When humans and large language models collaborate, problem-finding illuminates

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This study explores the role of Large Language Models (LLMs) in problem finding (PF) for ill-structured, wicked, and multi-stakeholder problems—an essential yet underexamined aspect of organizational innovation. While prior research has examined artificial intelligence (AI) in problem-solving (PS) and, more recently, the contributions of LLMs, their role in PF remains largely unexplored. Given that PF lays the foundation for effective PS, overlooking it can result in missed opportunities and inefficient resource allocation, ultimately hindering the innovation process. Drawing on a cognitive-behavioral perspective rooted in Simon's foundational work, this study identifies the key activities and cognitive skills essential for PF and examines how human-LLM collaboration can enhance this process. While humans possess innate PF abilities, cognitive limitations such as bounded rationality, satisficing, and uncertainty avoidance constrain their effectiveness. LLMs, with their advanced reasoning and data-processing capabilities, can help overcome these constraints by expanding the search space, generating alternative problem framings, and stimulating creativity. However, their inherent limitations, including biases, hallucinations, and challenges in handling less structured problems, necessitate a structured approach to human-LLM collaboration. To address this, we propose a framework that defines this interaction and illustrates its application through case studies in product development and social innovation. Our findings have significant implications for organizations, emphasizing the need for structured implementation, workforce training, and AI governance. We conclude with research propositions to guide future investigations into humans-LLMs collaboration in PF, positioning it as a critical driver of innovation in the era of Generative AI.

Keywords: Artificial intelligence (AI), innovation, large language models (LLMs), problem-finding.

Introduction

Problem-finding (PF), defined in this study as the two-step process of problem discovery and problem definition, and problem-solving (PS) play a critical role in catalyzing innovation and enhancing organizational performance (Büyükdamgacı, 2003; Crossan & Apaydin, 2010). While artificial intelligence (AI) has firmly established its role in PS (e.g., He et al., 2015; Raina et al., 2019; Silver et al., 2017), it has been particularly effective in handling well-defined problems with explicit initial and goal states, such as analyzing consumer responses to product launches on social media (Giannakis et al., 2020) and evaluating customer loyalty to luxury hotel brands (Brant, 2016).

However, AI's role becomes less straightforward when addressing problems that lack clear structure, such as ill-structured problems (Newell & Simon, 1972; Simon, 1973), wicked problems (McMillan & Overall, 2016), or multi-stakeholder problems (Verganti et al., 2021), which we collectively refer to in our study as less structured problems for the sake of consistency and clarity in discussion. As the initial, goal, and intermediate states become less defined, uncertainty increases (Reed, 2016), requiring engagement in processes of (re)construction, (re)definition, and (re)framing (Verganti et al., 2020; Dorst, 2015, 2019). Effectively navigating these less structured problems involves making sense of weak signals and ambiguous stimuli (Schwarz, 2014), a domain where AI has traditionally been considered less capable due to its limitations in abstraction, meaning-making, and insight generation (Boden, 2014 in Halina, 2021; Verganti et al., 2020). This perception, however, is increasingly challenged by the rapid advancements in generative AI (GenAI). GenAI, a subset of AI, focuses on developing algorithms and models capable of generating synthetic data that closely resemble real-world data (Bandi et al., 2023). Within GenAI, we focus on Large Language Models (LLMs). LLMs are language models trained on extensive textual data, designed to process and generate human-like text based on learned patterns, and characterized by a vast number of parameters (Bandi et al., 2023). Examples such as ChatGPT demonstrate human-like language comprehension, multimodal reasoning (Bouschery et al., 2023), advanced problem-solving (OpenAI, 2023), and creative potential (Girotra et al., 2023; Guzik et al., 2023; Haase & Hanel, 2023).These capabilities are essential for creative and effective PF for less structured problems (Abdulla et al., 2020; Dillon, 1982; Obieke et al., 2020; Reiter-Palmon et al., 1997; Reiter-Palmon, 2011). Despite this progress and the growing adoption of LLMs in various domains, limited research has examined how they affect PF in less structured problems, what impact they may have on organizational innovation processes, and how firms should respond to these changes.

Attending to this gap is critical, as prior research has demonstrated that failing to identify the right problem can lead to wasted time, misallocated resources, and missed opportunities (Archibald, 2020; Baer et al., 2013). Furthermore, problem discovery and problem definition in PF underpin the early stages of widely used corporate innovation frameworks, including the Double Diamond model (the first two steps: problem discovery and problem definition) (Design Council, 2006; Kakatkar et al., 2020), design thinking (the first two steps: empathize and define) (d.school, 2010), and customer development (the first step: customer discovery) (Blank & Dorf, 2015). This paper aims to address these gaps by integrating existing knowledge on PF, early-stage innovation processes, and GenAI, particularly LLMs, to propose new relationships between them. Specifically, we ask: How do LLMs affect problem-finding for less structured problems?

Building on Simon's (1955, 1956) foundational work, we introduce a cognitive-behavioral perspective to PF for less structured problems, delineating a two-step process of problem discovery and problem definition and examining the key activities and cognitive skills required at each stage. We analyze the advantages and limitations of both humans and LLMs in these steps and explore their application within the aforementioned innovation frameworks. While LLMs provide valuable cognitive support, we argue that they do not replace human judgment but rather necessitate structured collaboration. To facilitate this, we propose the Augmented Problem-Finding framework for organizing humans-LLMs collaboration, offering insights into how organizations can effectively integrate LLMs into their innovation processes.

By synthesizing diverse literature on PF across management, design-thinking-based innovation frameworks, bounded rationality, and LLMs, and applying a cognitive-behavioral lens, we offer new insights and expand perspectives on LLMs' role in PF for less structured problems. We introduce a conceptual framework for human-LLM collaboration while identifying key limitations, including biases, hallucinations, and over-reliance. Consistent with the objectives of conceptual papers (Gilson & Goldberg, 2015), we propose research directions to guide future inquiry and lay the groundwork for further theoretical and empirical exploration. Finally, we provide practical guidance for organizations on integrating LLMs into workflows, implementing targeted workforce training, and ensuring robust AI governance.

The paper proceeds as follows: We begin with a review of the literature on PF, focusing on its two key steps—problem discovery and problem definition—and introduce our cognitive-behavioral lens. We then analyze the respective advantages and limitations of both humans and LLMs in PF. Next, we examine how PF aligns with the aforementioned innovation frameworks and introduce our structured framework for human-LLM collaboration, illustrating its application through two case studies—one in product development and another in social innovation. Following this, we discuss the practical implications of LLMs-assisted PF for organizations. Finally, we conclude with a set of research propositions to guide future research on humans-LLMs collaboration in PF for less structured problems as a driver of innovation and competitive advantage.

Problem finding – a review of definitions

In order to fully comprehend the role of LLMs in the PF process, it is crucial to examine the process from multiple perspectives, examine its sub-components and sub-steps, and evaluate the potential impact on each of these elements. One pivotal component to consider is the definition of a "problem" itself. Volkema (1983) highlighted the lack of consensus in literature regarding what constitutes a problem. Simon (1973) categorized problems as either well-structured or ill-structured, referring to the latter as a residual concept. Reed (2016) provided illustrative examples of these categories, with well-structured problems encompassing puzzles and algorithmic problems, while ill-structured problems involve story problems, design problems, and dilemmas. Ill-structured problems are characterized by incomplete specifications of the initial, goal, and intermediate states. Hence, they possess multiple solutions and uncertainty about which concepts, rules, and principles are necessary for the solution (Jonassen 1997 In Reed, 2016). Similarly, wicked problems are defined as "dynamically complex, ill-structured problems that have highly uncertain causes and outcomes" (McMillan & Overall, 2016).

Next, we examine the term "problem-finding". Upon a thorough review of the literature on PF definitions, it becomes evident that various terms are employed to illustrate PF. In fact, Abdulla and Cramond (2018) identified at least 13 different terms, each with nuanced differences between them (Runco & Chand, 1994). Moreover, PF is frequently described as a cyclical and sequential process comprising two to seven distinct steps. To provide a comprehensive overview, Table-1 below summarizes these steps.

"Table 1 about here"

In contrast to a process-oriented approach, PF has been defined by scholars from various perspectives. For instance, some consider PF as a cognitive skill (Hoover, 1990) or an ability associated with creativity (Carson & Runco, 1999; Hoover, 1994). Csikszentmihalyi

(1988a, 1988b) views PF as a mental process distinct from PS, particularly in scientific discovery, where different cognitive strategies are employed. The initial steps of PF involve ideation, diverging to generate numerous problems, while subsequent steps focus on evaluation, converging to identify the most relevant problems (Basadur et al., 1994; Sturm et al., 2021).

We adopt a two-step approach to PF, as proposed by Basadur et al. (1994) and Reiter-Palmon and Murugavel (2016), while following the terminology used by Dillon (1982) and Abdulla and Cramond (2018). In the following sub-sections, we elaborate on each step, detailing the key activities and cognitive processes involved.

Problem discovery

Problem discovery is a critical phase in problem finding that requires a set of activities and skills. Previous studies have provided several views from multiple disciplines. Below, we integrate some of these views and link them to the above-mentioned innovation frameworks, namely the Double Diamond, design thinking, and customer development. We then highlight the human advantages and disadvantages associated with problem discovery.

