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The Model of Innovative Challenges with the Approach of Responding to Industrial Demands

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ABSTRACT

In today's competitive markets, innovation is essential for survival and success. Companies adopt various tools to foster innovation and address their challenges—one of which is hosting innovative challenges. These events allow firms to engage with problem-solving communities to generate solutions. This study aims to explore the conditions necessary for organizing such events and to identify the key factors that influence their success in addressing industrial demands. This research employs a mixed-methods approach (qualitative–quantitative). Initially, a qualitative method was used to extract relevant factors from existing literature through content analysis, expert interviews, and open coding. Subsequently, the identified factors were screened using a quantitative approach, specifically the fuzzy Delphi method, conducted in two rounds with expert input. To develop a conceptual model comprising indices and sub-indices, exploratory factor analysis was conducted based on expert evaluations. Finally, the proposed model was validated through confirmatory factor analysis using structural equation modeling in LISREL software. The results indicate that the process of conducting innovative challenges to address industrial needs consists of four main stages: Problem Definition, Information, Evaluation, and Acquisition. Additionally, 20 critical success factors were identified as essential for organizing an effective event. Based on these findings, a comprehensive model for implementing innovative challenges was developed.

Keywords: *Innovative Challenges, Industrial Demands, Problem-Solving, Innovation, Industry.*

1. Introduction

In the past, innovation processes were primarily closed, taking place within the confines of organizational boundaries. However, companies are increasingly rethinking their approaches to innovation management (Leimeister et al., 2009). Challenging the limitations of the traditional closed model, Chesbrough (2003) introduced the concept of **open innovation**—a framework in which customers are regarded as vital contributors to innovation, and the acquisition and integration of external knowledge is central to a firm's strategy (Chesbrough, 2003; Leimeister et al., 2009). Open innovation relies on the involvement of external actors who bring diverse knowledge and perspectives, making participation in innovation communities particularly valuable (Richard et al., 2016).

One widely adopted approach to implementing open innovation is the organization of innovation challenges. These events are grounded in the concept of crowdsourcing, a key component of Chesbrough's open innovation paradigm. This paradigm promotes the use of external ideas to drive internal innovation—a process often referred to as *open input innovation* (Schemmann et al., 2016). Crowdsourcing serves not only as an open innovation strategy but also as a collaborative production mechanism (Ghezzi et al., 2017). It encourages cooperation, strengthens capabilities, and expands networks, thereby accelerating the innovation process (De Mattosa et al., 2018). The rise of the internet has significantly amplified the effectiveness of crowdsourcing by enabling the formation of large-scale contributor networks, or "crowds" (Battistella & Nonino, 2012). In fact, digital technologies now form the backbone of collective platforms and applications that support open innovation (De Mattosa et al., 2018). Research on open innovation also underscores the importance of intermediary organizations, which act as facilitators by connecting various stakeholders and addressing specific innovation needs (Foege et al., 2019). Many participants depend on these intermediaries to fully leverage the potential of open innovation (Keinz & Marhold, 2021). These innovation mediators provide essential infrastructure and a range of support services during crowdsourcing initiatives. Solvers are often granted free access to relevant content (Egger et al., 2016). Moreover, as platform owners and system architects, intermediaries shape user engagement through the design of effective platform structures (Bakici, 2020).

Based on this context, the present study seeks to address two central research questions:

1. What are the necessary conditions for successfully implementing innovation challenges?
2. What are the critical success factors in organizing such challenges?

The remainder of the article proceeds as follows: first, the foundational concepts of crowdsourcing and innovation challenges are explored in detail. Then, three case studies of innovation challenges facilitated by an intermediary organization are presented and analyzed, focusing on their implementation processes and defining characteristics.

1.1. Theoretical foundations and research background

The term crowdsourcing was first introduced by Jeff Howe in his 2006 Wired magazine article titled "The Rise of Crowdsourcing". It refers to delegating tasks—previously handled by an organization's employees—to a large, often undefined group of individuals (Howe, 2006). One of the earliest examples of this concept dates back to 1714 with the British government's "Longitude Prize" competition, offering £20,000 for a navigational solution. Another historical case is the Toyota logo design competition in 1936 (Hossain & Kauranen, 2015).

At its core, crowdsourcing is based on the principle of collective intelligence, which posits that the knowledge and creativity of a group can outperform that of individuals (Leimeister et al., 2009). This model leverages large-scale volunteer participation and applies self-organization principles to labor processes and knowledge production (De Mattosa et al., 2018). It involves harnessing the crowd's collective capability to perform tasks traditionally carried out by experts, aiming to tap into a broad pool of knowledge, creativity, and value (Howe, 2006). Essentially, it is an online method of generating information and solutions (Brabham, 2008).

Crowdsourcing has evolved rapidly (Taeihagh, 2017). It encompasses various approaches—from open innovation intermediaries to organizers of innovation challenges. Unlike outsourcing, which focuses on specific individuals, crowdsourcing is centered around engaging a broader public (Richard et al., 2016).

In this model, three main parties are involved:

1. The Challenge Sponsor – organizations with specific problems,
2. The Solvers – individuals who submit solutions via online platforms, and

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3. The Intermediaries – professional entities that manage infrastructure and provide support services (Schemmann et al., 2016).

These platforms are often accessible to users worldwide, free of charge.

Governments have also adopted crowdsourcing. In 2010, the U.S. Congress formalized its use by permitting all federal agencies to participate in challenge-based innovation programs—widely applied in NASA and DARPA projects (Ettlinger, 2017). These challenges typically last weeks or months and aim to generate ideas or solve specific problems (Schemmann et al., 2016). The success of such initiatives often depends on the intermediary's active involvement throughout all stages—from planning to promotion (Presenza et al., 2019). Well-designed platforms streamline the open innovation process (Brabham, 2008).

Crowdsourcing is especially valuable for addressing technical challenges that lie beyond an organization's internal expertise (Pollok et al., 2019). Its major advantage lies in producing numerous solutions in a short timeframe (Ozaygen & Balague, 2018), thanks to the diversity of participants (De Mattosa et al., 2018). The crowd often generates more novel and radical ideas than experts or technologically advanced users (Schemmann et al., 2016), and external contributors often offer greater originality in idea generation compared to internal staff (Keinz & Marhold, 2021).

Utilizing this model allows companies to benefit from a wider range of contributors, significantly reducing research and development (R&D) costs (Ettlinger, 2017). Additional benefits include lower production costs, improved product quality, faster access to emerging technologies, greater organizational flexibility, and increased innovation potential (Leimeister et al., 2009; Ozaygen & Balague, 2018). Studies also confirm the positive impact of crowdsourcing on organizational profitability (Richard et al., 2016).

Compared to traditional innovation models, crowdsourcing offers quicker access to knowledge at lower costs (Pollok et al., 2018). If a sponsor selects problems they are relatively knowledgeable about, crowdsourcing can yield a higher volume of quality responses (Pollok et al., 2019). This process also enhances organizational learning (Keinz & Marhold, 2021) and shortens the time to market for new products and services (Richard et al., 2016).

Professionals also benefit from crowdsourcing as a source of income and experience (Sari et al., 2019). It promotes public participation in idea generation, problem-solving, innovation, production, and service delivery—enhancing product quality, customer loyalty, and satisfaction (Schemmann et al., 2016). Other benefits include increased confidence in collaborative work, decentralized and informal communication structures, and more transparent access to information (Keinz and Marhold, 2021; Schemmann et al., 2016).

However, this approach is not without challenges. Common risks include unexpected costs, intellectual property issues, delays, inconsistent solution quality, information accuracy concerns, difficulty in population management, slow response times, and reluctance from internal R&D teams to accept external ideas (Hossain & Kauranen, 2015; Keinz & Marhold, 2021; Richard et al., 2016). Moreover, prolonged timelines to attract more submissions can frustrate solvers (Ettlinger, 2017), and such events are not suitable for problems that require immediate solutions (Mergel & Desouza, 2013). Managing large-scale participation can be complex and time-consuming, especially when dealing with thousands of contributors (Chesbrough, 2006). Therefore, successful crowdsourcing requires careful project planning, clear task definitions, and transparent result evaluation (Sari et al., 2019).

As mentioned, innovation challenges are rooted in the crowdsourcing model. Their primary goal is to generate innovative solutions for organizational needs. Similar to crowdsourcing, there are no strict limitations on the types of problems addressed or the nature of contributions received. Accordingly, based on insights from interviewees in this study, the focus is placed on refining and enhancing the use of innovation challenges.

1.2. Research Background

In this section, previous studies related to the topic of the "model of innovation challenges with a demand-driven industrial approach" have been reviewed. Using a content analysis approach, the factors influencing the performance of innovation intermediaries in responding to industrial needs and their role in the successful development of new products have been identified. These analyses have been conducted with the aim of extracting and classifying the factors that, in various studies, have been recognized as key challenges and capabilities in aligning innovation with industrial demands.

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Colovic et al. (2025) examined the role of digital innovation intermediaries in the digital transition. Their findings indicate that these intermediaries facilitate technology adoption and diffusion by eliminating cognitive barriers, providing digital technology training, and developing supportive systems. Moreover, the institutional activities of intermediaries occur at three levels—organizational, network, and ecosystem—depending on their expertise and resources. The study highlights the importance of public financial support for intermediaries to maintain their impartiality and effectiveness (Colovic et al., 2025).

Bäumle (2025) investigated the role of knowledge intermediaries in regional innovation systems. The study shows that these intermediaries support R&D projects and the formation of academic spin-offs by continuously transferring information between academic and non-academic actors, building collaborative networks, and reducing mutual constraints. Furthermore, they play a crucial role in promoting knowledge-based innovation and social transformation through advisory processes and by strengthening regional networks. The research underscores the importance of sustained cooperation among intermediaries with diverse organizational backgrounds in supporting sustainable startups and entrepreneurial ecosystems (Bäumle, 2025).

Chu and Bai (2025) explored the impact of corporate digital transformation on reverse innovation in developing countries, emphasizing the role of regional market intermediaries. The results suggest that digital transformation—through convergence, connectivity, and shaping organizational image—can reduce alienation-related barriers in foreign markets and facilitate reverse innovation. Additionally, the development of regional market intermediaries and contextual factors such as managers' international backgrounds and the degree of firm internationalization positively influence this relationship. The study stresses the significance of regional intermediaries in enhancing innovation and guiding transformation processes in developing nations (Chu & Bai, 2025).

Strazzullo et al. (2025) examined the role of open innovation in improving corporate social responsibility (CSR) performance, highlighting the impact of various intermediaries in this process. The findings demonstrate that open innovation, by fostering collaboration between firms and diverse stakeholder groups, contributes to the achievement of sustainability and social responsibility goals. The study emphasizes the importance of integrating sustainability objectives into open innovation strategies and shows that establishing long-term relationships with diverse partners can enhance CSR outcomes and strengthen firms' positions in the business environment (Strazzullo et al., 2025).

Howells (2024) explored the impact of digitalization on innovation intermediaries and the transformation of their roles in this new context. The results reveal that innovation intermediaries can enhance their performance in facilitating collaboration, expanding innovation networks, and developing new business models through the use of digital tools and artificial intelligence. The study also emphasizes the importance of intermediaries' adaptability to digital changes and examines their role in advancing innovation policies and fostering sustainable transformation (Howells, 2024).

