1: 63–75.

Jahanmir, S. F., and J. Cavadas. 2018. "Factors Affecting Late Adoption of Digital Innovations." *Journal of Business Research* 88: 337–343.

Jahanmir, S. F., and L. F. Lages. 2016. "The Late-Adopter Scale: A Measure of Late Adopters of Technological Innovations." *Journal of Business Research* 69, no. 5: 1701–1706.

Jarvis, C. B., S. B. MacKenzie, and P. M. Podsakoff. 2003. "A Critical Review of Construct Indicators and Measurement Model Misspecification in Marketing and Consumer Research." *Journal of Consumer Research* 30, no. 2: 199–218.

Jeppesen, L. B., and K. Laursen. 2009. "The Role of Lead Users in Knowledge Sharing." *Research Policy* 38, no. 10: 1582–1589.

Kankanhalli, A., H. Ye, and H. H. Teo. 2015. "Comparing Potential and Actual Innovators." *MIS Quarterly* 39, no. 3: 667–682.

Khatri, M. 2021. "How Digital Marketing Along With Artificial Intelligence Is Transforming Consumer Behaviour." *International Journal for Research in Applied Science and Engineering Technology* 9, no. 7: 523–527.

Kratzer, J., and C. Lettl. 2008. "A Social Network Perspective of Lead Users and Creativity: An Empirical Study Among Children." *Creativity and Innovation Management* 17, no. 1: 26–36.

Kratzer, J., and C. Lettl. 2009. "Distinctive Roles of Lead Users and Opinion Leaders in the Social Networks of Schoolchildren." *Journal of Consumer Research* 36, no. 4: 646–659.

Kratzer, J., C. Lettl, N. Franke, and P. A. Gloor. 2016. "The Social Network Position of Lead Users." *Journal of Product Innovation Management* 33, no. 2: 201–216.

Lee, H., and S. K. Markham. 2016. "PDMA Comparative Performance Assessment Study (CPAS): Methods and Future Research Directions: NPD Future Research." *Journal of Product Innovation Management* 33, no. S1: 3–19.

Lettl, C., C. Hienerth, and H. G. Gemuenden. 2008. "Exploring How Lead Users Develop Radical Innovation: Opportunity Recognition and Exploitation in the Field of Medical Equipment Technology." *IEEE Transactions on Engineering Management* 55, no. 2: 219–233.

Lilien, G. L., P. D. Morrison, K. Searls, M. Sonnack, and E. von Hippel. 2002. "Performance Assessment of the Lead User Idea-Generation Process for New Product Development." *Management Science* 48, no. 8: 1042–1059.

Lohmöller, J. B. 1989. *Latent Variable Path Modeling With Partial Least Squares*. Physica-Verlag.

Lüthje, C. 2004. "Characteristics of Innovating Users in a Consumer Goods Field: An Empirical Study of Sport-Related Product Consumers." *Technovation* 24, no. 9: 683–695.

Lüthje, C., and C. Herstatt. 2004. "The Lead User Method: An Outline of Empirical Findings and Issues for Future Research." *R&D Management* 34, no. 5: 553–568.

Lüthje, C., C. Herstatt, and E. A. von Hippel. 2003. The Dominant Role of "Local" Information in User Innovation: The Case of Mountain Biking. (Working Paper no. 4377-02). MIT Sloan School of Management.

MacKenzie, S. B., P. M. Podsakoff, and N. P. Podsakoff. 2011. "Construct Measurement and Validation Procedures in MIS and Behavioral Research: Integrating New and Existing Techniques." *MIS Quarterly* 35, no. 2: 293–334.

Mahr, D., and A. Lievens. 2012. "Virtual Lead User Communities: Drivers of Knowledge Creation for Innovation." *Research Policy* 41, no. 1: 167–177.

Mandrik, C. A., and Y. Bao. 2005. "Exploring the Concept and Measurement of General Risk Aversion." *Advances in Consumer Research* 32: 531.