Each of these frameworks recognizes the importance of identifying and understanding problems before moving toward solutions. The Double Diamond model emphasizes an exploratory phase of discovering user needs, market gaps, and systemic challenges before moving into problem definition, ensuring that the right problem is being solved (Design Council, 2006). Similarly, design thinking begins with an empathize stage, where designers engage with users, observe behaviors, and uncover unmet needs, followed by the define stage, where the problem is framed in a way that guides the ideation process (d.school, 2010). In customer development, the first stage, customer discovery begins with testing customers' perception of the problem and their need to solve it (Blank & Dorf, 2015).

In alignment with these frameworks, research on problem discovery depicts two sub-steps. The first, emphasizes the importance of searching, sensing, and interpreting information to identify emerging challenges, inconsistencies, and opportunities (Dillon, 1982; Reiter-Palmon, 2011). The second involves recognizing gaps in knowledge, identifying emerging patterns or trends, expanding the problem space, and assessing whether observed cues indicate the presence of a problem (Büyükdamgacı, 2003; Basadur et al., 1994; Reiter-Palmon, 2011; Gavetti & Levinthal, 2000; Lyles, 1981). It also recognizes that the initially presented conditions may not fully capture the complexity of an issue, necessitating a critical evaluation of assumptions and an expansion of the problem space (Woolley & Pidd, 1981). This parallels the divergent thinking phase of the Double Diamond, where broad exploration of the problem space is encouraged before converging on a precise problem statement. Lyles (1981) describes the progression from awareness to incubation, which aligns with design thinking's empathize stage, where problem solvers must remain open to various perspectives before defining the problem. Similarly, in customer development, customer discovery involves iterative engagement with users to refine the problem before verifying that the solution effectively addresses it or fulfills the need sufficiently to attract a large customer base (Blank & Dorf, 2015).

To navigate problem discovery effectively, individuals require a set of cognitive skills. Cognitive flexibility is necessary to shift between different perspectives and reframe problems dynamically, preventing premature fixation on predefined structures (Reed, 2016; Dorst, 2015). Pattern recognition enables problem solvers to detect inconsistencies, anomalies, and emerging trends that indicate potential problem areas (Gavetti & Levinthal, 2000; von Hippel & von Krogh, 2016). Sensemaking, a key skill in design thinking and customer development, allows individuals to integrate disparate pieces of information into coherent insights (Verganti et al., 2020). Stakeholder engagement and critical questioning further support problem discovery, ensuring that diverse viewpoints are considered before a problem is formally defined (Mingers & Rosenhead, 2004).

Despite innate cognitive abilities, human limitations often hinder problem discovery. One major constraint is bounded rationality, broadly defined as the informational and computational limits on human rationality—the constraints on how much information individuals can process and the mental effort required to analyze and make decisions (Simon, 1955). These limitations restrict the number of possibilities individuals can explore at a given time, making it difficult to recognize alternative problem frames (Simon, 1973; Reed, 2016). People also tend to impose self-constructed constraints, which restrict their ability to consider novel problem formulations (Reed, 2016). In customer development and design thinking, cognitive biases such as confirmation bias can lead to reinforcing existing assumptions rather than discovering new problem spaces (Blank & Dorf, 2015; Verganti et al., 2020). In organizational contexts, solution-mindedness—the tendency to prioritize solutions over deep problem exploration—reduces the effectiveness of problem discovery (Büyükdamgacı, 2003), mirroring the risks of premature convergence in the Double Diamond's discovery phase.

Having explored the activities, skills, and limitations associated with problem discovery, we now turn to the second step of problem definition.

Problem definition

This step ensures that problem solvers transition from an initial, often ambiguous understanding of the issue to a precise problem statement that can effectively guide solution development. While discovery emphasizes divergence, definition requires a convergent process, narrowing the scope of inquiry and integrating insights into a structured framework that allows for actionable solutions (Dorst, 2015; Reiter-Palmon, 2011; Basadur et al., 1994).

As with problem discovery, problem definition plays a crucial role in the above-mentioned innovation frameworks, ensuring that identified problems are clearly structured before progressing to ideation and implementation. Within these frameworks, problem definition serves as a foundational step that guides creative solutions.

A crucial activity in problem definition is problem (re)construction, where individuals or teams (re)structure the problem space by integrating prior knowledge, stakeholder perspectives, and environmental constraints (Mumford et al., 1994). This process ensures that an issue is not merely addressed as it first appears but is critically examined and decomposed to better capture its underlying causes (Basadur et al., 1994). Another key activity is problem (re)framing, which involves examining the issue through different frames and perspectives, potentially leading to fundamentally different solutions (Dorst, 2015, 2019). These activities are inherently iterative, continuously refining the problem statement until a well-defined and actionable problem emerges (Dorst, 2019; Baer et al., 2013). This is particularly important because the way a problem is framed or represented can determine whether it is resolved efficiently or remains intractable (Hernando et al., 2008; Zamani, 2010).

To engage effectively in problem definition, individuals require a higher degree of cognitive abilities such as analytical reasoning, structured problem decomposition, and conceptual flexibility than in the discovery phase, as more evaluation and refinement are involved (Basadur et al., 1994). Analytical reasoning differentiates symptoms from root causes, preventing problem solvers from focusing on superficial aspects of a problem (Baer et al., 2013; Basadur et al., 1994). Conceptual flexibility supports adaptive problem framing, preventing premature closure and allowing for iteration based on new insights (Reiter-Palmon et al., 1997; Dorst, 2015). In organizational settings, facilitation, negotiation, and systemic thinking enable collaborative problem definition, particularly when multiple stakeholders must align on shared definitions (Büyükdamgacı, 2003).

Furthermore, numerous studies have explored the relationship between creativity and problem finding (Abdulla et al., 2020; Dillon, 1982; Obieke et al., 2020; Reiter-Palmon et al., 1997; Reiter-Palmon, 2011). Creative thinking and originality are considered essential for effective problem (re)construction, (re)framing, and definition, as they enable individuals to move beyond conventional perspectives and discover novel problem frames. For example, Getzels and Csikszentmihalyi (1976) found that artists who spent more time defining and exploring their problem space produced works that were rated as more original and aesthetically valuable. Similarly, Ambrosio (1993) reported a statistically significant correlation between the quantity of problems generated and measures of divergent thinking, a cognitive process strongly associated with creativity (Reiter-Palmon et al., 1997). Expanding on this, van der Voet and Lems (2022) argue that complex problems cannot be solved solely through search and retrieval but require creative problem creation and design (Schwarz et al., 2022).

These findings highlight that problem definition is not merely a structuring process but also an opportunity for innovation, as the way a problem is framed influences the range of possible solutions (Baer et al., 2013). In this regard, the ability to restate a problem in multiple ways and shift between different problem frames allows individuals to explore unconventional approaches rather than relying on established heuristics, thereby increasing the likelihood of generating more creative solutions (Reiter-Palmon & Robinson, 2009).

Despite these abilities, many human limitations that challenge problem discovery persist in problem definition, such as bounded rationality, premature closure, and cognitive biases (Simon, 1973; Gavetti & Levinthal, 2000; Dorst, 2015). Moreover, as Simon (1955, 1956) posited, individuals, constrained by bounded rationality and limited information processing capacity, often adopt a satisficing strategy—selecting the first solution that meets an acceptable threshold rather than continuing to search for an optimal one. This approach extends to problem definition, where individuals may settle for the first problem definitions or "good enough" problem formulations, calibrated against well-known variables such as the costs of problem identification and the expected benefits of problem resolution (Nickerson and Zenger, 2004).

Theories of bounded rationality further suggest that decision-making is shaped not only by cognitive limitations but also by biases stemming from individual backgrounds, experiences, personalities, education, and access to information (Sobolev, 2022). Moreover, individuals' ability to gather, interpret, and synthesize information is inherently constrained, leading them to simplify complex situations in ways that create discrepancies between mental representations and reality (Joseph & Gaba, 2020; Simon, 1955; Simon, 1995: 114 in Joseph & Gaba, 2020). In the context of PF, such simplifications can result in oversimplified and potentially inaccurate problem definitions, causing individuals to frame challenges in ways that fail to capture their true complexity. Additionally, mental models and cognitive biases—such as narrow search framing and confirmation bias—further limit problem solvers' ability to explore alternative formulations (Garbuio & Lin, 2021).

These tendencies can be further exacerbated by certainty effect theory (Kahneman & Tversky, 1979), which suggests that individuals undervalue uncertain outcomes compared to those perceived as certain. As a result, when defining problems, individuals may prefer familiar, well-structured problem frames that offer a clear path to resolution rather than exploring more ambiguous or novel problem formulations that might yield higher-value solutions but carry greater uncertainty. In other words, individuals may default to problems they know they can solve rather than risk defining problems they are uncertain how to approach.