Hyvärinen et al. (2024) studied the role of innovation intermediaries in resource-constrained environments and their impact on product development. The findings indicate that intermediaries, by assuming hybrid roles and providing services in entrepreneurship, financing, and facilitation, can overcome resource limitations and improve the innovation process. The study highlights that intermediaries, leveraging past experience in institutional development and capacity-building, can help reduce institutional gaps and complexity, thereby accelerating the commercialization of innovations in the final stages of product development (Hyvärinen et al., 2024).

Sala-Villar et al. (2024) examined the business models of innovation intermediaries and how they adapt to the growing need for digital service development. The findings indicate that the current level of digital resources among intermediaries positively influences their intention to offer digital services, while the existing level of digital services may reduce their motivation to introduce new ones. The study also reveals that intermediaries tend to outsource digital services rather than rely on their existing key partners. This research highlights the importance of digital resources and capabilities as essential components of the business models of innovation intermediaries and underscores their role in facilitating digital transformation in industry (Sala-Vilar et al., 2024).

Abi-Saab et al. (2024) explored the role of innovation intermediaries in facilitating the diffusion of emerging digital technologies in the healthcare sector. The findings show that intermediaries contribute through two main processes: "technology-focused intermediation" for cocreating new technologies based on existing demand, and "ecosystem-focused intermediation" for strengthening ecosystem components. This study emphasizes the dynamic and multi-level role of intermediaries in guiding digital innovations and fostering organizational and inter-organizational transformations (Abi Saad et al., 2024).

Scarbrough et al. (2024) investigated the role of innovation intermediaries in promoting the diffusion and sustainability of innovations in the healthcare sector. The results demonstrate that intermediaries support the expansion and institutionalization of innovations by leveraging evidence from pilot studies, building social networks across different groups, and facilitating knowledge and evidence transfer. The study also underscores the importance of managing the transfer of evidence from early stages to broader implementation phases, and the role of intermediaries in creating positive feedback loops (Scarbrough et al., 2024).

Lee and Cho (2024), through in-depth interviews with eight ICT companies experienced in technology transfer and collaboration with public research institutes, found that firms engaging with innovation intermediaries report a significant increase in the frequency of technological collaborations. This research contributes to understanding how intermediaries help foster and strengthen collaboration networks in knowledge-based industries (Lee & Cho, 2024).

Claire et al. (2024) investigated the role of innovation intermediaries in addressing major societal challenges, with a focus on emerging technologies such as bioengineering—a field that integrates biology, engineering, and information technology to offer innovative solutions to social issues. The findings show that innovation intermediaries play a vital role in bridging innovation gaps by facilitating technology development, supporting inter-organizational networking, and enabling technology transfer. The study emphasizes the need for a proactive definition of the role of intermediaries in tackling societal challenges (Claire et al., 2024).

Xiao et al. (2021) examined the relationship between innovation and new product development, highlighting the role of innovation intermediaries in this process. The results indicate that intermediaries accelerate and enhance product development by facilitating information flow, fostering interactions among diverse actors, and supporting knowledge transfer (Xiao et al., 2021).

Durmusoglu and Kawakami (2021) investigated the role of information technology in new product development. The researchers argue that the effective use of IT significantly contributes to the success of new product development. Furthermore, companies aiming to maximize the benefits of IT require an IT champion—a key figure to lead the technological efforts. This study provides insights for innovation intermediaries in establishing supportive IT infrastructures (Durmusoglu & Kawakami, 2021).

Vidmar (2021), in a case study from the Scottish space sector, introduced a new typology of innovation intermediary interventions. This typology defines the systemic roles of intermediaries in terms of enabling, equipping, shaping, and stimulating innovation. The research offers a valuable framework for intermediaries seeking to refine and enhance their roles in the new product development process (Vidmar, 2021).

Chen et al. (2021) investigated the impact of firms' diverse experiences and post-launch adaptive strategies (action-oriented strategies) on new product performance. The results show that while a diverse product portfolio contributes to initial success, repeated design iterations and continuous improvement after launch are crucial for maintaining product appeal. The study underscores the importance of combining varied experience with adaptive strategies to enhance new product performance and strengthen competitive advantage (Chen et al., 2021).

De Almeida et al. (2021) proposed a new model for new product development based on agile management and additive manufacturing. The model is divided into three phases—pre-development, development, and post-development—with clearly defined key activities for each stage. This model offers practical guidance for innovation intermediaries aiming to accelerate and improve the new product development process (De Almeida et al., 2021).

Keinz and Marhold (2021) examined the role of innovation intermediaries in projects based on technological capabilities. Their findings revealed that these intermediaries, through executing outsourced projects, not only facilitated the identification of new market opportunities for existing technologies but also contributed to enhancing project-based capabilities within core organizations. The study also identified several obstacles to the short- and long-term success of such projects, including the absence of an internal organizational vision and the assignment of project ownership to individuals lacking managerial responsibility (Keinz & Marhold, 2021).

Rivasa et al. (2020) proposed an integrated model aligning entrepreneurial orientation with alliance

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orientation for new product development. Their findings reveal that characteristics of the product development process (e.g., decision-making flexibility and market-focused learning), program features (meaningfulness and novelty), and performance (new product success) are significantly influenced by this alignment. This model offers valuable insights for innovation intermediaries in formulating coordinated product development strategies (Rivasa et al., 2020).

Bakici (2020), in a study titled *"Comparison of Crowdsourcing Platforms from Social-Psychological and Motivational Perspectives,"* analyzed user participation intentions across two types of crowdsourcing platforms: a third-party-hosted community (Atizo) and a brand-hosted platform (Nokia's IdeasProject). Integrating motivational and socio-cognitive perspectives, the research examined the impact of competitive and social dynamics on user engagement. The findings highlighted the critical influence of platform host type, domain specificity, and supporting mechanisms for various motivational and social drivers on participant behavior. These insights are instrumental in guiding the design and management of crowdsourcing platforms aimed at effectively responding to industrial demands and navigating innovation challenges (Bakici, 2020).

Mazzola et al. (2020), in their study *"Fair Play in the Crowd: Increasing Self-Selection of Solvers in Crowdsourcing Idea Contests,"* employed a netnographic approach to analyze data from 1,067 contests on the 99designs platform. The research explored how three components of fairness—prize assurance, appropriate reward amounts, and non-blind contests—affect voluntary solver participation. Findings indicated that participants' perceptions of fairness in contest design significantly influence their decision to engage, and that these perceptions are enhanced through transparency, guaranteed compensation, and opportunities to view and compare ideas (Mazzola et al., 2020).

Tam et al. (2020) investigated human factors influencing the success of agile software development projects. The study found that "team capability" and "customer involvement" are the most significant success factors, while other influential elements include "individual characteristics," "training and learning," and "social culture." By offering a conceptual model, this research helps managers and teams prioritize efforts to enhance project outcomes and highlights the importance of effective human resource management and interactions (Tam et al., 2020).

Zhua et al. (2019) examined the impact of open innovation and business models on new product development. Based on an analysis of 265 Chinese firms, the study reveals that both the breadth (horizontal) and depth (vertical) of open innovation positively affect the speed of product development. Shortening development time enables firms to gain a competitive edge, offering useful insights for innovation intermediaries to accelerate development processes (Zhua et al., 2019).

Cooper (2019) analyzed key success factors in new product development and identified three main categories: tactical project-related factors (e.g., customer engagement, early evaluations, global approach), strategic and organizational-level factors (e.g., innovation strategy, R&D investment decisions), and systems/methodologies (e.g., stage-gate systems, agile approaches). The study highlights the importance of implementing these factors to enhance innovation performance and increase development efficiency (Cooper, 2019).

Pollok, Lüttgens, and Piller (2019), in their study titled *"Attracting Solutions in Crowdsourcing Contests: The Role of Knowledge Distance, Identity Disclosure, and Seeker Status"* published in *Research Policy*, investigated how the strategic decisions of innovation seekers impact participant engagement in crowdsourcing contests. Drawing on uncertainty reduction theory and analyzing 637 crowdsourcing projects, the study found that knowledge distance between the problem and the solver's expertise, along with seeker identity disclosure, significantly influence solver attention. Specifically, a curvilinear relationship was identified in which moderate knowledge distance yielded the highest participation; however, high-status seekers who disclosed their identity were able to attract high engagement regardless of knowledge distance. The research highlighted the importance of problem formulation and contextual transparency in RFP (request for proposal) documents for building trust and reducing perceived risks among solvers (Pollok et al., 2019).

Chauhan et al. (2018) addressed risk management in the new product development process, providing a comprehensive overview of existing research and identifying gaps. The findings highlight that identifying, assessing, and mitigating risks are essential for improving the success of new product development. This study offers an integrated framework for managing risks and emphasizes reducing complexity and uncertainty in

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competitive and global environments (Chauhan et al., 2018).

Gutierrez-Gutierrez et al. (2018) explored the impact of human resource-related quality management on new product development, emphasizing the mediating roles of organizational learning, knowledge integration, and strategic flexibility. The study finds that such management enhances successful product development by fostering learning, facilitating knowledge integration, and boosting flexibility. It also stresses the strategic value of flexibility for adapting to environmental and competitive changes (Gutierrez-Gutierrez et al., 2018).

Zahaya et al. (2017) investigated managerial perspectives on crowdsourcing in new product development. The findings indicate that online crowdsourcing platforms are not yet widely used as primary tools for idea generation but can serve as valuable complements to traditional market research. This underscores the role of innovation intermediaries in leveraging crowdsourcing tools for idea identification and development (Zahaya et al., 2017).

Luo et al. (2017) emphasized the importance of control mechanisms in the success of open innovation-based new product development projects. The study showed that formal and professional internal control, as well as inter-organizational control, positively affect development outcomes. These insights on effective control modes are valuable for innovation intermediaries in optimizing both internal and external collaborations (Lu et al., 2017).

Schemmann et al. (2016) examined factors influencing crowdsourcing intermediaries' decisions to implement new product development ideas. Results reveal that idea popularity and its innovation potential positively affect the likelihood of implementation. Contrary to expectations, the idea contributor's motivation—as reflected by the number of submitted ideas—had no significant impact. These findings assist intermediaries in selecting and evaluating submitted ideas effectively (Schemmann et al., 2016).

Ye et al. (2012) titled *"Crowdsourcing for Open Innovations"*, four primary crowdsourcing models were introduced based on task content and synergy level. The study emphasized that collaborative models demonstrate greater effectiveness in open innovation due to their capacity for interaction and learning. Furthermore, it explored effective managerial mechanisms for implementing crowdsourcing in complex environments and provided practical recommendations for developing countries aiming to utilize internet-based open innovation. The study underscored the significance of institutional and cultural contexts in the success of crowdsourcing initiatives (Ye et al., 2012).

Dahlander and Gann (2010) titled *"How Open Is Innovation?"*, the authors aimed to revisit and redefine the concept of openness within the open innovation literature by establishing a conceptual and analytical framework for future research. Utilizing bibliometric analysis of articles from the ISI database and a systematic review of relevant literature, the study categorized open innovation processes into inbound (including sourcing and acquiring external knowledge) and outbound (including revealing and selling ideas) types, each with distinct advantages and disadvantages.

