



AI-Assisted Startup Readiness Assessment and Decision Support System Using Semantic Similarity and Personalized Recommendations

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ABSTRACT :

Assessing the readiness of an early-stage startup requires consideration of several factors related to its problem, market, product, business model, team, resources, finances, and growth plans. Existing startup evaluation approaches often concentrate on idea validation or prediction of future success, with comparatively less emphasis on diagnosing the startup's current level of readiness and identifying areas that require improvement.

This paper presents an AI-Assisted Startup Readiness Assessment and Decision Support System that combines structured assessment, data analytics, natural language processing, semantic similarity analysis, and generative artificial intelligence. The implemented Startup Readiness Assessment Framework (SRAF) contains 20 questions organized into eight dimensions: Problem and Innovation, Market, Product, Business Model, Founder and Team, Resources, Financial, and Growth and Incubation. Assessment responses are processed through a deterministic scoring engine to calculate dimension-level scores, Startup Readiness Score (SRS), Founder Readiness Score (FRS), Overall Readiness Score (ORS), and the corresponding readiness level.

The system additionally performs risk analysis and provides explainable assessment insights, benchmarking, and embedding-based semantic similarity analysis for identifying conceptually related startup profiles. A generative-AI component uses the assessment and analytical outputs to produce personalized improvement areas, recommended next steps, and incubation-support suggestions. The platform also includes interactive dashboards, assessment history, progress tracking, and PDF report generation.

The resulting platform integrates startup readiness assessment and AI-assisted decision support into a single workflow. Rather than predicting whether a startup will succeed in the future, the system focuses on evaluating its present readiness, highlighting areas that require attention, and providing actionable guidance to support founders and incubators.

Keywords:Startup Readiness Assessment, Artificial Intelligence, Data Science, Decision Support System, Natural Language Processing, Semantic Similarity, Sentence Embeddings, Recommendation System, Generative AI, Startup Analytics

Introduction

Startups contribute to technological innovation, employment creation, and the development of new products and services. For early-stage ventures, however, determining whether the business is sufficiently prepared for market entry, incubation, investment, and subsequent growth can be challenging. Startup readiness is influenced by several interconnected factors, including the founding team, problem and innovation, market understanding, product development, business model, financial preparedness, available resources, and growth potential. Evaluating these factors systematically can help founders recognize areas of strength and identify aspects that require further development before making important business decisions.

In many startup-evaluation settings, assessment is carried out using business plans, presentations, interviews, and expert reviews. These methods can require considerable time and may be influenced by the experience and judgment of the evaluator. Consequently, the resulting assessment may not provide a consistent quantitative view of the startup's present readiness or clearly indicate which areas should be improved. A structured assessment approach can therefore provide a more consistent way to examine multiple readiness factors and communicate the resulting strengths, gaps, and development needs.

The use of Artificial Intelligence (AI), Machine Learning (ML), Natural Language Processing (NLP), and Large Language Models (LLMs) has expanded across several startup-related tasks, including idea validation, success prediction, entrepreneurial readiness assessment, and recommendation generation. These studies demonstrate the usefulness of computational methods for analyzing startup-related information; however, many of the existing approaches address one particular aspect of evaluation rather than combining multiple readiness dimensions within a single assessment

process. From the perspective of the present study, this leaves several capabilities insufficiently integrated, including multidimensional readiness assessment, personalized recommendations, startup similarity analysis, benchmarking, risk analysis, and incubation-oriented decision support. The need is therefore not simply for another startup-success prediction model, but for a system that can assess the startup's current condition, explain the factors contributing to that assessment, and provide guidance for addressing identified gaps.

To address this requirement, this paper presents an AI-Assisted Startup Readiness Assessment and Decision Support System Using Semantic Similarity and Personalized Recommendations. The implemented system uses a Startup Readiness Assessment Framework (SRAF) containing 20 questions across eight dimensions: Problem and Innovation, Market, Product, Business Model, Founder and Team, Resources, Financial, and Growth and Incubation. The responses are processed through a structured scoring mechanism to obtain dimension-level scores, Startup Readiness Score (SRS), Founder Readiness Score (FRS), and Overall Readiness Score (ORS).

The system extends the assessment process with risk analysis, explainable insights, benchmarking, semantic similarity analysis, and generative-AI-based recommendations. Startup descriptions are represented through embeddings to identify conceptually related startup profiles, while the recommendation component uses the assessment results and analytical findings to generate personalized improvement guidance and incubation-support suggestions. The main contribution of the work is the integration of these capabilities into a unified decision-support platform that emphasizes the diagnosis of current startup readiness and actionable improvement guidance rather than prediction of future startup success.