In the above analysis, utilizing our cognitive-behavioral lens, we identified key cognitive and behavioral dimensions that shape both problem discovery and problem definition. The cognitive dimension encompasses bounded rationality (Simon, 1947, 1955; Joseph & Gaba, 2020), sensemaking (Verganti et al., 2020), and creativity (Abdulla et al., 2020; Dillon, 1982; Reiter-Palmon et al., 1997; Reiter-Palmon, 2011). The behavioral dimension includes satisficing (Simon, 1955, 1956) and uncertainty avoidance (Kahneman & Tversky, 1979), which influence how problems are framed and refined. These constructs help clarify how and where LLMs can support human problem finding, as well as their inherent limitations, highlighting the need for structured human-LLM collaboration. This discussion leads to our proposed framework for integrating LLMs into PF for less structured problems.

A cognitive-behavioral lens to LLMs role in problem finding

Cognitive dimension in problem finding & LLMs

Bounded rationality

Studies conducted before the recent widespread adoption of LLMs had already demonstrated how traditional AI supports problem discovery by mitigating human cognitive limitations, expanding the depth and breadth of the search field, and enabling human innovators to focus on abductive hypothesis generation (Garbuio & Lin, 2021). Building on this, AI's ability to uncover hidden connections or correlations through exploration, sensing capabilities, and fuzzy statistical analysis for text mining can aid in PF by illuminating previously unnoticed patterns or relationships (Daniati & Utama, 2020; Giannakis et al., 2020). From a design thinking perspective, which underlies the above-mentioned innovation frameworks, AI's ability to assist in observing and interviewing for understanding customer needs, creating personalized content, deriving insights, creating personas, and capturing the full customer journey can contribute to the expansion of the problem or solution space by providing a more comprehensive understanding and mapping of customer behavior and needs (Beckman & Eriksson, 2020; Haefner et al., 2021).

Various proposals have been made as to how AI can assist in problem representation (e.g., Sarkar et al., 2009; Zamani, 2010). Liao, Hansen, and Chai (2020) show how AI can inspire designers in design-related tasks by helping them recognize the underlying pattern of design entities, engage in visual thinking, and relate attributes, all of which assist in creating logical representations. AI can further provide feedback to humans' "mental maps" or own representation of the problem (Csaszar and Steinberger, 2022). In defining the problem, Beckman and Eriksson (2020) suggest that AI can assist through pain point analysis and insights, identification of lead users, and insights to better understand and reframe the problem. In the latter case, Dorst (2015, 2019) defines problem (re)framing as an act of shifting the mental model of the problem, implying a limited role for AI (Cukier et al., 2021; Gryz, 2013; Roitblat, 2020). However, Mothersill and Boove (2018) suggest that AI can help in framing by generating hypotheses and identifying novel directions using stochastic processes and machine learning algorithms.

The introduction of LLMs has made the expansion of human bounded rationality even more tangible. Bouschery et al. (2023) argued that LLMs can foster divergent processes by creating opportunities to access and generate larger amounts of knowledge, thereby helping to explore broader problem and solution spaces. This process is illustrated through their AI-augmented double diamond framework. Additionally, they highlighted three specific examples: text summarization, sentiment analysis, and customer insight generation, to demonstrate the diverse knowledge extraction capabilities of a leading LLM (GPT-3). These capabilities were further boosted by the launch of recent reasoning models by leading companies such as OpenAI’s o-series models (OpenAI, 2024), Google’s Gemini pro models (Google, 2024), among many others (Wang et al., 2025). We demonstrate the capabilities of OpenAI’s o3 model in our hypothetical case study on a fictitious startup, TaskFlow (Section

Framework implementation in product development), where the team struggled to process and analyze the vast and diversified feedback received from its customers.

Despite these apparent advantages, one might question the extent to which LLMs can broaden our bounded rationality. Beyond their computational limitations, they appear to be further constrained by the use of heuristics (as is generally the case with AI, according to Bettis and Hu, 2018) and efficiency requirements, evident in their tendency to provide shortened answers, offer limited options when asked to provide many, or use ellipses (...) when asked to fill tables or write code. Additionally, challenges such as hallucinations seem inevitable, despite ongoing efforts to mitigate them (Christensen et al., 2024; Xu et al., 2025; OpenAI, 2023). According to Wang et al. (2025), even the above-mentioned reasoning models continue to face interpretability challenges, requiring formal verification and error detection. They further posit that neuro-symbolic frameworks—hybrid AI systems that combine neural networks' pattern recognition with symbolic reasoning—are needed for tasks involving logic, mathematics, or structured problem-solving. Moreover, broader domain adaptation is essential for multi-modal reasoning, which processes and integrates information from multiple sources such as text, images, audio, and video, to improve real-world applications.

Sensemaking

Sensemaking has been studied across various disciplines, including psychology, decision-making, organizational behavior, information seeking, and human-computer interaction (Koesten et al., 2021). However, its role in innovation remains underexplored (Verganti et al., 2020), and even less is known about how LLMs influence sensemaking and their cognitive and behavioral implications in PF. Few scholars, including Verganti et al. (2020) and Leavitt (1975a, 1975b), have explicitly examined PF as an activity of meaning-making or sensemaking.

When reviewing the literature on sensemaking, we identify both advantages and limitations of integrating AI in general—and LLMs in particular—into this process. Sensemaking consists of both descriptive and constructive features (Weick et al., 2005). The descriptive aspects focus on information gathering and processing, where LLMs excel. Similarly, Koesten et al. (2021) highlight data-centric sensemaking activities, including inspecting data, engaging with content, and contextualizing information within broader frameworks. Recent studies suggest that while LLMs can support complex tasks, their linear conversational interfaces—where interactions unfold sequentially in a text-based format—limit their effectiveness in non-linear PS, which requires organizing and manipulating information dynamically rather than step by step (Suh et al., 2023). This limitation is particularly evident in tasks that involve spatially organizing information, where users must visually structure, compare, and analyze data across multiple dimensions instead of following a rigid, sequential flow. To address this, Suh et al. (2023) developed an interactive system that enhances LLM capabilities for handling complex, non-linear information tasks. This limitation is also relevant in PF for less structured problems, where information related to the problem is not concentrated in a single source but is instead widely dispersed among various stakeholders (Baer et al., 2013).

Moreover, the constructive dimension of sensemaking, particularly the role of individual and social constructivism (Schwarz, 2014) in interpreting weak signals, presents further challenges for LLMs. Less structured problems are not simply waiting to be discovered; rather, they are actively shaped by personal and collective cognitive frameworks (Schwarz, 2014). This process involves subjective interpretations, evolving perspectives, and social interactions, which LLMs could struggle to fully grasp. While existing research has explored AI's impact on individual cognitive conceptualization (e.g., Bouschery et al., 2023; Garbuio & Lin, 2021), its influence on social constructivism remains largely unexamined.

Given these insights, LLMs appear well-suited for the descriptive aspects of sensemaking, which align closely with problem discovery as they involve data inspection, content engagement, and contextual placement. However, their role in the constructive aspects—linked to problem definition—remains more challenging due to the need for subjective interpretation and social interaction. Further research is required to understand the role of LLMs in sensemaking withing this stage of PF.

Creativity

Creativity is commonly defined as the generation of novel and useful outcomes (Hennessey & Amabile, 2010; Metwaly et al., 2017; Runco, 2004). A longstanding debate exists regarding whether traditional AI can be considered truly creative. Some scholars argue that AI can exhibit all three recognized forms of creativity: combinational (producing unique combinations of familiar concepts), exploratory (generating novel ideas through structured conceptual exploration), and transformational (modifying dimensions of conceptual space to produce previously unattainable structures) (Boden, 1998, 2009). However, discussions about AI's "creativity" often extend into philosophical territory, raising questions about intentionality, evaluation, and shifting cultural perceptions (Boden, 1998). In contrast, other scholars contend that AI merely draws from historical data, replicates existing patterns rather than producing genuinely original creative thought (Wingström et al., 2022).

The introduction of LLMs has led scholars to formally assess their creative capacities using established measures such as the Alternate Uses Test (AUT) and the Torrance Tests for Creative Thinking (TTCT) (Haase & Hanel, 2023). Comparative studies have evaluated LLM-generated creativity against human creativity, with findings suggesting that recent models, such as GPT-4 and Gemini, can produce outputs that rival or even surpass those of the average human (Guzik et al., 2023; Girotra et al., 2023). Notably, their augmentative potential in enhancing human creativity has also been highlighted (Doshi & Hauser, 2023;

Eapen et al., 2023; Jia et al., 2023; Lyu et al., 2023; Wan et al., 2023). However, other studies have questioned the extent of their creative abilities (Noy & Zhang, 2023; Peng et al., 2023), raising concerns that they may lead to more homogeneous ideas rather than fostering true creative diversity (Dell'Acqua et al., 2023; Doshi et al., 2023). Feling and Holweg (2024) illustrate that AI relies on a probability-based approach to knowledge, making it predominantly retrospective and imitative, whereas human cognition is inherently forward-looking and capable of producing genuine novelty. Additionally, recent research underscores the necessity of preserving human ingenuity and creativity in augmented collaboration scenarios (Orwig et al., 2024).