Grönlund et al. (2010) studied open innovation processes and a modified stage-gate model for new product development. The results show that incorporating open innovation into development processes—by facilitating knowledge flows and information sharing among various actors—can significantly improve new product success. The study emphasizes that combining open innovation with the stage-gate approach enhances product quality and reduces development time (Grönlund et al., 2010).

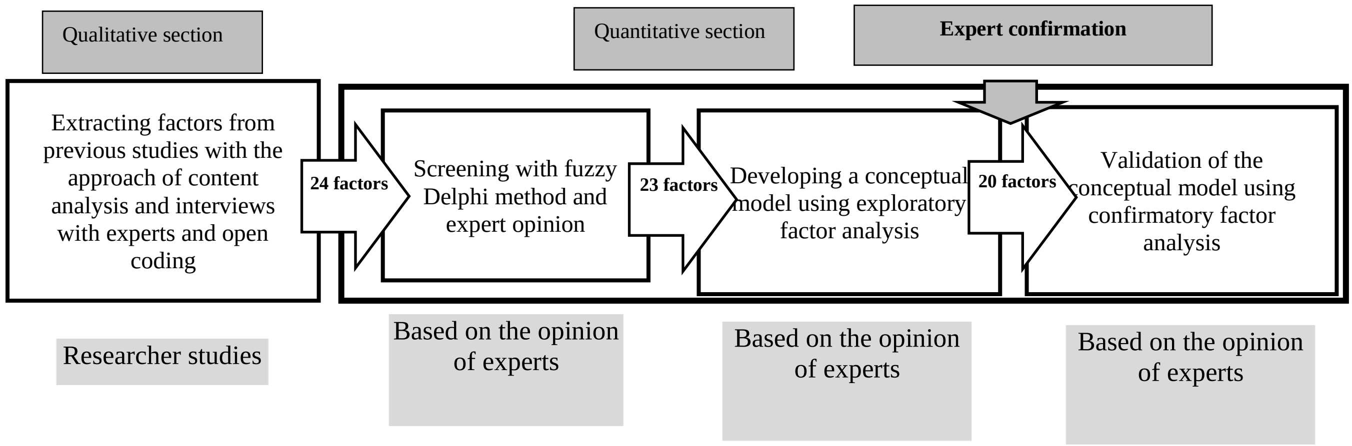
2. Methods and Materials

This research is of applied and survey nature. After identifying and extracting the effective factors from the content analysis method from previous studies and interviews with experts and open, central, selective coding with a qualitative approach, screening and validation of the factors with the opinion of 10 experts using the fuzzy Delphi method has been done in two stages. In the following, factorial and exploratory analysis questionnaire was completed by an expert and analyzed using SPSS software. Finally, with the opinion of the experts, names for the indicators were determined and the final model was analyzed using LISREL software. It should be noted that the community of experts were selected using the snowball sampling method and their characteristics are listed in Table No. 1. The community of experts has been selected by Cochran's sampling method, 73 people, according to the characteristics that experts have determined for experts. The experts have related bachelor's, master's and doctorate degrees and records of studies and expertise in this field. In the exploratory and confirmatory factor analysis questionnaires, a five-point Likert scale was used.

Cronbach's alpha coefficient was used to determine reliability.

Figure 1

The process is based on the research method (quantitative and qualitative)



To analyze the data in this study, three complementary methods were employed: the Fuzzy Delphi Technique (FDT), Exploratory Factor Analysis (EFA), and Confirmatory Factor Analysis (CFA). In the first phase, the Fuzzy Delphi Technique was used for the initial screening of indicators, aiming to eliminate ambiguous or low-relevance items. This process was conducted over two rounds with input from ten domain experts, ensuring that only the most relevant and valid indicators were retained for subsequent analysis. In the second phase, Exploratory Factor Analysis was applied to identify the underlying structure of the data and to group related variables into coherent factors. Prior to conducting the analysis, the data were tested for normality, and variables exhibiting significant deviations from a normal distribution were excluded. The reliability of the research instrument was also assessed and confirmed using Cronbach's alpha coefficient. Finally, in the third phase, Confirmatory Factor Analysis was conducted to validate the conceptual model developed during the exploratory phase. This analysis evaluated the model fit and the relationships among the identified factors, ultimately confirming the validity and structural integrity of the proposed framework.

3. Findings and Results

In this research, the validity of the structure has been ensured by using multiple evidences of document study, research literature review, observation and referring to experts. External validity is related to the generalizability of the research. In this research, to ensure the external validity of the requirements extracted using the open and axial coding method, they were re-examined using comparative studies. Also, the use of multiple case studies increases external validity. To ensure the reliability of the research, re-coding was done by another expert. In this case, the rate of no change or transformation in the process over time is considered, so that the coder is asked to re-code a series of data at another time. Also, due to the observation conditions, it was possible for the researcher to collect information (Yin, 2018).

Table 1

Characteristics of the people examined in the research

No	Position	Number of people	Minimum work experience (years)	Maximum work experience (years)	Education
1	Managers and specialists of the intermediary institution organizing the innovation challenge	5	4	9	Masters and Ph.D
2	Experts with research experience or related work experience	5	7	18	Masters and Ph.D

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In this study, three flagship innovation cases were selected from a broad portfolio of projects across various industries in Iran—specifically in the food, health, and energy sectors. These cases were chosen based on their technological diversity, sufficient maturity to produce functional prototypes, and proven success in attracting investment or securing industrial contracts. Beyond presenting summary outcomes—such as proof of concept and initial engagement with leading companies—the analysis was expanded to address several key dimensions. These included upcoming challenges, such as identifying suitable technology teams, securing post-prototype funding, and ensuring compliance with relevant standards. The study also introduced both quantitative and qualitative performance evaluation criteria, and emphasized outcomes beyond the prototype stage—namely, investment attraction, pilot production agreements, and field-testing contracts. It is important to note that the scope of this study is limited to demonstrating technological feasibility and initial industry integration. The final commercialization phases of these innovations will be the focus of future research. Table 2 below provides examples of three practical challenges across these key industries, offering a clearer illustration of the study's structure.

Table 2

Study items

No	Title	Result	Date	Technologist (person)	Time (month)
1	Solving the demand of an organization in the food industry	Finally, 2 teams were able to build the prototype successfully	2021	24	8
2	Identifying the best ideas in the health industry	Finally, 2 teams managed to attract capital	2021	46	7
3	Product development in the energy industry	1 team was able to successfully build the prototype	2021	17	10

To identify the key factors influencing the success of the open innovation process, a mixed-method approach was employed. This comprehensive methodology included semi-structured interviews with domain experts, case study analysis, and an extensive review of academic and institutional literature.

Phase One: Design of the Research Instrument

Drawing on prior studies and a detailed literature review, a semi-structured questionnaire was developed to serve as the primary tool for data collection. The instrument was designed to capture multiple dimensions of the research topic and to provide a coherent framework for eliciting qualitative insights.

Phase Two: Expert Interviews

Semi-structured interviews were conducted with ten seasoned professionals in the field of innovation. These interviews—carried out both in-person and online—yielded in-depth insights grounded in both practical experience and theoretical understanding. The interviews covered a broad range of issues critical to the open innovation process.

Phase Three: Qualitative Analysis via Open Coding

Following the completion of interviews, key insights and statements from participants were extracted and analyzed using a systematic open coding method. This process involved categorizing responses to identify underlying concepts and recurrent patterns. The analysis revealed consistent themes, including the importance of effective promotional strategies, clarity in documentation and procedures, and the critical role of accurate and fair evaluation mechanisms. A summary of selected results from the open coding process is presented below, highlighting core findings derived from the expert interview data.

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Table 3

Open coding results from the semi-structured interview process

Expert code	Semantic expressions	Open coding	Expert code	Semantic expressions	Open coding
E1	If the poster isn't attractive, no one's going to pay attention to it	Suitable poster and clip design	E2	The application form needs to be really clear, so no one misunderstands it	Request Form and Classification (RFP)
E10	A lot of users didn't participate because the site wasn't working well	Effective website preparation	E6	When everything is clear from the beginning, participants can plan more easily	Providing supplementary files and event guide
E6	Once we used a simple form, and the evaluation results were inconsistent and lacked justification	Designing arbitration forms effectively	E9	The process of selecting judges needs to be precise and based on relevant experience	An effective mechanism for selecting relevant referees
E2	Judges should have an industrial perspective as well, not just a research one	Correct assessment in terms of industrialization	E7	Technical evaluation should be based on standards and expertise—not on personal feelings	Technically correct assessment
E5	Truly understanding the problem is often more important than the solution itself	Comprehensive demand discovery	E5	The timeline should be set based on the type of project—not arbitrarily	Determining the execution period based on the correct estimate
E7	Only someone with technical experience can identify technical issues	Technically correct assessment	E4	If the evaluation form is vague, each judge scores differently	Designing arbitration forms effectively
E10	Market analysis and cost-benefit analysis are essential for a good evaluation	Economically correct assessment	E10	We need to assess from the start how feasible this idea is for industrial implementation	Correct assessment in terms of industrialization
E8	We sent the event guide too late, and it caused a lot of confusion	Providing supplementary files and event guide	E1	If the website is slow or heavy, people just leave	Effective website preparation
E9	The structure of the form should guide judges to assess based on clear criteria	Designing arbitration forms effectively	E5	It's a good design if it can be developed at different levels	Vertical and horizontal development of products and services
E10	When the applications are categorized, it makes evaluation and recruitment much easier	Request Form and Classification (RFP)	E4	We made a short video—it was way more effective than just text	Suitable poster and clip design
E8	The ability to be used in various industries is an important competitive advantage	Vertical and horizontal development of products and services	E10	I've seen judges give feedback that clearly showed they didn't understand the topic at all	An effective mechanism for selecting relevant referees
E1	When a judge lacks expertise, they can't provide an accurate evaluation	An effective mechanism for selecting relevant referees	E3	If the agreement isn't correct, future collaboration will lead to misunderstandings	Conclusion of an effective cooperation agreement
E4	A good collaboration is impossible without a professional contract	Conclusion of an effective cooperation agreement	E9	If negotiations lack a framework, they'll lead to conflicts	Developing a suitable structure for negotiation
E10	We need to know when, how, and with whom to negotiate	Developing a suitable structure for negotiation	E1	When the feedback system is intelligent, participants can improve more effectively	Comprehensive and effective intelligent feedback mechanisms
E3	A project that's given too little time won't deliver proper results	Determining the execution period based on the correct estimate	E2	Accurate feedback leads to better quality proposals in future rounds	Comprehensive and effective intelligent feedback mechanisms
E8	The initial appearance needs to look professional to give off a good impression	Suitable poster and clip design	E10	There have been many times when we had a great solution, but there was no real need for it	Comprehensive demand discovery
E2	We need to clearly understand what participants are actually looking for—not just guess	Comprehensive demand discovery	E3	At the last event, poor design made a lot of people think we weren't serious	Suitable poster and clip design

Phase Four: Consolidation and Cross-Verification

To enrich and validate the findings from the interviews, insights from authoritative academic sources and institutional reports—such as those from Innocentive—were integrated. This cross-verification helped ensure that the identified factors were both theoretically grounded and practically relevant.