Matthing, J., P. Kristensson, A. Gustafsson, and A. Parasuraman. 2006. "Developing Successful Technology-Based Services: The Issue of Identifying and Involving Innovative Users." *Journal of Services Marketing* 20, no. 5: 288–297.

Mitchell, A. A., and P. A. Dacin. 1996. "The Assessment of Alternative Measures of Consumer Expertise." *Journal of Consumer Research* 23, no. 3: 219–239.

Mitchell, R. C., and R. T. Carson. 1989. *Using Surveys to Value Public Goods: The Contingent Valuation Method*. Resources for the Future.

Moore, G. C., and I. Benbasat. 1991. "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation." *Information Systems Research* 2, no. 3: 192–222.

Morrison, P. D., J. H. Roberts, and D. F. Midgley. 2004. "The Nature of Lead Users and Measurement of Leading Edge Status." *Research Policy* 33, no. 2: 351–362.

Morrison, P. D., J. H. Roberts, and E. von Hippel. 2000. "Determinants of User Innovation and Innovation Sharing in a Local Market." *Management Science* 46, no. 12: 1513–1527.

Mütterlein, J., R. E. Kunz, and D. Baier. 2019. "Effects of Lead-Usership on the Acceptance of Media Innovations: A Mobile Augmented Reality Case." *Technological Forecasting and Social Change* 145: 113–124.

Nijssen, E. J., B. Hillebrand, J. P. J. de Jong, and R. G. M. Kemp. 2012. "Strategic Value Assessment and Explorative Learning Opportunities With Customers." *Journal of Product Innovation Management* 29, no. 11: 91–102.

Nørskov, S., Y. M. Antorini, and M. B. Jensen. 2016. "Innovative Brand Community Members and Their Willingness to Share Ideas With Companies." *International Journal of Innovation Management* 20, no. 6: 1650046.

Nylén, D., and J. Holmström. 2015. "Digital Innovation Strategy: A Framework for Diagnosing and Improving Digital Product and Service Innovation." *Business Horizons* 58, no. 1: 57–67.

Olson, E. L., and G. Bakke. 2001. "Implementing the Lead User Method in a High Technology Firm: A Longitudinal Study of Intentions Versus Actions." *Journal of Product Innovation Management* 18, no. 6: 388–395.

Ozer, M. 2009. "The Roles of Product Lead-Users and Product Experts in New Product Evaluation." *Research Policy* 38, no. 8: 1340–1349.

Roehrich, G. 2004. "Consumer Innovativeness: Concepts and Measurements." *Journal of Business Research* 57, no. 6: 671–677.

Rogers, E. M. 2003. *Diffusion of Innovations*. 5th ed. Free Press.

Rossiter, J. R. 2002. "The C-OAR-SE Procedure for Scale Development in Marketing." *International Journal of Research in Marketing* 19, no. 4: 305–335.

Runco, M. A., and S. Acar. 2012. "Divergent Thinking as an Indicator of Creative Potential." *Creativity Research Journal* 24, no. 1: 66–75.

Sarstedt, M., J. F. Hair Jr., J. H. Cheah, J. M. Becker, and C. M. Ringle. 2019. "How to Specify, Estimate, and Validate Higher-Order Constructs in PLS-SEM." *Australasian Marketing Journal* 27, no. 3: 197–211.

Schreier, M., S. Oberhauser, and R. Prügl. 2007. "Lead Users and the Adoption and Diffusion of New Products: Insights From Two Extreme Sports Communities." *Marketing Letters* 18, no. 1/2: 15–30.

Schreier, M., and R. Prügl. 2008. "Extending Lead-User Theory: Antecedents and Consequences of Consumers' Lead Userness." *Journal of Product Innovation Management* 25, no. 4: 331–346.