These insights suggest that LLMs have a limited capacity for generating genuinely creative problem definitions, particularly when compared to the well-documented creative abilities of humans (Abdulla et al., 2020; Dillon, 1982; Obieke et al., 2020; Reiter-Palmon et al., 1997; Reiter-Palmon, 2011).

Behavioral dimension in problem finding & LLMs

Satisficing & uncertainty avoidance

Will LLMs influence the human tendency to settle for the first problem definitions or "good enough" problem framings? Satisficing, as previously discussed, occurs when individuals select an acceptable rather than optimal problem framing due to bounded rationality (Simon, 1955, 1956). Bettis and Hu (2018) argue that traditional AI primarily employs heuristics, particularly search heuristics, rather than true optimization strategies, which may limit its effectiveness in improving problem definition. Similarly, Joseph and Gaba (2020) caution that while AI can process large amounts of information, attempts to assimilate too much data could paradoxically narrow focus due to cognitive overload. Conversely, Nauhaus et al. (2021) suggest that increased information availability enhances senior managers' decision-making, particularly in resource allocation across strategic business units. In the same vein, in the PS context, Elgendy et al. (2022) claim that AI can help humans transition from satisficing behaviors to optimizing or near-optimizing.

LLMs introduce new opportunities in this space. Their ability to analyze extensive datasets and detect hidden patterns can expand the problem space, enabling organizations to identify overlooked or emerging issues (Bouschery et al., 2023).

Will this mitigation contribute to reducing uncertainty avoidance as well? Individuals and organizations, as previously discussed, often favor well-structured, familiar problem definitions, as they offer greater predictability and perceived control (Kahneman & Tversky, 1979; Nickerson & Zenger, 2004). This tendency can limit innovation, as problem solvers may hesitate to explore novel or ambiguous problem framings that introduce greater risk. This is where LLMs' capabilities can help address such uncertainties. With their ability to scan vast amounts of data, detect early signals, and identify trends, organizations can anticipate potential yet ambiguous problems rather than reactively addressing them (Joseph & Gaba, 2020). This proactive stance encourages a more exploratory and innovative approach, breaking away from the constraints of short-term reactive thinking (Joseph & Gaba, 2020).

Ilagan et al. (2024) further demonstrate how LLMs, such as ChatGPT, can function as simulation tools for customer development in technology startups. Given that LLMs are trained on extensive human-generated data, they inherently encode latent social knowledge, allowing them to approximate human interactions (Brand et al., 2023). As such, LLMs may extend their role beyond being mere assistants to acting as simulators of human behavior, offering virtual testing environments to validate assumptions about problem definitions and framings while reducing uncertainty and risks. These simulations do not replace feedback from real customers but serve as quick and cost-effective approximations that help mitigate uncertainty (Ilagan et al., 2024), making them particularly valuable for early-stage ventures and startups. These capabilities actually expand the scope of the second step of problem definition as detailed in the next section.

In sum, while LLMs can help humans overcome bounded rationality, enhance sensemaking and creativity, and positively influence satisficing and uncertainty avoidance behaviors, their inherent limitations—along with the necessity of preserving human contribution and ingenuity—justify the need for a structured framework for human-LLM collaboration in PF in less defined problems. This framework is presented in the following section.

The Augmented Problem-Finding framework

We propose an innovative framework, the Augmented Problem-Finding framework (Figure 1), which emphasizes the continuous and dynamic collaboration between humans and LLMs in PF for less structured problems. This framework aligns with the two-step approach to PF—problem discovery and problem definition—delineating the previously identified sub-steps. Additionally, it introduces an extra sub-step to problem definition: running simulations, such as modeling human behaviors and interactions—to validate the problem definition and reduce uncertainty, as previously discussed (Brand et al., 2023; Ilagan et al., 2024).

"Figure 1 about here"

At the core of this framework is a structured and cooperative humans-LLMs relationship, where humans and LLMs collaborate to leverage their respective strengths while compensating for each other's limitations (Huang & Rust, 2022). This approach aligns with recent studies on human-LLM collaboration (e.g., Boussioux et al., 2024; Bouschery et al., 2024; Dell'Acqua et al., 2023; Ameen et al., 2024; Mollick, 2024), which emphasize moving beyond the traditional division of tasks based solely on individual strengths (Choudhary et al., 2023).

For instance, in problem-solving contexts, Boussioux et al. (2024) demonstrate that while human-only solutions tend to exhibit higher novelty, human-LLM solutions perform better in terms of strategic viability, financial and environmental value, and overall quality. Their findings further suggest that structured human-LLM collaboration—where human-guided prompts instruct the LLM to iteratively generate distinct outputs in each cycle—outperforms solutions generated through independent searches. Similarly, Bouschery et al. (2024) show that in brainstorming sessions, hybrid human-LLM teams outperform human-only teams in both productivity and idea creativity. This advantage is partly attributed to the absence of production blocking (e.g., team members interrupting or overshadowing each other's ideas) and social inhibition (e.g., hesitancy to share ideas in a group setting), both of which are common limitations in human-only brainstorming sessions.

Additionally, our framework builds upon the Human-in-the-Loop concept (Liang et al., 2017) and extends the historical collaborative interaction between AI and Operations Research (OR) proposed by Simon (1987). Prior literature has introduced various notions of collaborative interaction, where humans and traditional AI engage in mutual learning through active learning (Vocke & Bauer, 2020), coupled and vicarious learning (Puranam, 2020), and joint decision-making efforts (Vincent, 2021).

Our use of the terms *humans* and *LLMs* in the framework indicates that either a single human or multiple humans, along with one or multiple LLMs, may be involved in the process. Moreover, the term *Augmented* refers not only to the integration of LLMs but also to the expanded scope of problem finding, particularly problem definition, which now extends to running simulations to test the problem definition before transitioning to solution ideation.

Despite the promising aspects of human-LLM collaboration, recent studies also highlight potential downsides that warrant careful consideration. Eisenreich et al. (2024) caution that while LLM-generated solutions can introduce novelty, this may come at the expense of feasibility. Additionally, their involvement in the ideation process may diminish human creativity and intrinsic motivation. Similarly, Lee et al. (2025) find that among knowledge workers using GenAI, greater confidence in GenAI correlates with reduced critical thinking, whereas higher self-confidence is linked to enhanced critical thinking. Their findings suggest that GenAI reshapes critical thinking by shifting emphasis toward information validation, response synthesis, and task oversight, rather than fostering deeper problem exploration. These concerns align with prior research warning against over-reliance on AI across various domains, including decision-making (Keding & Meissner, 2021) and ideation (Dell'Acqua et al., 2023).

Beyond these shifts, additional concerns arise from the inherent biases in LLMs. Rajesh et al. (2024) highlight that these models can reinforce and even amplify societal biases embedded in their training data. Such biases may take various forms, including gender, racial, and contextual biases, potentially leading to unfair or discriminatory outcomes in real-world applications (Binns et al., 2017; Gupta et al., 2024 In Rajesh et al., 2024). This issue aligns with a growing body of research on AI biases (e.g., Arrieta et al., 2019; Cockburn et al., 2018; Mariani & Wamba, 2020; Johnk et al., 2020; Sundar, 2020; Makarius et al., 2020). In the PF context, biases in LLMs can result in problem definitions that reflect skewed perspectives or fail to identify critical issues, leading to wasted time, misallocated resources, and missed opportunities (Archibald, 2020; Baer et al., 2013). An example of how LLMs may reinforce historical biases due to limitations in training data is further explored in section *Framework implementation in social innovation.*

Finally, key issues outlined in our discussion on *Bounded rationality*—such as reliance on heuristics (Bettis & Hu, 2018), the prevalence of hallucinations (Christensen et al., 2024; Xu et al., 2025; OpenAI, 2023), and the need for formal verification and error detection through neuro-symbolic frameworks (Wang et al., 2025)—must also be addressed. These challenges underscore the necessity of structured human oversight, as exemplified in our proposed framework.

Framework implementation in product development

Within the context of technology innovation, we apply our Augmented Problem-Finding framework to a fictitious startup called TaskFlow, which has developed a mobile productivity application called Beams. This application is designed to help users organize their daily tasks and collaborate with colleagues in real time. Over the past quarter, TaskFlow's user engagement has steadily declined.

Below is a detailed step-by-step scenario illustrating how TaskFlow's team may leverage an LLM, such as OpenAI's o3-mini model, to assist in problem discovery and problem definition within our proposed framework.

Step 1 – Problem discovery

1(a) o3-mini:

- Role: o3-mini conducts a comprehensive scan and analysis of the obtained customers feedback on social media.
- Bounded Rationality: o3-mini extends the team's bounded rationality by processing vast amount of customer feedback and datasets beyond human capabilities.

1(b) TaskFlow's Team:

- Role: Taskflow's team make independent study on the market to learn the competitive landscape in this field. They then feed this information to o3-mini and request a summarized list of potential challenges.

2(a) o3-mini:

- Role: o3-mini analyzes the data to identify hidden trends or patterns and produces a list of 10 representative pieces of customer feedback, attached as Appendix A-1.