Final Outcome: Categorized Contributing Factors

All extracted data—both from interviews and secondary sources—were categorized and consolidated into a comprehensive list of contributing factors. These factors were mapped to their corresponding sources to demonstrate their origin and relevance. The table below provides a structured summary of these findings:

Table 4

Summary of extracted factors and their sources

No	Step	References
1	Suitable poster and clip design	Interview
2	Comprehensive demand discovery	Interview
3	Request Form and Classification (RFP)	Interview & (InnoCentive, 2021)
4	Determining the execution period based on the correct estimate	Interview & (InnoCentive, 2021)
5	Providing supplementary files and event guide	Interview
6	Effective website preparation	Interview & *Sala-Villar et al., (2024)*
7	An effective mechanism for selecting relevant referees	Interview
8	Designing arbitration forms effectively	Interview
9	Technically correct assessment	Interview
10	Economically correct assessment	Interview
11	Correct assessment in terms of industrialization	Interview
12	Vertical and horizontal development of products and services	Interview
13	Conclusion of an effective cooperation agreement	Interview
14	Developing a suitable structure for negotiation	Interview
15	Comprehensive and effective intelligent feedback mechanisms	Interview & (Scarbrough et al., 2024)
16	Choosing the right open innovation broker	(Claire et al., 2024; Colovic et al., 2025; Howells, 2024; Keinz & Marhold, 2021)
17	Taking a comprehensive and effective field test	(Hyvärinen et al., 2024; Ye et al., 2012)
18	Paying a suitable bonus according to the event	(Mazzola et al., 2020)
19	Effective mechanisms in verifying the applicant	(Abi Saad et al., 2024; Pollok et al., 2019)
20	Provide tangible rewards such as financial rewards	(Dahlander & Gann, 2010)
21	Provide appropriate intangible rewards such as credit	(Dahlander & Gann, 2010)
22	The existence of comprehensive and effective evaluation mechanisms	(Mazzola et al., 2020; Scarbrough et al., 2024; Xiao et al., 2021; Ye et al., 2012)
23	Effective identification and introduction of the applicant	(Pollok et al., 2019)
24	Effective communication and networking	(Bakici, 2020; Bäumle, 2025; Claire et al., 2024; Lee & Cho, 2024; Ye et al., 2012)

This integrative and layered methodology ensured that the identified success factors are not only empirically grounded through expert opinion but also theoretically validated through scholarly research. The result is a robust framework that stakeholders can utilize for designing and implementing more effective open innovation processes.

In this section, the Fuzzy Delphi Technique (FDT) was employed to validate and screen the proposed factors prior to conducting Exploratory Factor Analysis (EFA). The process was based on expert input from ten research specialists and was carried out in two iterative rounds. The technique involves calculating the average absolute difference between the defuzzified values obtained in the first and second rounds. If this difference is less than 0.2, the level of consensus among experts is considered acceptable, and no further rounds are required. In this study, the threshold was met after two rounds, and a third round was not necessary. Furthermore, factors with a

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defuzzified average of 0.70 or higher were accepted for inclusion in the next stage of analysis, while those falling below this threshold were excluded. The Fuzzy Delphi questionnaire employed a five-point Likert-type scale, providing a structured and consistent approach for expert evaluation.

Table 5

Screening results with the fuzzy Delphi method

No	Acceptance threshold 0.7	Average fuzziness			Average fuzziness	Absolute Difference First Second	Result
	Criteria	L	M	U			
1	Choosing the right open innovation broker	0.727	0.992	1.000	0.928	0.006	Accepted
2	Vertical and horizontal development of products and services	0.719	0.984	1.000	0.922	0.055	Accepted
3	Comprehensive demand discovery	0.508	0.750	0.875	0.721	0.029	Accepted
4	Existence of comprehensive and effective evaluation mechanisms	0.555	0.813	0.969	0.787	0.119	Accepted
5	An effective mechanism for selecting relevant referees	0.680	0.945	1.000	0.893	0.010	Accepted
6	Designing arbitration forms effectively	0.703	0.961	1.000	0.906	0.021	Accepted
7	Suitable poster and clip design	0.695	0.961	1.000	0.904	0.014	Accepted
8	Provide appropriate intangible rewards such as credit	0.633	0.891	1.000	0.854	0.061	Accepted
9	Conclusion of an effective cooperation agreement	0.750	1.000	1.000	0.938	0.039	Accepted
10	Effective communication and networking	0.594	0.859	1.000	0.828	0.018	Accepted
11	Provide tangible rewards such as financial rewards	0.523	0.766	0.945	0.750	0.115	Accepted
12	Providing supplementary files and event guide	0.734	1.000	1.000	0.934	0.027	Accepted
13	Determining the execution period based on the correct estimate	0.672	0.938	1.000	0.887	0.033	Accepted
14	Developing a suitable structure for negotiation	0.695	0.961	1.000	0.904	0.037	Accepted
15	Taking a comprehensive and effective field test	0.484	0.719	0.883	0.701	0.109	Accepted
16	Request Form and Classification (RFP)	0.695	0.961	1.000	0.904	0.020	Accepted
17	Effective mechanisms in verifying the applicant	0.711	0.977	1.000	0.916	0.004	Accepted
18	Technically correct assessment	0.570	0.836	0.953	0.799	0.113	Accepted
19	Effective identification and introduction of the applicant	0.695	0.961	1.000	0.904	0.033	Accepted
20	Effective website preparation	0.711	0.977	1.000	0.916	0.020	Accepted
21	Comprehensive and effective intelligent feedback mechanisms	0.617	0.875	1.000	0.842	0.055	Accepted
22	Correct assessment in terms of industrialization	0.469	0.727	0.898	0.705	0.002	Accepted
23	Paying a suitable bonus according to the event	0.383	0.594	0.773	0.586	0.084	Rejected
24	Economically correct assessment	0.500	0.734	0.891	0.715	0.025	Accepted

The factor “Paying a suitable bonus according to the event” was excluded from the model based on clear methodological and statistical justifications. First, its defuzzified average value was 0.586, falling significantly below the predefined acceptance threshold of 0.70 established by the Fuzzy Delphi method to retain only the most relevant and consensus-based factors. Second, the corresponding triangular fuzzy values *(L = 0.594, M = 0.586, U = 0.773)* indicate a low central tendency and moderate uncertainty, suggesting that expert evaluations did not strongly endorse the significance of this factor. Third, the absolute difference between the first and second rounds was 0.084, which was comparatively higher than those of the accepted factors, indicating persistent disagreement and lack of convergence among expert opinions. Taken together, these criteria support the decision to exclude this factor from further analysis. Its failure to meet the methodological standards, along with its relatively low perceived importance, demonstrates that it was not considered critical by the expert panel.

Prior to conducting the Exploratory Factor Analysis (EFA), the assumption of normality in the data distribution was examined to ensure the statistical validity of the analysis. As shown in Table 6, skewness and kurtosis values were calculated for each item. According to the generally accepted threshold of ±1, three factors—*"Vertical and Horizontal Development of Products and Services"*, *"Developing a Suitable Structure for Negotiation"*, and *"Effective Website Preparation"*—exhibited significant deviations from normality, with both skewness and kurtosis values falling outside the acceptable range. Given the sensitivity of factor analysis to violations of the normality assumption, and to enhance the accuracy and reliability of the extracted factors, these three items were excluded from the dataset prior to the EFA. It is important to note that although these items were initially identified as relevant through expert judgment and the Fuzzy Delphi method, their exclusion was based solely on statistical grounds, in order to maintain the analytical integrity of the model. Following this refinement, the reliability of the revised questionnaire was reassessed. The Cronbach's alpha coefficient remained at an acceptable level ($\alpha = 0.814$), confirming the internal consistency of the instrument. Furthermore, the dataset was confirmed to be suitable for factor analysis based on the Kaiser-Meyer-Olkin (KMO) index (0.715) and the results of Bartlett's Test of Sphericity ($p < 0.05$), as presented in Table 7.

Table 6

Statistical distribution of data, effective factors in criteria

No	Criteria	Number	Minimum	Maximum	Skewness		Kurtosis	
					Number	Standard deviation figures	Number	Standard deviation figures
1	Choosing the right open innovation broker	61	2.00	5.00	-0.245	0.201	0.178	0.399
2	Request Form and Classification (RFP)	61	2.00	5.00	-0.396	0.201	0.193	0.399
3	Technically correct assessment	61	2.00	5.00	-0.444	0.201	-0.818	0.399
4	Effective identification and introduction of the applicant	61	2.00	5.00	0.299	0.201	0.813	0.399
5	Existence of comprehensive and effective evaluation mechanisms	61	3.00	5.00	-0.160	0.201	-1.658	0.399
6	An effective mechanism for selecting relevant referees	61	3.00	5.00	-0.182	0.201	-1.538	0.399
7	Designing arbitration forms effectively	61	2.00	5.00	-0.161	0.201	-1.318	0.399
8	Correct assessment in terms of industrialization	61	3.00	5.00	0.162	0.201	-1.104	0.399
9	Vertical and horizontal development of products and services	61	3.00	5.00	1.188	0.201	-1.137	0.399
10	Developing a suitable structure for negotiation	61	3.00	5.00	1.400	0.201	0.874	0.399
11	Economically correct assessment	61	3.00	5.00	0.128	0.201	-1.259	0.399
12	Comprehensive demand discovery	61	2.00	5.00	-0.163	0.201	-0.188	0.399
13	Effective identification and introduction of the applicant	61	3.00	5.00	0.151	0.201	-1.249	0.399
14	Suitable poster and clip design	61	3.00	5.00	-0.107	0.201	-1.105	0.399
15	Effective identification and introduction of the applicant	61	3.00	5.00	0.043	0.201	-1.122	0.399
16	Effective website preparation	61	2.00	5.00	-1.724	0.201	2.042	0.399
17	Comprehensive and effective intelligent feedback mechanisms	61	3.00	5.00	-0.331	0.201	0.565	0.399
18	Providing supplementary files and event guide	61	3.00	5.00	-0.197	0.201	0.608	0.399
19	Provide tangible rewards such as financial rewards	61	3.00	5.00	-0.255	0.201	0.436	0.399
20	Conclusion of an effective cooperation agreement	61	3.00	5.00	-0.218	0.201	0.480	0.399
21	Taking a comprehensive and effective field test	61	2.00	5.00	-0.125	0.201	-1.309	0.399
22	Determining the execution period based on the correct estimate	61	3.00	5.00	0.233	0.201	-1.323	0.399
23	Effective communication and networking	61	3.00	5.00	0.010	0.201	-0.993	0.399

Based on the calculated Cronbach's alpha coefficient of 0.814, it can be concluded that the questionnaire demonstrates acceptable reliability. As shown in Table 6, Factors 10, 9, and 16 were identified for removal due to skewness and a non-normal distribution, which violated the assumption of normality. Following the elimination of these non-normally distributed items, Cronbach's alpha was recalculated to reassess the reliability of the revised questionnaire, confirming that the instrument remained robust for exploratory factor analysis (EFA). As a preliminary step to EFA, the Kaiser-Meyer-Olkin (KMO) index was calculated. A higher KMO value, closer to 1, indicates greater adequacy of the sample for factor analysis. Additionally, Bartlett's Test of Sphericity yielded a significance level of 0.018, which is below the 0.05 threshold, confirming that the data are suitable for factor extraction (see Table 7).