Literature Survey

1.1. AI-Based Startup Idea Assessment and Validation

Prajapati and Albert (2025) introduced *IdeaSense*, an AI-driven framework for assessing and validating startup ideas before market entry or investment. The framework combines Natural Language Processing (NLP), Large Language Models (LLMs), market-related analysis, competitive analysis, and scoring techniques to examine factors such as idea originality, market demand, competition, revenue potential, and technical feasibility. It also produces structured evaluation outputs, including identified strengths, weaknesses, and recommendations for early-stage entrepreneurs.

The work demonstrates how AI can be applied to organize and support startup idea evaluation. However, its main emphasis is on validating the business idea, rather than evaluating the broader operational readiness of an existing startup venture. The framework does not combine multidimensional readiness scoring with benchmarking, startup similarity analysis, risk diagnostics, and incubation-oriented support as addressed in the present study.

1.2. Machine Learning and LLM-Based Startup Success Prediction

Machine learning and Large Language Models have also been applied to the problem of predicting startup success. Abdurahman Maarouf, Stefan Feuerriegel, and Nicolas Pröllochs (2024) developed a fused LLM approach that combines structured startup information with textual descriptions. Their study used 20,172 Crunchbase startup profiles and incorporated textual representations together with characteristics such as funding, founders, and business sector. The study reported that incorporating textual information improved balanced accuracy compared with using structured information alone.

This research demonstrates the value of combining structured and unstructured startup information for predictive analysis. However, its objective is to estimate future startup success, particularly in the context of investment decision-making. It does not provide a multidimensional readiness framework for diagnosing a startup's current condition or generating improvement-oriented recommendations.

Abdurahman Maarouf, AlketBakiaj, and Stefan Feuerriegel (2026) further investigated startup-success prediction using a k-Nearest Neighbor In-Context Learning (kNN-ICL) approach. The method retrieves relevant historical startups based on similarity and supplies them as contextual examples to an LLM. Their study used 4,034 Crunchbase profiles and evaluated different few-shot configurations, with the 50-shot setting achieving approximately 71.3% balanced accuracy.

This study is relevant to the present work because it illustrates how similarity between startups can be incorporated into AI-based analysis. However, in that work, similarity primarily supports the prediction task rather than being presented as an independent decision-support feature for founders. The approach also does not provide the readiness scoring, risk analysis, benchmarking, or improvement guidance implemented in the proposed platform.

Dominik Dellermann, Nikolaus Lipusch, Philipp Ebel, Karl Michael Popp, and Jan Marco Leimeister (2017) investigated early-stage startup success prediction through a Hybrid Intelligence approach. Their work combines machine intelligence with human judgment to address the uncertainty associated with evaluating early-stage startups. It highlights the relevance of qualitative characteristics, including team-related factors, innovativeness, entrepreneurial experience, and technological maturity, alongside measurable business information.

Other research has examined startup-success prediction using conventional and hybrid machine-learning approaches based on historical startup information (Potanin et al., 2023; Bangdiwala et al., 2022; Choi, 2024; Sompura et al., 2024). Collectively, these studies demonstrate the application of machine learning to identifying patterns associated with startup outcomes. Their primary objective, however, remains outcome prediction, whereas the present work focuses on diagnosing the startup's current readiness and translating the assessment into actionable development guidance.

1.3. Entrepreneurial and Startup Readiness Assessment

Alicia Coduras, José Manuel Saiz-Alvarez and Jesús Ruiz (2016) proposed an information tool for measuring *readiness for entrepreneurship*. Their framework addresses the lack of specific tools for measuring individual entrepreneurial readiness and organizes relevant factors into sociological, psychological, and managerial-entrepreneurial categories. A scoring system is used to generate both overall and partial readiness scores.

This study establishes an important theoretical basis for *multidimensional readiness measurement*. However, the framework focuses primarily on the readiness of an individual entrepreneur rather than the operational and strategic readiness of a complete startup venture. It also does not incorporate semantic startup similarity, AI-assisted recommendations, benchmarking, or incubation analytics.

Nita Ambarita and SuwatnoSuwatno (2024) examined entrepreneurial education and readiness through bibliometric analysis, identifying major research themes associated with entrepreneurial preparedness, education, and related competencies. This work further supports the importance of understanding readiness as a multidimensional concept rather than a single measurable characteristic.