- It further flags the following three potential challenges:
    (1) Interface overload: The interface is perceived as overly cluttered, potentially causing cognitive overload and detracting from usability.
    (2) Insufficient personalization: Users experience a lack of personalized and adaptive features, limiting the app's effectiveness in addressing diverse and evolving workflows.
    (3) Fragmented integration: There is a notable deficiency in seamless integration with other productivity tools, which disrupts workflow continuity and diminishes overall efficiency.

2(b) TaskFlow's Team:

- Role: Recognizing that they are facing a genuine problem worth addressing, the team engages with o3-mini regarding the first identified challenge and explores it further.
- Bounded Rationality / Satisficing: The selection of the first challenge identified by o3-mini may signal bounded rationality that led to a satisficing behavior or settling for a 'good enough' problem by the team.

Step 2 – Problem definition

3(a) o3-mini:

- Role: o3-mini suggests framing the first challenges as a clutter frame: "The clutter frame views the problem as an overly busy interface, where too many visual elements crowd the screen, overwhelming users and making it difficult to identify key functionalities quickly."

3(b) TaskFlow's Team:

- Role: The team asks o3-mini to reframe the problem.
- Reframing: After a few iterations with o3-mini, the team realizes that a more suitable frame is cognitive load. This means that "instead of solely focusing on reducing visual

elements, the goal is to realign the information architecture so that it naturally guides users through a coherent and adaptive workflow, thereby minimizing cognitive strain and enhancing usability."

- Role: The team also asks o3-mini to frame the next most important challenge. o3-mini produces the following frame: "failure to deliver a unified digital ecosystem that forces users to manually reconcile data, thereby disrupting workflow continuity and efficiency."

4(b) TaskFlow's Team:

- Role: Given their limited resources and budget, and to reduce uncertainty regarding which problem framing to prioritize, the team seeks customer perceptions of the problem (Blank & Dorf, 2015) and runs a simulation using o3-mini, following the four-step approach outlined by Ilagan et al. (2024). First, they ask o3-mini to create personas of 30 professionals from diverse roles and backgrounds, representing typical users of the Beams app. Second, they provide the scenario, coupled with the personas, to o3-mini and request the simulation (detailed in Appendix A-3). Third, they run the simulation through o3-mini. Fourth, they analyze the rationale behind the behavior observed in the simulation.
- Judgement and critical thinking: The team exercises its judgment to determine the acceptable level of risk or uncertainty and selects the final problem frame. After reviewing the simulation results, they validate the logic behind the simulated behavior, decide to accept the frame of a unified digital ecosystem, and move to the ideation stage to determine the appropriate solution.

4(a) o3-mini:

- Role: Under TaskFlow's team guidance, o3-mini creates 30 personas of typical users—professionals from various industries and diverse backgrounds—to simulate their interaction with the newly framed problems and prioritize them. These personas are captured in Appendix A-2.

- Simulation: It then runs a simulation based on the scenario provided by the team and produces the following conclusion: “Based on the simulated feedback from the varied personas, the unified digital ecosystem frame appears to be the priority for TaskFlow’s Beams application.”

Framework implementation in social innovation

In the context of social innovation, we evaluated o3-mini's ability to reframe the well-known issue of violence in Kings Cross, Sydney, as analyzed in Dorst's (2015, 2019) work. In response to our prompt detailing the problem, o3-mini initially framed the issue as “complex urban dynamics.” When prompted to offer a different cognitive perspective, it generated “socio-environmental interactions.” Further request for alternative perspectives led to a “media-framing lens shaped by media narratives, political rhetoric, and societal biases.” When asked to reimagine the situation, it provided a somewhat new perspective, describing it as a “dynamic urban laboratory.” However, only when asked to conceptualize the situation as a music festival did it produce the following response, closely resembling the ultimate approach adopted by authorities in Kings Cross using that same frame: “A music festival invites a reconfiguration of the space from a static urban zone into a dynamic, event-like environment where vibrancy, temporality, and deliberate management play central roles…”. The complete prompts and responses are documented in Appendix A-4.

This example illustrates that while advanced reasoning models like o3-mini can generate alternative perspectives, as outlined in step 3(a) of our framework, their creative input remains largely confined to conventional approaches, such as social perspectives and urban planning. The introduction of the human-framed concept of a music festival was pivotal in prompting o3-mini to adopt an event management perspective, which ultimately aligned more closely with the real-world intervention. However, the final resolution of the Kings Cross case involved a comprehensive set of measures beyond o3-mini's suggestions, integrating aspects such as transportation, public infrastructure, and entertainment offerings.

In sum, both cases emphasize the necessity of humans-LLMs collaboration in iteratively engaging with problem discovery and definition in less structured problems which could lead to more effective and creative solutions. The next section builds on these insights by formulating research propositions to further explore the implications of structured human-LLM collaboration in both theory and practice.

Managing problem-finding in the era of GenAI: research propositions and implications for practice

As our findings and prior research suggest, the rise of GenAI in general, and LLMs in particular, is expected to reshape how organizations engage in PF for less structured problems. To fully leverage the opportunities presented by LLMs, companies must reassess, refine, and adapt their early-stage innovation management practices related to PF.

(1) Our findings underscore the strategic importance of addressing the right problems (Archibald, 2020; Baer et al., 2013) and highlight the need for structured human-LLM collaboration in PF for less structured problems. Specifically, LLMs are particularly valuable in problem discovery and problem definition, where they can surface patterns, uncover hidden connections, generate alternative framings, and run simulations. By integrating the cognitive and behavioral strengths of both humans and LLMs, this approach enhances problem discovery and definition, leading to a deeper understanding of complex challenges. In turn, this fosters more creative and innovative solutions (Reiter-Palmon & Robinson, 2009), strengthening an organization's innovation capability and driving improved performance (Crossan & Apaydin, 2010).

Proposition 1. Humans-LLMs collaboration in problem-finding for less structured problems will foster more creative solutions and drive innovation, ultimately enhancing organizational performance.

(2) Using the resource-based view (Wernerfelt, 1984), Krakowski et al. (2022) argued that businesses can gain a competitive advantage by developing augmentation capabilities that both complement and substitute their conventional domain-specific expertise. Likewise, Makarius et al. (2020) posited that the combination of AI technology and human capabilities within organizations fosters sociotechnical capital, which serves as a source of competitive advantage. Sociotechnical capital is defined as the 'productive combinations of social relations and information and communication technology' (Resnick 2001 In Makarius et al., 2020). Similarly, we posit that in the GenAI era, the ability to systematically discover and define the right problems will become an increasingly critical source of competitive advantage. As Simon (1973) noted, problem structuring is often more consequential than PF itself, particularly in complex environments where the way a problem is framed determines the range of viable solutions. Our findings suggest that companies that strategically integrate LLMs into their PF workflows can gain a competitive edge by uncovering latent market opportunities, reframing challenges, and driving early-stage innovation. However, this advantage is not static; it requires continuous refinement. Drawing on dynamic capabilities theory (Teece et al., 1997; Teece 2007), we argue that organizations that actively iterate and improve their LLMs-assisted PF processes will sustain their advantage over those that rely solely on traditional, human-driven approaches. By embedding LLMs into adaptive, evolving workflows, companies can enhance their ability to identify and respond to emerging challenges with greater responsiveness and insight.

Proposition 2. In the era of GenAI, the ability to systematically engage in problem-finding for less structured problems will emerge as a distinct source of competitive advantage.

(3) As LLMs become more integrated into problem-finding workflows for less structured problems, organizations must prioritize workforce training to develop essential skills in prompting, critical judgment, ingenuity, and creativity to mitigate potential negative effects (Lee et al., 2025; Eisenreich et al., 2024). Research indicates that prompting is an emerging skill that requires deliberate learning (Oppenlaender et al., 2023), with evidence showing that proficiency in crafting high-quality prompts directly impacts the effectiveness of GenAI outputs (Knoth et al., 2024). Moreover, prompt engineering is not merely a technical skill but a creative process that demands a deep understanding of GenAI's capabilities to optimize performance (Bozkurt, 2024). Beyond prompting, building AI literacy among employees is essential to ensuring they understand both the capabilities and limitations of LLMs, including risks such as hallucinations, biases, and overgeneralizations, as previously outlined (Christensen et al., 2024; Xu et al., 2025; OpenAI, 2023). Employees must be trained not only to interpret LLM-generated insights critically but also to recognize when human intuition and domain expertise should take precedence (Jarrahi, 2018; Lebovitz et al., 2022). As demonstrated in our case studies, while LLMs can surface patterns and suggest potential problem definitions, human teams must critically assess, contextualize, and refine these outputs to ensure relevance and originality (Orwig et al., 2024). To further strengthen AI-augmented problem-finding, structured training programs should focus on enhancing employees' cognitive abilities essential for creativity, such as sensemaking (Verganti et al., 2020), reframing (Dorst, 2015, 2019), divergent thinking (Reiter-Palmon et al., 1997), and associative thinking—the

ability to connect seemingly unrelated concepts (Seelig, 2012). To fully leverage the potential of LLM-assisted PF, organizations should treat workforce training as a strategic priority, allocating dedicated budgets and resources to ensure effective implementation.

Proposition 3. In the era of GenAI, it is a strategic priority for organizations to train employees in prompting, critical thinking, and creativity to optimize LLM-assisted problem finding and maximize innovation.