Table 7

Cronbach's alpha coefficient/Bartlett's sphericity test results

Cronbach's alpha coefficients	Number of items	
0.814	20	
KMO sampling adequacy measure	0.715	
Bartlett's sphericity test	Chi square	278.514
	Degrees of freedom	190
	Significance level	0.018

In the next step, the amount of extracted commonalities of the factors is calculated in order to evaluate the relationship of the factors with the developed model.

Table 8

Commonalities in research subjects

No	Research factors	Basic commons	Extractive commons
1	Effective mechanisms in verifying the applicant	1.000	0.848
2	Request Form and Classification (RFP)	1.000	0.720
3	Technically correct assessment	1.000	0.756
4	Mechanisms effective in verifying the applicant	1.000	0.542
5	The existence of comprehensive and effective evaluation mechanisms	1.000	0.910
6	An effective mechanism for selecting relevant referees	1.000	0.877
7	Designing arbitration forms effectively	1.000	0.843
8	Correct assessment in terms of industrialization	1.000	0.593
9	Economically correct assessment	1.000	0.712
10	Comprehensive demand discovery	1.000	0.732
11	Effective identification and introduction of the applicant	1.000	0.749
12	Suitable poster and clip design	1.000	0.839
13	Providing supplementary files and event guide	1.000	0.794
14	Comprehensive and effective intelligent feedback mechanisms	1.000	0.638
15	Provide appropriate intangible rewards such as credit	1.000	0.710
16	Provide tangible rewards such as financial rewards	1.000	0.849
17	Conclusion of an effective cooperation agreement	1.000	0.825
18	Taking a comprehensive and effective field test	1.000	0.551
19	Determining the execution period based on the correct estimate	1.000	0.656
20	Effective communication and networking	1.000	0.714

Table 8 presents the extraction communalities for each research variable, representing the proportion of variance in each item explained by the extracted factors. As shown, all variables exhibited relatively high communalities, with values ranging from 0.542 to 0.910, indicating that the factor solution successfully accounted for a substantial portion of variance in each item. Notably, the items *"existence of comprehensive and effective evaluation mechanisms"* (0.910), *"an effective mechanism for selecting relevant referees"* (0.877), and *"tangible rewards such as financial incentives"* (0.849) demonstrated the highest levels of shared variance, highlighting their strong representation within the underlying factor structure. These findings collectively affirm the adequacy of the extracted factors in capturing the latent constructs underlying the research variables.

In the next phase, the initial eigenvalues, extraction sums of squared loadings, and rotated component values were calculated to determine the optimal number of factor groupings. These calculations guided the classification of variables into distinct factor clusters. Subsequently, the results of the total variance explained by the factor analysis solution were assessed. Specifically, the total variance, percentage of variance, and cumulative percentage of variance were computed for each extracted component, as presented in Table 9 and Table 10.

Table 9

The total variance explained by the factor analysis solution in the research subjects

Factors	Initial eigenvalues			Extraction values			Values of extraction factors after rotation		
	Total variance	Percentage of variance	The cumulative percentage of variance	Total variance	Percentage of variance	The cumulative percentage of variance	Total variance	Percentage of variance	The cumulative percentage of variance
1	5.502	27.511	27.511	5.502	27.511	27.511	4.501	22.505	22.505
2	3.951	19.755	47.266	3.951	19.755	47.266	3.770	18.852	41.357
3	3.336	16.678	63.944	3.336	16.678	63.944	3.348	16.742	58.099
4	1.770	8.850	72.794	1.770	8.850	72.794	2.939	14.695	72.794
5	0.961	4.807	77.601						
6	0.878	4.391	81.992						
7	0.822	4.111	86.103						
8	0.574	2.871	88.974						
9	0.428	2.139	91.114						
10	0.367	1.836	92.950						
11	0.336	1.679	94.629						
12	0.271	1.357	95.985						
13	0.193	0.967	96.953						
14	0.161	0.805	97.757						
15	0.125	0.625	98.382						
16	0.114	0.571	98.952						
17	0.094	0.470	99.422						
18	0.047	0.235	99.658						
19	0.042	0.211	99.868						
20	0.026	0.132	100.00						

In the subsequent stage of the analysis, initial eigenvalues, extraction sums of squared loadings, and rotated factor loadings were computed to determine the optimal number of factors for grouping the variables. As shown in Table 9, the total variance explained by the factor solution was evaluated across three phases: initial extraction, post-extraction, and post-rotation. The results revealed that the first four components had eigenvalues greater than 1 and collectively accounted for approximately 72.79% of the total variance prior to rotation. Specifically, the first factor explained 27.51% of the variance, followed by the second (19.75%), third (16.68%), and fourth (8.85%). After applying rotation, the variance was more evenly distributed, with the first factor accounting for 22.50%, the second 18.85%, the third 16.74%, and the fourth 14.70%, maintaining the cumulative variance of 72.79%. This redistribution enhanced the interpretability of the factors while preserving explanatory power.

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Components with eigenvalues below 1 were deemed insignificant and excluded from the final model. These findings support the decision to retain four primary factors in the structure of the research model.

Figure 2

The pattern of holding innovative challenges

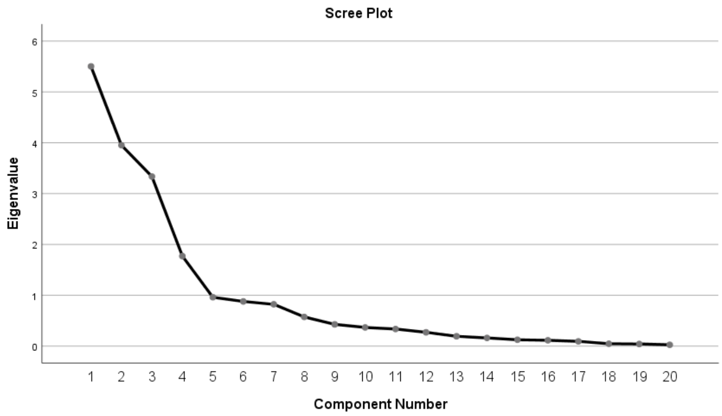

Diagram 1. Scree plot

The scree plot obtained from the exploratory factor analysis depicted the eigenvalues associated with each extracted component. The curve demonstrated a steep decline across the first four components, followed by a marked leveling off beginning with the fifth component. This distinct inflection point—commonly referred to as the *"elbow"*—signified the optimal number of factors to retain. Based on this visual cue and in alignment with the Kaiser criterion (which considers components with eigenvalues greater than 1 as significant), it was determined that the data should be grouped into four main factors. These four components accounted for the majority of the total variance and effectively captured the latent structure underlying the observed variables.

Table 10

Matrix of rotated factor structure with four criteria factors

No	Criteria	Factors			
		1	2	3	4
X5	The existence of comprehensive and effective evaluation mechanisms	0.940			0.162
X6	An effective mechanism for selecting relevant referees	0.920			0.172
X7	Designing arbitration forms effectively	0.872	0.104	0.156	0.217
X3	Technically correct assessment	0.855	0.122		
X11	Economically correct assessment	0.646		0.323	0.428
X8	Correct assessment in terms of industrialization	0.645	0.220	0.282	0.221
X14	Suitable poster and clip design		0.896	0.143	0.126
X15	Providing supplementary files and event guide		0.860	0.202	
X13	Effective identification and introduction of the applicant		0.849	0.149	
X23	Effective communication and networking		0.842		
X22	Determining the execution period based on the correct estimate		0.803		
X19	Provide tangible rewards such as financial rewards			0.917	
X20	Conclusion of an effective cooperation agreement			0.906	
X18	Provide appropriate intangible rewards such as credit	0.257		0.734	0.321
X21	Taking a comprehensive and effective field test	0.208	0.222	0.640	0.221
X17	Comprehensive and effective intelligent feedback mechanisms	0.336		0.633	0.349
X1	Choosing the right open innovation broker	0.268		0.120	0.873
X12	Comprehensive demand discovery	0.168	0.130		0.828
X2	Request Form and Classification (RFP)	0.304			0.786
X4	Effective mechanisms in verifying the applicant				0.481

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After placing each of the factors in the groups determined based on the commonality of their factor loads and determining the final classification of the factors in order to determine the name of each of the groups/indices according to the common attribute and The experimental commonalities between them have been named groups based on the opinion of experts (Table 11).

Table 11

Factors, items and factor load of items related to criteria

No	Criteria	Symbol	Criteria	Factor load
1	Problem definition index	X1	Choosing the right open innovation broker	0.873
2		X12	Comprehensive demand discovery	0.828
3		X2	Request Form and Classification (RFP)	0.786
4		X4	Comprehensive and effective intelligent feedback mechanisms	0.481
5	Notification index	X14	Suitable poster and clip design	0.896
6		X15	Provide supplementary files and event guide	0.860
7		X13	Effective identification and introduction of the applicant	0.849
8		X23	Effective communication and networking	0.842
9		X22	Determining the execution period based on the correct estimate	0.803
10	Acquisition index	X19	Provide tangible rewards such as financial rewards	0.917
11		X20	Conclusion of an effective cooperation agreement	0.906
12		X18	Provide appropriate intangible rewards such as credit	0.734
13		X21	Taking a comprehensive and effective field test	0.640
14		X17	Comprehensive and effective intelligent feedback mechanisms	0.633
15	Evaluation index	X5	The existence of comprehensive and effective evaluation mechanism	0.940
16		X6	An effective mechanism for selecting relevant referees	0.920
17		X7	Designing arbitration forms effectively	0.872
18		X3	Technically correct assessment	0.855
19		X11	Economically correct assessment	0.646
20		X8	Correct assessment in terms of industrialization	0.645

Based on the results obtained, the four primary factors affecting the success of crowdsourcing events in order to respond to industrial demands are: the problem definition index with four items, the acquisition index with five items, the information index with five items and the evaluation index with six items.

In this section, confirmatory factor analysis (CFA) was performed to validate the factorial structure of the research variables and assess the overall fit of the conceptual model. To begin, the Kolmogorov–Smirnov test was applied to evaluate the normality of data distribution for each of the four primary indices. The results confirmed that all indices followed a normal distribution. The four indices under examination included: *Problem Definition* (comprising four items), *Notification* (five items), *Acquisition* (five items), and *Evaluation* (six items). Next, Cronbach's alpha coefficients were calculated for each index as well as for the overall model. All values exceeded the commonly accepted threshold of 0.70, thereby indicating satisfactory internal consistency and reliability. CFA was then conducted using structural equation modeling (SEM) to assess the relationships between indices and their corresponding sub-indices. The significance of these relationships was confirmed based on standardized factor loadings and associated t-values. Additionally, model fit indices were examined and are presented in the corresponding diagrams and tables, further supporting the adequacy of the model fit.

In this research, the Kolmogorov-Smirnov test was used to check the normality of the data (Table 12).