The readiness literature therefore provides a conceptual foundation for evaluating preparedness, but there remains a need to extend this concept from *individual entrepreneurial readiness toward integrated startup-level readiness assessment*.

1.4. Recommendation Systems and Personalized Decision Support

Recommendation systems have been developed to provide users with personalized information and decision-support outputs across a wide range of application domains. Zeshan Fayyaz, Mahsa Ebrahimian, Dina Nawara, Ahmed Ibrahim, and Rasha Kashef (2020) reviewed major recommendation-system approaches, evaluation measures, application areas, and associated challenges. Their review covers content-based, collaborative, demographic, utility-based, knowledge-based, and hybrid recommendation methods. It also discusses challenges including cold-start conditions, data sparsity, scalability, privacy, and recommendation quality.

This body of research demonstrates the usefulness of personalized recommendation mechanisms for assisting users in decision-making. However, conventional recommendation systems are commonly designed around domains such as products, media, healthcare, or education, where user preferences and historical interactions are central to recommendation generation.

In the present system, recommendations are generated from the startup's assessment profile, readiness scores, identified risks, and analytical results. The purpose is therefore different from conventional item recommendation: the system converts diagnostic assessment information into startup-specific improvement actions, next steps, and incubation-support suggestions.

1.5. Startup Development Under Uncertainty

Anh Nguyen Duc, Yngve Dahle, Martin Steinert, and Pekka Abrahamsson (2017) examined software startup development from the perspective of entrepreneurial theory. Their work highlights the uncertainty surrounding early-stage startup development and the dynamic decisions founders must make concerning product development, business direction, and resource allocation.

This perspective is relevant to the present research because startup decisions are made under changing conditions and incomplete information. A decision-support system can therefore help founders understand their current position and identify areas that require additional attention. However, the study is primarily concerned with understanding startup development under uncertainty and does not provide an automated computational framework for multidimensional readiness scoring, semantic comparison, or personalized AI-assisted guidance.

1.6. Research Gap

The reviewed studies indicate that startup research has developed along several related but largely separate directions. AI-based idea-assessment approaches concentrate on evaluating the viability of business concepts, while machine-learning and LLM-based studies primarily attempt to predict future startup success. Entrepreneurial-readiness research focuses mainly on measuring the preparedness of individuals, whereas recommendation-system research has traditionally concentrated on personalized information delivery.

These research streams leave a gap in venture-level assessment of current startup readiness. Existing approaches provide limited integration of multiple startup dimensions with systematic identification of readiness gaps and areas requiring improvement. There is also limited combination of risk analysis, explainability, semantic startup similarity, benchmarking, personalized recommendations, and incubation-oriented support within a single platform.

Therefore, the present study addresses the need for an integrated decision-support framework that evaluates the current state of a startup rather than only predicting its future success. The framework is designed to identify readiness gaps and potential risks, provide contextual comparison through semantic similarity and benchmarking, and convert assessment findings into actionable recommendations.

The proposed AI-Assisted Startup Readiness Assessment and Decision Support System addresses this gap by combining a structured Startup Readiness Assessment Framework, deterministic readiness scoring, risk analysis, explainable insights, semantic similarity, benchmarking, and AI-assisted personalized recommendations within one platform.

Problem Statement and Objectives

1.7. Problem Statement

Early-stage startups must evaluate their level of preparedness before moving toward activities such as incubation, investment, market entry, and business expansion. This evaluation involves multiple interconnected aspects, including the problem being addressed, innovation, market conditions, product development, business model, founding team, available resources, financial preparedness, and growth plans. Assessing these factors independently can make it difficult to obtain a clear and consistent view of the startup's overall readiness.

Existing approaches generally address either the evaluation of a startup idea or the prediction of future startup success. While these approaches provide useful analytical information, they offer limited support for diagnosing the startup's **present readiness** and identifying the specific dimensions that require improvement (Prajapati & Albert, 2025; Maarouf, Feuerriegel, & Pröllochs, 2024; Maarouf, Bakiaj, & Feuerriegel, 2026; Dellermann et al., 2017).

Startup evaluation may also involve business plans, presentations, interviews, and expert assessment. Such processes can require substantial effort and may vary according to the evaluator's experience and judgment. Although machine learning, natural language processing, recommendation systems, and generative AI have been applied to different entrepreneurship-related tasks, these capabilities are generally distributed across separate applications rather than combined into a unified startup-readiness assessment process (Coduras, Saiz-Alvarez, & Ruiz, 2016; Ambarita & Suwatno, 2024; Fayyaz et al., 2020; Duc et al., 2017).