Schuhmacher, M. C., and S. Kuester. 2012. "Identification of Lead User Characteristics Driving the Quality of Service Innovation Ideas." *Creativity and Innovation Management* 21, no. 4: 427–442.

Schweisfurth, T. G. 2017. "Comparing Internal and External Lead Users as Sources of Innovation." *Research Policy* 46, no. 1: 238–248.

Schweisfurth, T. G., and M. P. Dharmawan. 2019. "Does Lead Userness Foster Idea Implementation and Diffusion? A Study of Internal Shopfloor Users." *Research Policy* 48, no. 1: 289–297.

Schweisfurth, T. G., and C. Herstatt. 2015. "Embedded (Lead) Users as Catalysts to Product Diffusion." *Creativity and Innovation Management* 24, no. 1: 151–168.

Schweisfurth, T. G., and C. Raasch. 2015. "Embedded Lead Users—The Benefits of Employing Users for Corporate Innovation." *Research Policy* 44, no. 1: 168–180.

Spann, M., H. Ernst, B. Skiera, and J. H. Soll. 2009. "Identification of Lead Users for Consumer Products via Virtual Stock Markets." *Journal of Product Innovation Management* 26: 322–335.

Steenkamp, J. B. E. M., F. ter Hofstede, and M. Wedel. 1999. "A Cross-National Investigation Into the Individual and National Cultural Antecedents of Consumer Innovativeness." *Journal of Marketing* 63, no. 2: 55–69.

Talke, K., and S. Heidenreich. 2014. "How to Overcome Pro-Change Bias: Incorporating Passive and Active Innovation Resistance in Innovation Decision Models." *Journal of Product Innovation Management* 31, no. 5: 894–907.

Taylor, J. W. 1974. "The Role of Risk in Consumer Behavior: A Comprehensive and Operational Theory of Risk Taking in Consumer Behavior." *Journal of Marketing* 38, no. 2: 54–60.

Tenenhaus, M., V. E. Vinzi, Y. M. Chatelin, and C. Lauro. 2005. "PLS Path Modeling." *Computational Statistics & Data Analysis* 48, no. 1: 159–205.

The Academic Journal Guide. 2021. Chartered Association of Business Schools. Retrieved June 28, 2022, from https://charteredabs.org/academic-journal-guide-2021-view/.

Urban, G. L., and E. von Hippel. 1988. "Lead User Analyses for the Development of New Industrial Products." *Management Science* 34, no. 5: 569–582.

Van Eck, P. S., W. Jager, and P. S. Leeflang. 2011. "Opinion Leaders' Role in Innovation Diffusion: A Simulation Study." *Journal of Product Innovation Management* 28, no. 2: 187–203.

von Hippel, E. 1986. "Lead Users: A Source of Novel Product Concepts." *Management Science* 32, no. 7: 791–805.

Wellner, K., and C. Herstatt. 2014. "Determinants of User Innovator Behaviour in the Silver Market." *International Journal of Innovation Management* 18, no. 6: 1440014.

Wetzels, M., G. Odekerken-Schröder, and C. van Oppen. 2009. "Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration." *MIS Quarterly* 33, no. 1: 177–195.

Wigert, B. G., V. R. Murugavel, and R. Reiter-Palmon. 2022. "The Utility of Divergent and Convergent Thinking in the Problem Construction Processes During Creative Problem-Solving." *Psychology of Aesthetics, Creativity, and the Arts* 18, no: 5: 858–868.

Wu, C. H., J. P. J. de Jong, C. Raasch, and S. Poldervaart. 2020. "Work Process-Related Lead Userness as an Antecedent of Innovative Behavior and User Innovation in Organizations." *Research Policy* 49, no. 6: 103986.

Ye, H., and A. Kankanhalli. 2018. "User Service Innovation on Mobile Phone Platforms: Investigating Impacts of Lead Userness, Toolkit Support, and Design Autonomy." *MIS Quarterly* 42, no. 1: 165–187.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.