(4) The integration of LLMs into PF for less structured problems, particularly in mapping multi-modal data to understand and define discovered problems, presents significant governance and security challenges. Key concerns include safeguarding proprietary data, mitigating model biases (OpenAI, 2023; Sobolev, 2022; Rajesh et al., 2024), ensuring accountability in decision-making (von Krogh, 2018; Shrestha et al., 2019), and implementing stringent data security measures (Markova et al., 2024; Sagi, 2024). To mitigate these risks, organizations can enhance data security and compliance by adopting customized LLMs from enterprise AI providers, such as Microsoft Copilot or OpenAI's enterprise solutions, deploying proprietary fine-tuned models, or implementing LLMs via API access rather than relying on publicly available models that may log user inputs. These approaches enable employees to leverage LLMs for PF while protecting proprietary information from external exposure, aligning with best practices in AI governance (Markova et al., 2024; Sagi, 2024). Ensuring the reliability of LLM-generated insights is equally crucial. Proposals for incorporating formal verification and error detection through neuro-symbolic frameworks (Wang et al., 2025) warrant further exploration to address the risks of biased outputs and hallucinations. Given these challenges, organizations must develop

or extend comprehensive AI governance frameworks that explicitly define the role and limitations of LLMs in PF for less structured problems. Establishing such frameworks will be essential for ensuring both ethical and effective deployment while maintaining human oversight and accountability.

Proposition 4. Establishing or extending robust governance, security, and ethical guidelines for LLM-assisted problem finding in less structured problems is crucial for responsible and effective deployment.

(5) The successful adoption of LLMs in PF depends not only on their technical and cognitive capabilities but also on employee perception, motivation, and trust in these tools. Prior research suggests that workers may see LLMs as either an enabler or a threat, largely depending on how its integration is managed (Bullock & Kim, 2020; Eisenreich et al., 2024). Employees may resist LLMs adoption due to concerns about job displacement (Sundar, 2020) or a diminished sense of ownership over their work (Saifer & Dacin, 2022). If not carefully implemented, LLM-assisted workflows could lead to reduced engagement and increased skepticism (Bullock & Kim, 2020) rather than enhanced productivity and innovation. Similarly, if humans experience a lack of agency, autonomy, or control, their aversion or avoidance of AI may intensify (Freisenger et al., 2022). To mitigate these risks, organizations should design humans-LLMs collaboration models that position LLMs as augmentation tools rather than replacements, aligning with our proposed framework. Fostering a workplace culture where LLMs support rather than undermine employee agency will be critical in ensuring both motivation and trust in LLMs-assisted PF.

Proposition 5. Employee engagement and trust in LLM-assisted problem finding for less structured problems depend on how effectively organizations balance human-LLM collaboration, maintaining motivation, agency, and trust rather than fostering aversion or avoidance stemming from concerns over job displacement.

Conclusion

Responding to the growing need to understand the implications of LLMs in early-stage innovation processes, this study explores their role in PF for less structured problems. We examine how LLMs influence problem discovery and definition by reviewing relevant literature and applying a cognitive-behavioral lens. Building on this, we develop a structured framework for humans-LLMs collaboration in PF, identifying both its advantages and limitations. To illustrate its practical application, we present two case studies—one in product development and another in social innovation. Finally, we summarize our key insights as research propositions, outlining their strategic and operational implications for organizations aiming to integrate LLMs into their innovation workflows.

This conceptual study makes three key contributions. First, it synthesizes diverse literature on PF across management, design-thinking-based innovation frameworks, bounded rationality, and LLMs, expanding the theoretical foundation for understanding PF in less structured problems. By integrating these perspectives, we bridge the gap between traditional PF approaches and the emerging role of LLMs, offering a more comprehensive view of how organizations can leverage LLMs to enhance innovation. Second, we introduce a cognitive-behavioral lens to examine LLMs' role in PF, presenting a conceptual framework for structured human-LLM collaboration. This framework highlights how LLMs can support problem discovery and definition by augmenting human cognitive and behavioral strengths rather than replacing them. Additionally, we address key limitations, including biases, hallucinations, and the risk of over-reliance, underscoring the need for organizations to implement safeguards when integrating LLMs into PF workflows.

Third, given that PF remains an underexplored area (Lyles, 1981; Dillon, 1982; Büyükdamgaci, 2003; Baer et al., 2013)—particularly in the context of GenAI—our conceptual approach and research propositions provide novel insights that can inspire future research on human-LLM collaboration in PF for less structured problems. By positioning PF as a critical yet overlooked component of GenAI-augmented innovation, this study lays the groundwork for further theoretical and empirical exploration.

Limitations and future research

Our study has certain limitations that should be acknowledged. Firstly, while we have focused primarily on the role of LLMs in PF for less structured problems, we recognize that other factors, such as organisational culture, leadership style, and the rapidly evolving nature of AI technology, may also significantly influence the process. Future research could explore the interplay between these factors and LLMs in the context of PF, particularly how changing their capabilities may affect the applicability of our findings over time. Additionally, it could examine whether general LLMs or more specialized models are more effective and the advantages of using retrieval-augmented generation (RAG) to train these models on organization-specific data. Secondly, our framework is conceptual in nature and relies on anecdotal examples for illustration. Further empirical research, across diverse industries and organisational contexts, is needed to validate and refine the framework using real-world data. This would provide a more robust understanding of its effectiveness and potential impact on innovation management processes.

Thirdly, the paper assumes an ideal state of collaboration between humans and AI, which may not always be feasible or desirable in practice. Whilst we flagged issues such as data privacy, ethical considerations, and the potential for LLMs to constrain human creativity and motivation if their outputs are taken at face value without further exploration (Eisenreich et al., 2024), future studies are needed on these issues.

For scholars, there are several avenues for further research. Investigating the effects of LLMs on a wider range of cognitive processes such as intuition, judgment, and decision-making under uncertainty in the PF for less structured problems would contribute to a deeper understanding of AI's influence on innovation processes. Longitudinal studies to observe the long-term effects and sustainability of LLMs integration in PF for less structured problems are also crucial. Furthermore, empirical studies are necessary to optimize the proposed framework, considering the key factors and challenges outlined. This research should explore how the framework affects the efficiency and quality of the PF process and the overall innovation management processes over time. A comparative analysis of the performance between human-only and LLMs-assisted PF processes would provide valuable insights into the advantages and limitations of each approach. Additionally, exploring how LLMs integration in PF processes might influence or be influenced by organisational culture can provide insights into the readiness of employees to embrace AI-driven changes. Lastly, examining the relationship between LLMs and individuals versus teams, as well as whether single or multiple LLMs should be used, would offer valuable insights.

By conducting such studies, we can enhance our understanding of the effective utilization of human-LLMs collaboration in PF for less structured problems and its impact on organisational outcomes, helping organisations to adapt and thrive in the dynamic landscape of modern business.

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Declaration of interest

The authors of this paper declare that there are no conflicts of interest regarding the publication of this work. This research was conducted independently and impartially, with no specific external funding or financial support that could have influenced its outcomes. The authors affirm that they have no financial, personal, or professional interests that could be construed to have influenced the research presented in this paper.

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Appendix A-1

(1) Several users indicate that the current visual layout is overly busy, hindering their ability to quickly identify and focus on key functionalities.
(2) Some early adopters observe that although the design appears modern, its complexity contributes to a steep learning curve for new or less experienced users.
(3) Multiple users report that the arrangement of interface elements requires additional cognitive effort to navigate, thereby detracting from overall task efficiency.
(4) There is feedback suggesting that the plethora of on-screen options disrupts a streamlined workflow, leading to difficulties in locating critical features.
(5) Numerous users express frustration with the app's limited synchronization capabilities, particularly when integrating with external calendars, which raises concerns about data reliability.
(6) Several users note that the application’s connectivity with other productivity tools is inconsistent, resulting in a fragmented digital ecosystem.
(7) Feedback highlights that the app often operates in isolation from complementary platforms, necessitating manual efforts to consolidate information across different systems.
(8) A recurring observation is that the lack of seamless integration forces users to juggle multiple tools, thereby undermining overall workflow efficiency.
(9) Some users feel that the application does not adequately adapt to their individual work patterns, missing opportunities for tailored experiences.
(10) A subset of feedback reveals that the absence of predictive personalization features prevents the app from offering timely, context-aware shortcuts that could enhance productivity.

Appendix A-2

Executives & Senior Managers

(1) James Thompson (52, Male) – CEO, Technology Industry
Background: MBA, 25 years in leadership. Believes innovation is crucial but struggles to foster open collaboration. Prefers structured innovation programs.
(2) Sophie Chan (48, Female) – HR Director, Financial Services
Background: Master's in HR, 20 years of experience. Values knowledge-sharing but finds traditional suggestion boxes ineffective.
(3) Raj Patel (50, Male) – Chief Innovation Officer, Manufacturing
Background: Engineering degree, 25 years in R&D. Advocates for structured ideation workshops but sees resistance to digital collaboration tools.
(4) Helen Garcia (45, Female) – VP of Product Development, Consumer Goods
Background: Marketing & Business Strategy, 18 years of experience. Supports cross-team collaboration but finds idea-sharing remains siloed.
(5) William Edwards (55, Male) – Director of IT, Healthcare
Background: MSc in IT, 30 years in healthcare tech. Encourages digital transformation but believes employees hesitate to use new tools.