Consequently, there is a need for a system that can examine the current readiness of a startup across multiple dimensions, identify strengths and areas requiring improvement, analyze associated risks, provide contextual comparison with other startup profiles, and convert the assessment results into actionable recommendations. The proposed system addresses this requirement by combining a structured Startup Readiness Assessment Framework (SRAF), deterministic scoring, data analytics, semantic similarity analysis, benchmarking, and generative-AI-based recommendations.

1.8. Objectives

The major objectives of the implemented system are:

- **To develop** a structured Startup Readiness Assessment Framework (SRAF) covering eight dimensions: Problem and Innovation, Market, Product, Business Model, Founder and Team, Resources, Financial, and Growth and Incubation.
- **To implement** a deterministic scoring mechanism for calculating dimension-level scores, Startup Readiness Score (SRS), Founder Readiness Score (FRS), Overall Readiness Score (ORS), and the corresponding readiness level.
- **To generate** analytical and explainable insights by identifying startup strengths, improvement areas, risk categories, dimension contributions, and a diagnostic confidence score.
- **To apply** sentence-embedding-based semantic similarity analysis for identifying conceptually similar startup profiles and deriving similarity, novelty, and competitive-overlap indicators.
- **To provide** benchmarking functionality for comparing startup assessment results with available platform cohort data and selected benchmark groups.
- **To generate** personalized AI-assisted recommendations from assessment and analytical results, including improvement areas, recommended next steps, and suggested incubation support.
- **To develop** an integrated interface and reporting mechanism that supports dashboards, assessment history, progress tracking, PDF-based assessment reports, and administrative analytics for cohort-level monitoring.

Proposed Methodology

The methodology is organized as a modular workflow for evaluating startup readiness and producing decision-support outputs. It integrates structured assessment, deterministic scoring, diagnostic analysis, semantic similarity, benchmarking, and generative artificial intelligence within a single platform.

1.9. Startup Readiness Assessment Framework

The Startup Readiness Assessment Framework (SRAF) contains 20 structured questions organized into eight readiness dimensions:

Table 1 - Startup Readiness Assessment Framework

Dimension	Number of Questions
Problem and Innovation	3
Market	3
Product	2
Business Model	3
Founder and Team	3
Resources	2
Financial	2
Growth and Incubation	2
Total	20

Each question contains predefined response options, and every selected response is assigned a score ranging from 0 to 5. The responses are therefore converted into standardized numerical values that can be processed consistently by the scoring engine.

1.10. Readiness Score Calculation

The submitted responses are first validated to confirm that all required assessment questions have been completed. The scores obtained for each dimension are then converted into percentage values based on the corresponding question scores.

Three primary readiness indicators are calculated by the system:

- **Startup Readiness Score (SRS):** represents readiness across the seven dimensions other than Founder and Team.
- **Founder Readiness Score (FRS):** represents the percentage score for the Founder and Team dimension.
- **Overall Readiness Score (ORS):** combines the startup-level and founder-level readiness scores.

For each dimension, the percentage score is obtained by comparing the average response score with the corresponding maximum average score.

Equation (1) — SRS

$$SRS = \frac{\sum_{d \in D} P_d W_d}{\sum_{d \in D} W_d} \quad (1)$$

In Equation (1), the calculation considers the seven dimensions other than Founder and Team. Each dimension contributes according to its assigned weight and percentage score.

Equation (2) — FRS

$$FRS = P_{\text{Founder and Team}} \quad (2)$$

Equation (2) calculates the percentage score for the Founder and Team dimension.

Equation (3) — OR

$$ORS = (SRS \times 0.70) + (FRS \times 0.30) \quad (3)$$

Equation (3) combines the startup and founder readiness components to obtain the Overall Readiness Score (ORS).

Table 2 - Startup Readiness Levels

Overall Readiness Score	Readiness Level
0–<35	Not Ready
35–<55	Early Stage
55–<75	Developing
75–<90	Validation Ready
90–100	Incubation Ready

The calculated ORS is subsequently mapped to one of five predefined readiness levels: Not Ready, Early Stage, Developing, Validation Ready, and Incubation Ready.

1.11. Analytical and Risk Assessment

Once the readiness scores have been calculated, the system performs a further diagnostic analysis of the assessment results. Dimension-level scores are examined to identify relatively strong areas and dimensions that may require improvement. Risk indicators are also calculated across five categories: Market, Financial, Execution, Technology, and Business.