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Table 12

Statistical population normality test using Kolmogorov-Smirnov

No	Research indicators and sub-indices	K-S	Significance level	Test result
1	Problem definition index	0.151	0.127	Normal
2	Notification index	0.139	0.108	Normal
3	Acquisition index	0.147	0.125	Normal
4	Evaluation index	0.205	0.186	Normal

Because the significance level of the Kolmogorov-Smirnov test for all variables is greater than 0.05, the distribution of all studied variables is normal. Using Cronbach's alpha coefficient, the reliability of each component and the final model was calculated separately (Table 13).

Table 13

Cronbach's alpha value for research dimensions

Research indicators and sub-indices	Cronbach's alpha coefficients	Test result
Problem definition index	0.819	A reliable asset
Notification index	0.869	A reliable asset
Acquisition index	0.837	A reliable asset
Evaluation index	0.872	A reliable asset
The general pattern of the model	0.751	A reliable asset

Based on the results for both constructs, the t-values confirmed the statistical significance of the relationships between each index and its corresponding sub-indices within the model. Furthermore, the standardized coefficients indicated that the correlations among the factors were also statistically significant. These findings support the structural validity of the proposed model. In the subsequent section, these results are further analyzed, and additional goodness-of-fit indices for the structural equation model are presented in Figure 3, and Table 14.

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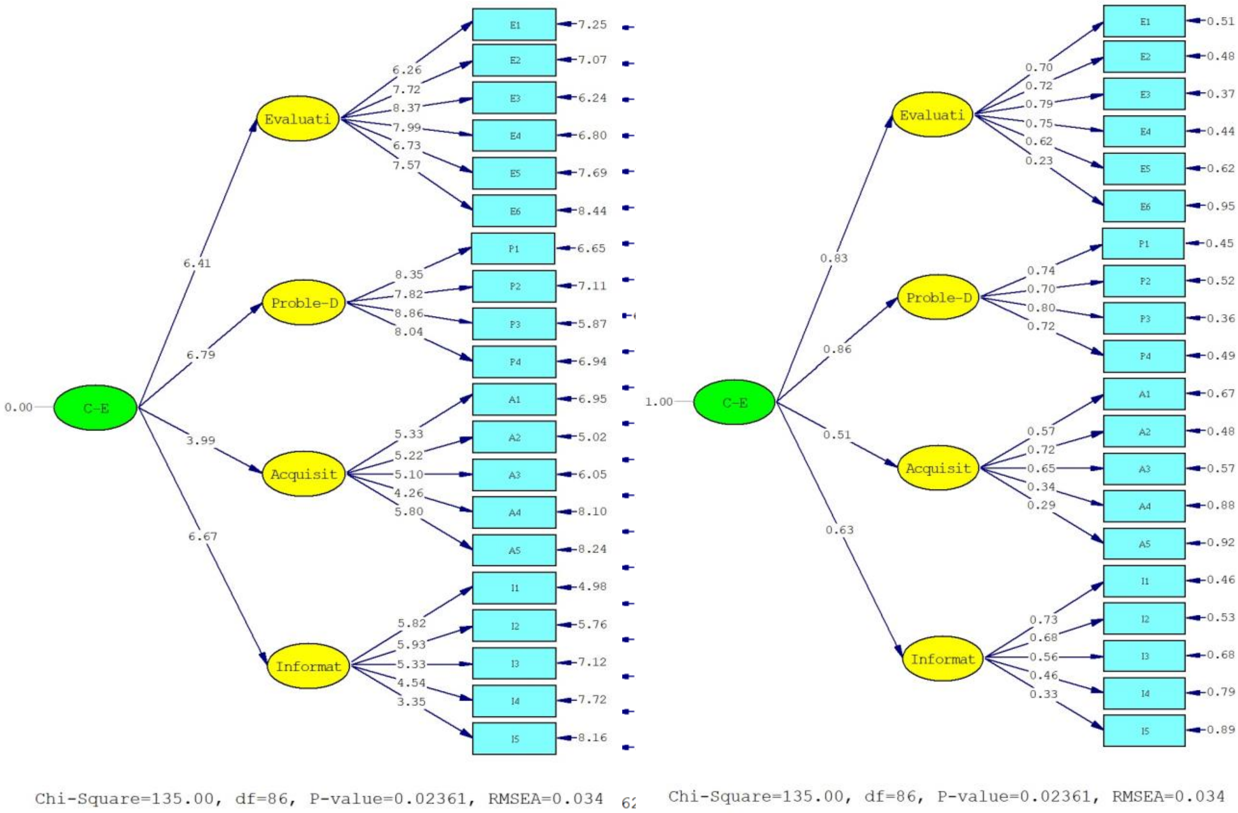
Figure 3

Initial model (Left: t-values, right: factor loadings)



In the confirmatory factor analysis (CFA), the relationships between the four main constructs—*Problem Definition*, *Notification*, *Acquisition*, and *Evaluation*—and their corresponding observed indicators were examined. The first model reports the t-values for each path, all of which exceed the critical threshold of 1.96, indicating that the paths are statistically significant at the 95% confidence level. This confirms that each indicator meaningfully represents its associated latent construct, thereby supporting the model's factorial validity. The second model presents the standardized factor loadings, which predominantly surpass the accepted threshold of 0.50, ranging from 0.29 to 0.95. These results demonstrate adequate convergent validity, although some items—specifically *A4* and *I5*—exhibited lower loadings and may warrant reconsideration in future refinements of the model due to their limited contribution to construct measurement. In terms of model fit, the reported indices suggest that the model is both acceptable and robust. The Chi-square statistic is 135.00 with 86 degrees of freedom, and the associated p-value is 0.02361. Although a p-value below 0.05 could indicate poor fit, this metric is known to be highly sensitive to sample size and is therefore not considered a major concern in larger datasets. More importantly, the Root Mean Square Error of Approximation (RMSEA) is 0.034, which falls well below the standard cutoff of 0.05, indicating a good fit. Overall, the model demonstrates strong reliability, validity, and goodness of fit, thereby confirming the adequacy of the proposed structure for evaluating the key factors influencing the success of crowdsourcing initiatives designed to address industrial challenges.

In the confirmatory factor analysis (CFA), the relationships between the four primary constructs—*Problem Definition*, *Notification*, *Acquisition*, and *Evaluation*—and their corresponding observed indicators were examined. The first model presents the t-values for each path, all of which exceed the critical threshold of 1.96, indicating statistical significance at the 95% confidence level. These findings confirm that each indicator significantly contributes to its respective latent construct, thereby supporting the model's factorial validity. The second model reports the standardized factor loadings, most of which surpass the generally accepted threshold of 0.50, ranging from 0.29 to 0.95. These results demonstrate acceptable convergent validity, though a few indicators—specifically *A4* and *I5*—displayed relatively low loadings and may require reconsideration or refinement in future model iterations due to their weaker contributions to construct representation. With respect to model fit, the reported indices suggest a well-fitting and statistically sound structure. The Chi-square statistic is 135.00 with 86 degrees of freedom, accompanied by a p-value of 0.02361. While a p-value below 0.05 may indicate potential model misfit, this measure is known to be highly sensitive to sample size and should be interpreted with caution in large samples. More importantly, the Root Mean Square Error of Approximation (RMSEA) is 0.034, which is well below the conventional cutoff of 0.05, indicating a good fit between the model and the observed data. In summary, the CFA results provide robust evidence of the model's reliability, convergent validity, and overall goodness of fit, thus validating the proposed structural framework for analyzing the critical factors that influence the success of crowdsourcing initiatives aimed at addressing industrial challenges.

Figure 4

t-values of relationships in the structure

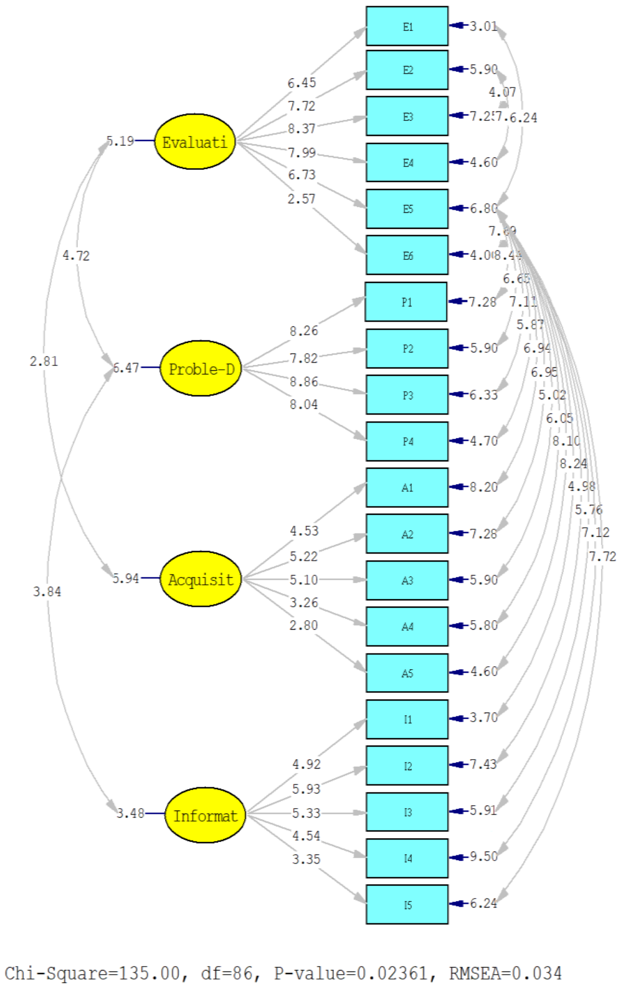


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Table 14

Accuracy indices of the model compiled from structural equations

Index title	Calculated value	Acceptance limit	Result
χ^2/df	1.4629	Less than 3	Confirmation
RMSEA	0.039	Smaller than 0.8	Confirmation
RMR	0.037	Smaller than 0.1	Confirmation
NFI	0.97	Above 0.9	Confirmation
AGFI	0.95	Above 0.9	Confirmation
GFI	0.95	Above 0.9	Confirmation
CFI	0.96	Above 0.9	Confirmation
NNFI	0.94	Above 0.9	Confirmation

In the proposed structural equation model, four core constructs—*Problem Definition*, *Notification*, *Acquisition*, and *Evaluation*—were identified as key dimensions influencing the success of crowdsourcing initiatives targeting industrial demands. The results of the confirmatory factor analysis (CFA) demonstrated that all observed indicators loaded significantly and appropriately onto their corresponding latent constructs. Items such as *E6*, *E4*, *P2*, and *A5* exhibited the highest explanatory power within their respective dimensions, confirming the adequacy of the indicator-to-construct alignment. Further analysis of the correlations between latent constructs revealed that the strongest association occurred between *Problem Definition* and *Evaluation*, underscoring the critical role of clearly conceptualizing challenges in enhancing the quality and rigor of the evaluation process. Additionally, the significant correlation observed between *Notification* and *Acquisition* highlighted the pivotal influence of effective communication in attracting and engaging participants. Overall, the model exhibited acceptable fit, as reflected by key fit indices, including RMSEA = 0.034 and a relatively low Chi-square value, thereby affirming the conceptual soundness and statistical reliability of the proposed structural framework.