Middle Management & Team Leaders

(6) Liam Baker (40, Male) – Marketing Manager, Retail
Background: Business degree, 15 years in brand management. Feels employees lack a platform to contribute fresh ideas across departments.
(7) Isabelle Laurent (38, Female) – Engineering Manager, Aerospace

Background: PhD in Mechanical Engineering, 12 years in aerospace innovation. Sees a disconnect between R&D and frontline engineers.

(8) Mohammed Yusuf (42, Male) – Operations Lead, Logistics

Background: MSc in Supply Chain, 18 years in logistics. Sees daily inefficiencies but lacks a structured system for workers to share process improvements.

(9) Emily Tran (37, Female) – Head of Learning & Development, Hospitality

Background: MSc in Education, 14 years in HR training. Wants a knowledge-sharing system but struggles with employee engagement.

(10) David Cohen (43, Male) – Creative Director, Advertising

Background: Fine Arts degree, 20 years in creative industries. Believes idea-sharing happens informally but lacks structured documentation.

Specialists & Knowledge Workers

(11) Carlos Mendes (35, Male) – Software Engineer, FinTech

Background: MSc in Computer Science, 10 years coding. Finds idea-sharing limited to teams and not across departments.

(12) Anna Volkova (32, Female) – UX Designer, E-Commerce

Background: Bachelor’s in Graphic Design, 8 years in UX. Wants a space to share small UX improvements without bureaucracy.

(13) Jacob Matthews (36, Male) – Data Analyst, Pharmaceuticals

Background: MSc in Data Science, 12 years in analytics. Prefers structured feedback loops but finds leadership slow to adopt ideas.

(14) Sara O’Connor (29, Female) – Sustainability Specialist, Energy Sector

Background: MSc in Environmental Science, 6 years in energy consultancy. Wants a space to collaborate on green initiatives.

(15) Javier Lopez (34, Male) – Mechanical Engineer, Automotive

Background: BEng in Mechanical Engineering, 9 years in design. Frustrated that manufacturing teams don’t share process innovations.

Frontline & Customer-Facing Employees

(16) Mia Robinson (27, Female) – Customer Support Representative, SaaS

Background: Bachelor's in Communications, 5 years in customer service. Feels insights from customers rarely reach decision-makers.

(17) Kevin White (30, Male) – Sales Executive, Consumer Tech

Background: Bachelor's in Business, 7 years in tech sales. Thinks sales teams have valuable feedback but lack a proper forum.

(18) Angela Kim (26, Female) – Social Media Manager, Fashion

Background: Bachelor’s in Marketing, 4 years in digital campaigns. Wants a centralized space for creative input across global teams.

(19) Omar Hussein (31, Male) – Field Technician, Telecommunications

Background: Technical diploma, 10 years in telecoms. Often encounters real-world inefficiencies but has no way to share solutions.

(20) Natalie Brooks (33, Female) – Account Manager, B2B Services

Background: Bachelor's in Economics, 9 years in client management. Sees a gap between client needs and internal innovation efforts.

Creative & Research-Oriented Professionals

(21) Mark Zhao (28, Male) – Research Scientist, Biotech

Background: PhD in Biology, 6 years in R&D. Sees a need for cross-disciplinary idea exchange but struggles with rigid corporate structures.
(22) Lena Fischer (41, Female) – Innovation Consultant, Management Consulting
Background: MBA, 15 years in corporate strategy. Helps businesses build innovation cultures but finds internal engagement challenging.
(23) Patrick Nolan (37, Male) – Policy Analyst, Government Sector
Background: Master's in Public Policy, 12 years in regulatory affairs. Wants better tools for sharing policy ideas across agencies.
(24) Aisha Ahmed (29, Female) – Journalist, Media
Background: Bachelor's in Journalism, 7 years in investigative reporting. Struggles with cross-team collaboration in newsrooms.
(25) Tom Richardson (48, Male) – Architect, Real Estate Development
Background: M.Arch, 22 years in architecture. Wants better platforms for collaborative design discussions.

Technical & Blue-Collar Roles
(26) Bruno Silva (39, Male) – Factory Supervisor, Manufacturing
Background: Diploma in Industrial Engineering, 15 years in manufacturing. Believes workers have practical process improvement ideas but lack a forum to share them.
(27) Rachel Evans (44, Female) – Logistics Coordinator, Supply Chain
Background: Bachelor's in Business, 20 years in logistics. Thinks operational teams have great efficiency insights that aren't being captured.
(28) Samir Khan (36, Male) – Electrician, Construction
Background: Technical certification, 14 years in electrical work. Wants a space to share safety best practices across job sites.
(29) Diana Rodriguez (31, Female) – Nurse, Healthcare
Background: BSN, 8 years in hospital settings. Feels bedside nurses could contribute to process improvements but have no way to share ideas efficiently.
(30) Ethan Walsh (25, Male) – Retail Associate, Grocery Chain
Background: High school diploma, 6 years in retail. Thinks employee ideas on customer experience improvements rarely reach decision-makers.

Appendix A-3

TaskFlow team: Let's run the following simulation. A startup called TaskFlow that has developed a mobile productivity application called Beams designed to help users organize their daily tasks and collaborate with colleagues in real time. Over the past quarter, TaskFlow's user engagement has steadily declined. They have identified the following potential problem frames: 1. the goal is to realign the information architecture so that it naturally guides users through a coherent and adaptive workflow, thereby minimizing cognitive strain and enhancing usability 2. failure to deliver a unified digital ecosystem that forces users to manually reconcile data, thereby disrupting workflow continuity and efficiency Using the following personas, and given the limited budget and resources of Taskflow, let's gauge with these personas which framing should take priority and help address the decline in user engagement [provides Appendix A-2].
o3-mini: Based on the simulated feedback from the varied personas, the unified digital ecosystem frame appears to be the priority for TaskFlow's Beams application. Executives such as Raj Patel and Helen Garcia, along with middle management figures like Isabelle

Laurent and Mohammed Yusuf, have signaled that the inability to consolidate inputs from diverse departments is creating silos, which in turn disrupts workflow continuity. Frontline and technical roles—represented by Mia Robinson and Diana Rodriguez—emphasize that the current disjointed setup forces them to manually reconcile information, thereby reducing efficiency and dampening engagement. Given TaskFlow's limited budget and resources, focusing on delivering a cohesive, integrated experience should address the broad cross-sectional concerns and help revive user engagement more effectively than a sole emphasis on refining information architecture for cognitive ease.

Appendix A-4

How can you reframe this problem: The late-night problems in Kings Cross, an entertainment district in the city of Sydney, have been labelled 'alcohol-related violence' in the media and in public discourse. This statement names the important elements of the situation (a) and contains the frame (b) that safety and security should be assured by combatting violence e and that the violence is causally related to alcohol consumption.

o3-mini: One way to reframe the problem is to shift from viewing the incidents solely as "alcohol-related violence" to understanding them as manifestations of complex urban dynamics that involve a range of socio-economic, cultural, and environmental factors. Instead of focusing narrowly on alcohol consumption as the primary causal factor for violence, the issue could be conceptualized as a multifaceted public safety challenge in which alcohol plays a contributory, but not exclusive, role.

In this reframed perspective, the late-night disturbances in Kings Cross are seen as the result of interacting forces such as urban design, economic pressures, policing practices, community relationships, and broader social inequalities. This approach recognizes that while alcohol consumption may exacerbate certain behaviors, the overall pattern of violence is also shaped by structural conditions and policy environments that influence both individual and group behaviors during nighttime activities.

By broadening the frame, policy responses can be developed that go beyond targeting alcohol consumption alone, incorporating interventions aimed at improving urban planning, enhancing social services, fostering community engagement, and ensuring that law enforcement strategies are tailored to the specific dynamics of the entertainment district. This comprehensive analysis supports a more nuanced understanding of public safety that addresses the underlying causes of violence rather than attributing it to a single factor.

How can you look at this problem from a different cognitive frame or perspective?

o3-mini: Another cognitive frame is to conceptualize the issue as a problem of socio-environmental interactions rather than solely as a matter of individual behavior driven by alcohol consumption. In this view, the late-night disturbances in Kings Cross are considered within the broader context of environmental design, social networks, and community resilience. This perspective shifts attention from a reductionist cause—alcohol—to an exploration of how the spatial configuration, urban infrastructure, and socio-cultural dynamics of the entertainment district collectively contribute to behaviors that may escalate into violence.

In this reframed approach, the physical environment (e.g., lighting, public space design, and accessibility) and the temporal patterns of economic activity intersect with social dynamics, such as group behavior, collective identity, and community response. It emphasizes that violence can emerge as a byproduct of these complex interactions, where factors like inadequate urban planning, insufficient social support, and the lack of alternative late-night activities might amplify the potential for conflict.

Such a perspective encourages a multidimensional strategy for intervention—one that includes urban planning reforms, community engagement initiatives, and policy measures that address socio-economic inequities—thus moving beyond a singular focus on alcohol consumption as the cause of violence.

Can you give me another alternative perspective?

o3-mini: Another alternative perspective is to analyze the issue through a discursive and media-framing lens. In this view, the way in which late-night incidents in Kings Cross are labeled as "alcohol-related violence" is not simply a factual description of events but a construct shaped by media narratives, political rhetoric, and societal biases. This perspective emphasizes that language and discourse play crucial roles in defining what is perceived as a problem, influencing public opinion and policy responses.

By focusing on the framing process, researchers can examine how the choice of language (e.g., "alcohol-related") may obscure other contributing factors such as urban inequality, social dislocation, or even the commercial interests of local stakeholders. It encourages a critical assessment of whose interests are served by framing the problem in a particular way and how alternative narratives might highlight structural conditions like economic marginalization or the impact of urban policy on community safety.

This discursive approach shifts attention from viewing violence as an inevitable outcome of alcohol consumption to understanding it as a socially constructed phenomenon. It underscores the importance of interrogating the sources and implications of media narratives and how these narratives inform both public perception and the policy measures that are subsequently implemented.

Can you reimagine the whole situation?

o3-mini: In a reimagined scenario, Kings Cross can be conceptualized as a dynamic urban laboratory where the challenges of late-night activities are transformed into opportunities for fostering community engagement, cultural expression, and innovative urban planning. Instead of defining the situation solely through the lens of "alcohol-related violence," one might envision the area as a vibrant, multifaceted ecosystem that invites diverse nighttime economies, social interactions, and creative interventions. Here, the physical environment could be deliberately designed to promote safety and inclusivity, integrating adaptive lighting, public art installations, and flexible spaces that accommodate both leisure and community programming. Social policies would shift from punitive measures toward supportive frameworks that empower local residents, businesses, and visitors to collaboratively shape a secure yet lively public sphere. By redefining the problem in this manner, the focus moves from controlling specific behaviors to cultivating an urban milieu where the interplay between cultural vibrancy, economic opportunity, and public safety generates a resilient and self-regulating community. This reimagination encourages interdisciplinary approaches—drawing on urban studies, sociology, and public policy—to co-create environments that not only mitigate risks but also enhance the overall quality of urban life (Gehl, 2010; Jacobs, 1961).

Can you look at the situation as a musical festival and provide a perspective accordingly?

o3-mini: Viewing Kings Cross through the lens of a musical festival invites a reconfiguration of the space from a static urban zone into a dynamic, event-like environment where vibrancy, temporality, and deliberate management play central roles. In this perspective, the late-night disturbances are akin to the challenges faced by large-scale festivals, where the influx of participants, the consumption of alcohol, and the energy of the crowd require carefully orchestrated strategies to maintain safety and enhance the overall experience.

In a festival context, the physical environment is purposefully designed to manage crowd movement and encourage positive interactions. Temporary installations—ranging from designated areas for different activities to clearly marked zones for rest and refreshment—can serve as both a means of directing behavior and as symbols of a community's commitment to safety. For example, well-lit pathways, modular barriers, and strategically placed security checkpoints might be implemented not as reactive measures, but as integral components of the festival's design. Such strategies are reflective of practices in event management, where temporary infrastructure is utilized to create a controlled yet vibrant setting (Getz, 2012; Connell & Gibson, 2003).

Furthermore, the festival frame emphasizes a proactive rather than punitive approach. Instead of solely criminalizing behavior linked to alcohol consumption, organizers might integrate harm-reduction programs, real-time monitoring, and culturally resonant messaging that encourages responsible enjoyment. This model shifts the focus from problematizing individual behavior to managing the collective experience, highlighting how a well-planned, temporary environment can foster a sense of community, inclusivity, and shared responsibility.

Reimagining Kings Cross in this way also opens up opportunities for collaboration among various stakeholders, including local authorities, community groups, and event organizers. By drawing on the strategies used in successful musical festivals, interventions can be designed that not only address potential safety issues but also enhance the urban cultural experience. This perspective transforms the discourse from one of inevitable disorder to one of creative, inclusive urban management, where challenges are anticipated and addressed through innovative, temporary, yet impactful solutions (Silvers, 2013).

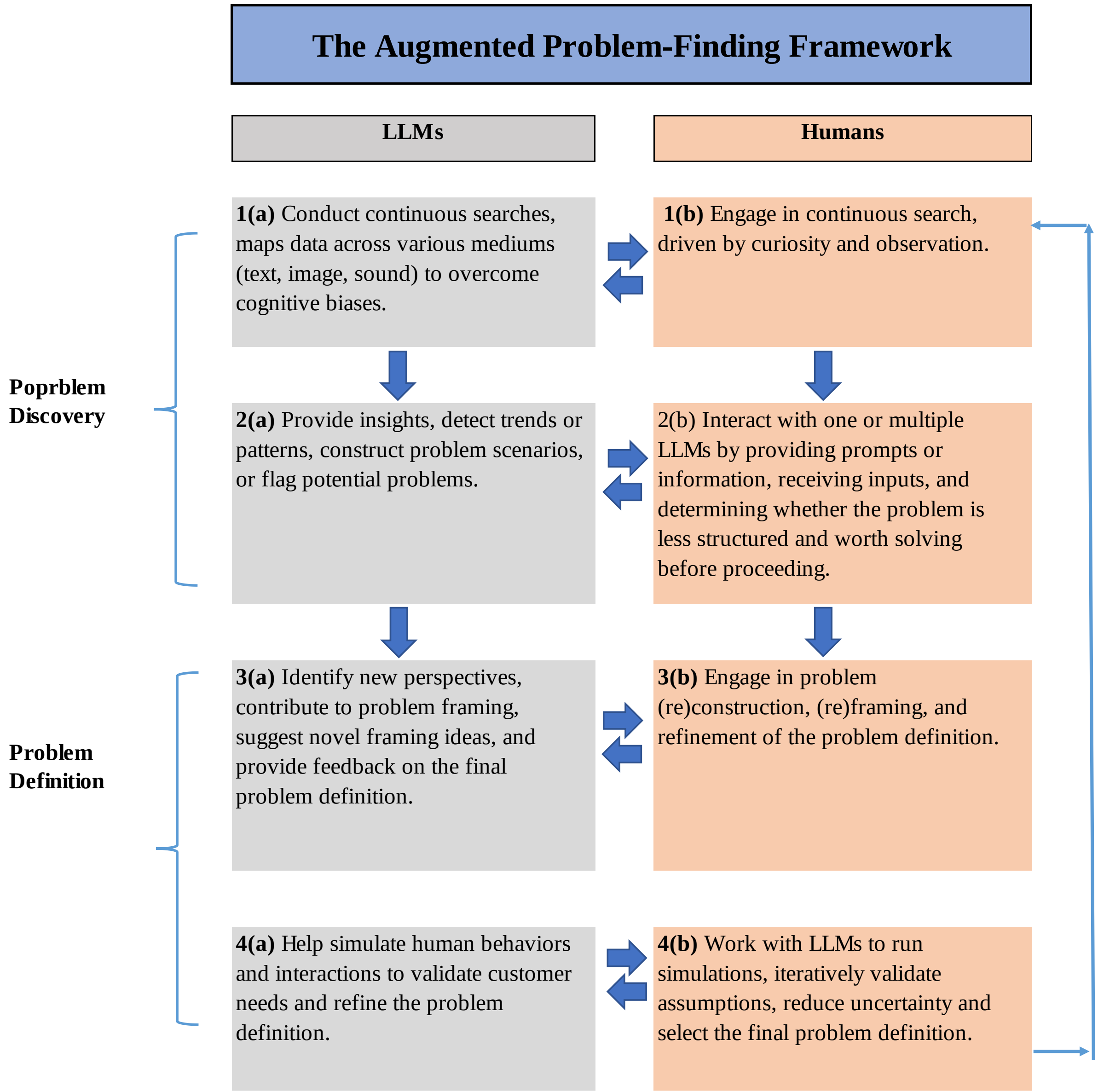
Tables

TABLE-1. Summary of numbers of steps used in problem-finding

Paper	No. of steps	Details of steps
Basadur, Ellspermann, and Evans (1994)	Two	Problem generating and formulating
Reiter-Palmon and Murugavel (2016)	Two	Problem anticipation and problem identification
Dillon (1982)	Three	Problem discovering, formulating, and posing
Sturm, Fecho, and Buxmann (2021)	Three	Problem finding -recognize, identify, and construct problems
Garbuio and Lin (2021)	Three	Problem search frame, abductive hypothesis generation, and abductive hypothesis evaluation
Abdulla and Cramond (2018)	Five	Problem discovery, formulation, construction, identification, and definition
Niederman and DeSanctis (1995)	Seven	Scanning, noting, clarification, classification, information search, inference, and problem definition

Figures

FIGURE-1 – The Augmented Problem-Finding Framework



Flowchart of a framework illustrating LLM-human collaboration in problem-finding through two steps—problem discovery and definition—each comprising two sub-steps involving various activities such as search, insights, framing, simulations, and iterative interactions.