The average variance extracted (AVE) of the variables is more than 0.5, which confirms the appropriateness of convergent validity (Table 15).

Table 15

Average Variance Extracted Index (AVE)

Criteria	Average variance extracted (AVE>0.5)	Result
Problem definition index	0.806	Optimal
Notification index	0.869	Optimal
Acquisition index	0.821	Optimal
Evaluation index	0.803	Optimal

Also, three values of weak (between 0.1 and 0.25), medium (between 0.25 and 0.36) and strong (more than 0.36) have been considered to evaluate the GOF index (Table 16).

Table 16

Results of goodness of fit index of GOF

Criteria	Average variance extracted (AVE>0.5)	R^2
Problem definition index	0.806	0.372
Notification index	0.869	0.689
Acquisition index	0.821	0.281
Evaluation index	0.803	0.740

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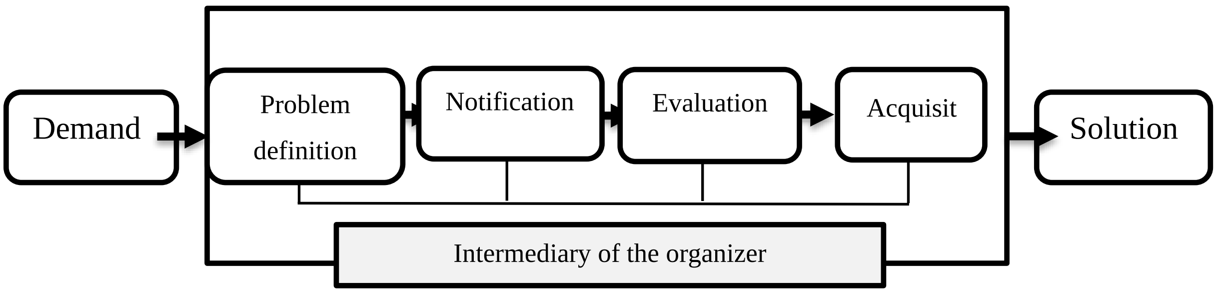
In the assessment of the model's convergent validity, the Average Variance Extracted (AVE) values for all constructs exceeded the recommended threshold of 0.50, confirming that convergent validity was established across all dimensions. Specifically, the AVE values were 0.806 for *Problem Definition*, 0.869 for *Notification*, 0.821 for *Acquisition*, and 0.803 for *Evaluation*—all indicating that the observed indicators effectively captured the variance of their respective latent constructs. Furthermore, to evaluate the overall model fit, the Goodness of Fit (GOF) index was calculated using the AVE and R^2 values. According to established criteria, the R^2 values ranged from moderate to strong across the constructs: *Problem Definition* (0.372) and *Acquisition* (0.281) fell within the moderate range, while *Notification* (0.689) and *Evaluation* (0.740) demonstrated strong explanatory power. These results indicate that the proposed model exhibits a satisfactory level of overall fit, and that the latent constructs are capable of explaining a substantial proportion of the variance in the dependent variables.

Based on the collected data and the results of the quantitative analysis, a four-step implementation process is proposed. These stages include: Problem Selection, Notification, Evaluation, and Acquisition. Accordingly, a model outlining the recommended structure for organizing innovation challenges has been developed and is illustrated in Figure 4.

Figure 5

The pattern of holding innovative challenges



4. Discussion and Conclusion

Based on the empirical data and existing theoretical literature, particularly the foundational works of Brabham (2008), Pollok et al. (2019), and the more recent findings of Buemel (2025), this study proposes a practical four-stage model for running innovation challenges: problem definition, notification, evaluation, and acquisition (Bäumle, 2025; Brabham, 2008; Pollok et al., 2019). This model outlines the dynamic role of intermediaries in uncovering real industrial needs, communicating effectively, evaluating proposals, and facilitating knowledge transfer — especially in developing contexts.

Problem Definition: While most prior models assume that firms can clearly articulate their challenges, our findings (Pollok et al., 2019) reveal that intermediaries are critical in co-defining problems due to applicants' limited awareness of technical roots. These intermediaries often bridge cognitive gaps and reduce institutional complexity (Hyvärinen et al., 2024) by translating latent needs into solvable challenge statements.

Notification: Dissemination involves a blend of digital and traditional methods to gain traction among solvers. Trust-building practices (Brabham, 2008) and credible organizational involvement are key. Recent studies (Bakici, 2020; Mazzola et al., 2020) further emphasize that transparency in rewards and process design greatly enhances solver participation — which our field observations also confirm.

Evaluation: Evaluation criteria — scientific validity, feasibility, cost-efficiency, and prototyping — reflect the dual need for academic rigor and industrial applicability. Studies such as Widmar (2021) and Abi-Saab et al. (2024) support the notion that intermediaries serve as quality filters, validating designs through their systemic roles and enhancing trust between stakeholders (Abi Saad et al., 2024; Vidmar, 2021).

Acquisition: The final phase involves facilitating direct engagement and IP negotiation. We echo concerns raised in Xiao et al. (2021) and Cho & Bai (2025), noting that successful acquisition depends heavily on intermediaries' ability to reduce alienation, ensure equitable agreements, and sustain post-challenge collaborations — especially

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where IP frameworks are weak (Chu & Bai, 2025; Xiao et al., 2021).

This study enriches the crowdsourcing and open innovation literature by offering a practical and context-aware framework tailored to the realities of developing economies. The proposed model centers the innovation intermediary as a catalyst — a view supported by recent literature (Howells, 2024) that redefines intermediaries as not just facilitators, but active enablers of innovation ecosystems through digitalization, knowledge brokerage, and systemic support. Practically, this implies:

For intermediaries: There is growing pressure to go beyond matchmaking and engage in demand articulation (Bäumle, 2025), evidence-based validation (Scarbrough et al., 2024), and even policy advocacy (Howells, 2024).

For policy makers: As noted by Clair et al. (2024) and Cho & Bai (2025), intermediaries flourish when supported by public funding, robust digital infrastructure, and formalized innovation policies — all vital for building trust and reducing risk in fragile innovation systems (Chu & Bai, 2025; Claire et al., 2024). However, despite these insights, current guidance for policymakers lacks specificity. To address this, our study proposes five targeted policy actions, prioritized based on their urgency and contextual relevance to Iran's innovation ecosystem. The foremost priority should be the establishment of government-backed innovation challenge funds. This cornerstone initiative responds to the chronic underinvestment in R&D and risk aversion among SMEs in Iran, unlocking innovation pipelines through direct public co-financing. In parallel, legal sandboxes for experimental IP regimes and cross-sector collaboration models should be developed, allowing safe environments for testing and institutional learning. Performance-based subsidies tied to clear outcome indicators can improve resource efficiency and strengthen the accountability of intermediaries. In the medium term, national accreditation systems for intermediaries can foster trust and signal credibility to both domestic and international stakeholders. Lastly, embedding mandatory public-private partnerships (PPPs) within national innovation initiatives ensures systemic coherence, though their effectiveness depends on foundational reforms in funding and legal frameworks. These policy levers collectively reposition the government from a passive funder to a strategic orchestrator of innovation. Prioritization is key: starting with financial activation and legal flexibility, and gradually advancing toward institutional maturity and systemic trust.

For applicants: The model encourages firms to develop internal mechanisms for solver engagement and IP management, while recognizing intermediaries' role in building collaborative capacity (Lee & Cho, 2024).

Despite superficial similarities between the model presented in this study and some global models such as InnoCentive, the innovation of this model lies in its adaptability to the local conditions and institutional structure of Iran (InnoCentive, 2021). Unlike international models that primarily focus on leveraging global innovation networks and open international competitions, the four-stage model in this research has been designed with a proactive approach aimed at identifying hidden industrial needs, enhancing domestic capabilities, and facilitating effective interaction among local innovation actors.

In this model, active engagement with industrial companies is pursued to uncover their actual demands—not only through formal requests but also through on-site visits and in-depth interactions. This approach to discovering hidden and prioritized needs is not typically seen in international models and constitutes a theoretical and practical innovation in the proposed model.

Furthermore, the identification and activation of technological capabilities among academics and knowledge-based companies through targeted outreach—unlike global models which largely wait to receive proposals—demonstrate a fundamentally different approach on the supply side. In addition, the model involves government institutions, private investors, venture capital funds, and NGOs in an effort to prevent resource fragmentation and direct support toward addressing real industrial challenges.

Given Iran's structural challenges, specific measures have also been taken to build trust between industrial players and technology providers. These include creating a suitable legal framework such as non-disclosure agreements and protection of intellectual property, which hold particular significance in the Iranian context.

Overall, while drawing on core concepts of open innovation and innovation intermediation, the presented model stands out in practice—in terms of processes, actors, and objectives—through its localization strategy and focus on strengthening internal capacities.

Despite its valuable contributions, this study is not without limitations. The empirical foundation is rooted in Iran's innovation ecosystem, which is characterized by weak intellectual property enforcement and a culturally

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cautious stance toward external collaboration. While this context offers important insights into underexplored environments, it also limits the generalizability of the findings to other, more open innovation systems.

A key limitation lies in the small sample of innovation intermediaries included in the study, which may introduce bias and overfit the model to local dynamics. For instance, the observed intermediation practices were relatively limited in diversity, potentially leading to an incomplete portrayal of broader patterns. Additionally, cultural factors—such as high uncertainty avoidance and low institutional trust—may have influenced the model's assumptions by encouraging informal coordination, discouraging open data sharing, and limiting experimentation. These contextual constraints could reduce the model's applicability in ecosystems with stronger institutional frameworks or higher openness. Future research should:

- Examine how intermediaries adapt their business models to meet digital service demands under varying regulatory and cultural conditions (Sala-Vilar et al., 2024);
- Compare the functioning of ecosystem-focused intermediation across different industrial sectors (Abi Saad et al., 2024);

Investigate which reward mechanisms are most effective in low-trust, resource-constrained environments, and assess the transferability of these mechanisms to other contexts (Mazzola et al., 2020; Ye et al., 2012).

Authors' Contributions

Authors equally contribute to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

References

Abi Saad, E., Tremblay, N., & Agogué, M. (2024). A multi-level perspective on innovation intermediaries: The case of the diffusion of digital technologies in healthcare. *Technovation*, *129*, 102899. https://doi.org/10.1016/j.technovation.2023.102899

Bakici, T. (2020). Comparison of crowdsourcing platforms from social-psychological and motivational perspectives. *International Journal of Information Management*, *54*. https://doi.org/10.1016/j.ijinfomgt.2020.102121

Battistella, C., & Nonino, F. (2012). Open innovation web-based platforms: the impact of different forms of motivation on collaboration. *Innovations*, *14*(4), 557-575. https://doi.org/10.5172/impp.2012.14.4.557

Bäumle, P. (2025). *Knowledge intermediaries in regional innovation systems*.

Brabham, D. C. (2008). Crowdsourcing as a model for problem solving. *Convergence*, *14*(1), 75-90. https://doi.org/10.1177/1354856507084420

Chauhan, A. S., Nepal, B., Soni, G., & Rathore, A. P. S. (2018). Examining the state of risk management research in new product development process. *Engineering Management Journal*, *30*(2), 85-97. https://doi.org/10.1080/10429247.2018.1446120

Chen, L., Wang, M., Cui, L., & Li, S. (2021). Experience base, strategy-by-doing and new product performance. *Strategic management journal*, *42*(7), 1379-1398. https://doi.org/10.1002/smj.3262

Chesbrough, H. (2006). *Open Business Models*. Harvard Business School Press.

Chesbrough, H. W. (2003). *Open Innovation: The New Imperative for Creating and Profiting from Technology*. Harvard Business School Press.

Chu, X., & Bai, Y. (2025). Effect of the digital transformation of firms in a developing country on their reverse innovation: the complementary roles of multi-contexts. *Int. J. Technology Management*, *97*(2/3), 275-304. https://doi.org/10.1504/IJTM.2025.143582

Claire, H., McCarthy, A., Ferri, P., & Shapira, P. (2024). Innovation intermediaries at the convergence of digital technologies, sustainability, and governance: A case study of AI-enabled engineering biology. *Technovation*, *129*, 102875. https://doi.org/10.1016/j.technovation.2023.102875

Colovic, A., Caloffi, A., Rossi, F., & Russo, M. (2025). Institutionalising the digital transition: The role of digital innovation intermediaries. *Research Policy*, *54*(1), 105146. https://doi.org/10.1016/j.respol.2024.105146

AITBSS AI and Tech in Behavioral and Social Sciences E-ISSN: 3041-9433

Cooper, R. G. (2019). The drivers of success in new-product development. *Industrial Marketing Management*, *76*, 36-47. https://doi.org/10.1016/j.indmarman.2018.07.005

Dahlander, L., & Gann, D. (2010). How open is innovation? *Research Policy*, *39*(6). https://doi.org/10.1016/j.respol.2010.01.013

De Almeida, J. F., Amaral, D. C., & Coelho, R. T. (2021). *Innovative Framework to manage New Product Development (NPD) Additive Manufacturing (AM) and Agile Management*

De Mattosa, C. A., Kissimotob, K. O., & Laurindoc, F. J. B. (2018). The role of information technology for building virtual environments to integrate crowdsourcing mechanisms into the open innovation process. *Technological Forecasting & Social Change*, *129*. https://doi.org/10.1016/j.techfore.2017.12.020

Durmusoglu, S. S., & Kawakami, T. (2021). Information technology tool use frequency in new product development: The effect of stage-specific use frequency on performance. *Industrial Marketing Management*, *93*. https://doi.org/10.1016/j.indmarman.2021.01.014

Egger, R., Gula, I., & Walcher, D. (2016). Towards a Holistic Framework of Open Tourism. In R. Egger, I. Gula, & D. Walcher (Eds.), *Open Tourism: Open Innovation, Crowdsourcing and Co-Creation Challenging the Tourism Industry*. Springer. https://doi.org/10.1007/978-3-642-54089-9

Ettlinger, N. (2017). Open innovation and its discontents. *Geoforum*, *80*. https://doi.org/10.1016/j.geoforum.2017.01.011

Foege, J. N., Dragsdahl Lauritzen, G., Tietze, F., & Salge, T. O. (2019). Reconceptualizing the paradox of openness: How solvers navigate sharingprotecting tensions in crowdsourcing. *Research Policy*, *48*. https://doi.org/10.1016/j.respol.2019.01.013

Ghezzi, A., Gabelloni, D., Martini, A., & Natalicchio, A. (2017). Crowdsourcing: A Review and Suggestions for Future Research. *International Journal of Management Reviews*.

Grönlund, J., Sjödin, D. R., & Frishammar, J. (2010). Open innovation and the stage-gate process: A revised model for new product development. *California Management Review*, *52*(3), 106-131. https://doi.org/10.1525/cmr.2010.52.3.106

Gutierrez-Gutierrez, L. J., Barrales-Molina, V., & Kaynak, H. (2018). The role of human resource-related quality management practices in new product development: A dynamic capability perspective. *International Journal of Operations & Production Management*, *38*(1), 43-66. https://doi.org/10.1108/IJOPM-07-2016-0387

Hossain, M., & Kauranen, I. (2015). Crowdsourcing: a comprehensive literature review. *Strategic Outsourcing: An International Journal*, *8*(1). https://doi.org/10.1108/SO-12-2014-0029

Howe, J. (2006). The Rise of Crowdsourcing. *WIRED*, *14*.

Howells, J. (2024). Innovation intermediaries in a digital paradigm: A theoretical perspective. *Technovation*, *129*, 102889. https://doi.org/10.1016/j.technovation.2023.102889

Hyvärinen, A. M., Keskinen, M., & Levänen, J. (2024). Intermediaries as drivers of innovation development in resource-constrained environments: Insights from the Kenyan water sector. *Technovation*, *131*, 102956. https://doi.org/10.1016/j.technovation.2024.102956

InnoCentive. (2021). *InnoCentive.com*. www.Innocentive.com

Keinz, P., & Marhold, K. (2021). Technological competence leveraging projects via intermediaries: Viable means to outbound open innovation and mediated capability building? *International Journal of Project Management*, *29*. https://doi.org/10.1016/j.ijproman.2020.10.006

Lee, H., & Cho, N. (2024). Relationship between Absorptive Capacity, Technology Collaboration Performance, and Innovation Intermediaries: A Grounded Theory Approach. *Journal of Information Technology Applications and Management*, *31*(3), 105-117. https://doi.org/10.21219/JITAM.2024.31.3.105

Leimeister, J. M., Huber, M., Bretschneider, U., & Krcmar, H. (2009). Leveraging Crowdsourcing: Activation-Supporting components for IT-based ideas competition. *Journal of Management Information Systems (JMIS)*, *26*(1), 197-224. https://doi.org/10.2753/MIS0742-1222260108

Lu, P., Yuan, S., & Wu, J. (2017). The interaction effect between intra-organizational and inter-organizational control on the project performance of new product development in open innovation. *International Journal of Project Management*, *35*(8). https://doi.org/10.1016/j.ijproman.2017.09.009

Mazzola, E., Piazza, M., Acur, N., & Perrone, G. (2020). Treating the crowd fairly: Increasing the solvers' self-selection in idea innovation contests. *Industrial Marketing Management*, *91*, 16-29. https://doi.org/10.1016/j.indmarman.2020.07.019

Mergel, I., & Desouza, K. C. (2013). Implementing Open Innovation in the Public Sector: The Case of Challenge.gov. *Public Administration Review*, *73*, 882-890. https://doi.org/10.1111/puar.12141

Ozaygen, A., & Balague, C. (2018). Idea Evaluation in Innovation Contest Platforms: A Network Perspective. *Decision Support Systems*, *112*, 15-22. https://doi.org/10.1016/j.dss.2018.06.001

Pollok, P., Lüttgens, D., & Piller, F. T. (2018). How firms develop capabilities for crowdsourcing to increase open innovation performance: The interplay between organizational roles and knowledge processes. *Journal of Product Innovation Management*, *36*(4). https://doi.org/10.1111/jpim.12485

Pollok, P., Lüttgens, D., & Piller, F. T. (2019). Attracting solutions in crowdsourcing contests: The role of knowledge distance, identity disclosure, and seeker status. *Research Policy*, *48*(1), 98-114. https://doi.org/10.1016/j.respol.2018.07.022

Presenza, A., Abbate, T., Cesaroni, F., & Appio, F. P. (2019). Enacting Social Crowdfunding Business Ecosystems: The case of the platform Meridonare. *Technological Forecasting & Social Change*, *143*. https://doi.org/10.1016/j.techfore.2019.03.001

Richard, B., Ford, R., & Perry, W. (2016). Crowdsourcing in the lodging industry: Innovation on a budget. In R. Egger, I. Gula, & D. Walcher (Eds.), *Open Tourism - Open Innovation, Crowdsourcing and Collaborative Consumption challenging the tourism industry* (pp. 79-94). https://doi.org/10.1007/978-3-642-54089-9_6

Rivasa, A. A., Chenb, Y.-C., & Yang, T.-K. (2020). Entrepreneurial and alliance orientation alignment in new product development. *Technological Forecasting & Social Change*, *153*, 119916. https://doi.org/10.1016/j.techfore.2020.119916

Sala-Vilar, L. R., Li-Ying, J., & Traunecker, T. (2024). How do innovation intermediaries' business models cope with their need to develop new digital services? *Technovation*, *131*, 102950. https://doi.org/10.1016/j.technovation.2023.102950

Sari, A., Tosun, A., & Alptekin, G. I. (2019). A systematic literature review on crowdsourcing in software engineering. *The Journal of Systems and Software*, *153*. https://doi.org/10.1016/j.jss.2019.04.027

Scarbrough, H., Sanfilippo, K. R. M., Ziemann, A., & Stavropoulou, C. (2024). Mobilizing pilot-based evidence for the spread and sustainability of innovations in healthcare: The role of innovation intermediaries. *Social Science &*

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E-ISSN: 3041-9433

Medicine, *340*, 116394. https://doi.org/10.1016/j.socscimed.2023.116394

Schemmann, B., Herrmann, A., Chappin, M. M. H., & Heimeriks, G. J. (2016). Crowdsourcing ideas: Involving ordinary users in the ideation phase of new product development. *Research Policy*, *45*. https://doi.org/10.1016/j.respol.2016.02.003

Strazzullo, S., Mauriello, R., Corvello, V., Cricelli, L., & Grimaldi, M. (2025). How open innovation can improve companies' corporate social responsibility performance? *Business Ethics, the Environment & Responsibility*, *34*(1), 1-16. https://doi.org/10.1111/beer.12535

Taeihagh, A. (2017). *Examination of crowdsourcing as a tool for policy making*

Tam, C., da Costa Moura, E. J., Oliveira, T., & Varajão, J. (2020). The factors influencing the success of on-going agile software development projects. *International Journal of Project Management*, *38*(3), 165-176. https://doi.org/10.1016/j.ijproman.2020.02.001

Vidmar, M. (2021). Enablers, Equippers, Shapers and Movers: A typology of innovation intermediaries' interventions and the development of an emergent innovation system. *Acta Astronautica*, *179*. https://doi.org/10.1016/j.actaastro.2020.10.011

Xiao, S., Lew, Y. K., & Park, B. I. (2021). International new product development performance, entrepreneurial capability, and network in high-tech ventures. *Journal of Business Research*, *124*. https://doi.org/10.1016/j.jbusres.2020.11.048

Ye, W., Xu, P., Jia, Y., & Jiang, F. (2012). Crowdsourcing for open innovations. *Applied Mathematics*, *6*(3S).

Yin, R. K. (2018). *Case study research and applications*. Sage publications.

Zahaya, D., Hajlib, N., & Sihic, D. (2017). Managerial perspectives on crowdsourcing in the new product development process. *Industrial Marketing Management*. https://doi.org/10.1016/j.indmarman.2017.11.002

Zhua, X., Xiaob, Z., Dongc, M. C., & Gud, J. (2019). The fit between firms' open innovation and business model for new product development speed: A contingent perspective. *Technovation*. https://doi.org/10.1016/j.technovation.2019.05.005

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