To support interpretation of the assessment, the system provides explainability information based on the contribution of individual dimensions to the overall readiness result. A Diagnostic Confidence Score is additionally calculated as a heuristic indicator of assessment quality using assessment completion, dimension balance, and score variation.

1.12. Semantic Similarity and Benchmarking

The platform uses semantic similarity analysis to provide additional context about the assessed startup. Startup profile information is transformed into 384-dimensional embeddings using the Xenova/all-MiniLM-L6-v2 sentence-embedding model.

Cosine similarity is applied to compare the embedding of the current startup with the available startup profiles. These similarity values are used to derive similarity, novelty, and competitive-overlap indicators.

The resulting similarity measure represents semantic relatedness between the available startup profiles and is not treated as a definitive indicator of direct market competition.

Benchmarking is also provided by comparing the startup's assessment results with available cohort and benchmark data. These comparisons are intended to provide contextual information and should not be interpreted as statistically validated industry benchmarks.

1.13. AI-Assisted Recommendation Generation

The analytical outputs are supplied to a generative-AI component powered by Google Gemini. The recommendation module receives the startup's dimension scores, SRS, FRS, ORS, readiness level, Diagnostic Confidence Score, and identified risk information.

The generative-AI component is not responsible for calculating the numerical readiness scores. These values are produced independently by the deterministic scoring engine.

Using the assessment and analytical inputs, the system generates the following outputs:

- Overall assessment
- Strengths
- Areas requiring improvement
- Recommended next steps
- Structured recommendations
- Suggested incubation support
- Final recommendation

The generated recommendations are intended to support founders and incubators in interpreting assessment results and planning improvement activities. They do not function as autonomous decisions for startup approval, rejection, investment, or incubation.

1.14. Reporting and Progress Tracking

Assessment results and generated recommendations are presented through an interactive dashboard. Users can access their readiness scores, analytical findings, risk indicators, similarity results, recommendations, and assessment history. The system also produces a consolidated PDF report containing the principal assessment and recommendation outputs.

Overall, the methodology forms a complete workflow beginning with startup profiling and structured assessment and continuing through readiness scoring, diagnostic analysis, semantic similarity, benchmarking, AI-assisted recommendation generation, and report creation.

This workflow extends the system beyond the presentation of a single readiness score by providing additional diagnostic and actionable decision-support information.

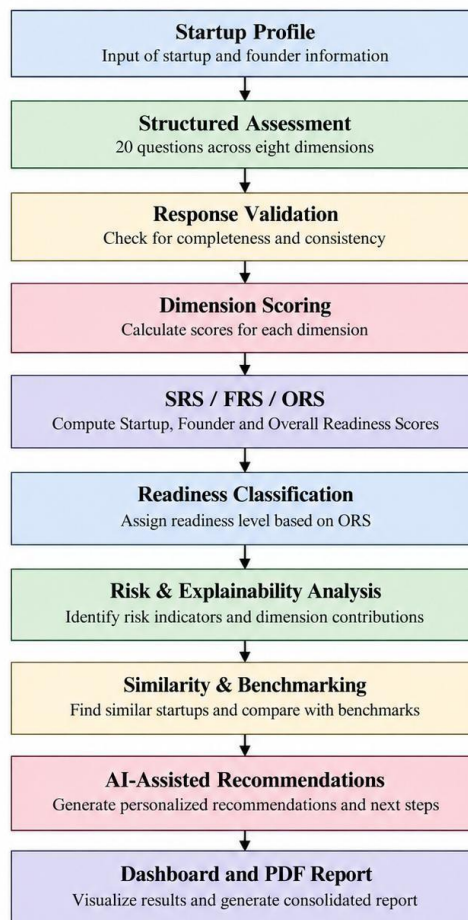


Fig. 1 – Proposed Methodology Workflow

System Architecture and Implementation

The implemented platform follows a three-tier architecture consisting of a Presentation Layer, Business Logic Layer, and Data Layer. This separation organizes the user interface, application processing, assessment logic, and persistent data management into distinct components.

The Presentation Layer is developed using React and TypeScript. It provides the user-facing interfaces for authentication, startup profile management, readiness assessment, dashboards, recommendations, progress tracking, and report generation.

The Business Logic Layer is implemented with Node.js and Express. It manages authentication and assessment-response validation and performs the core processing operations, including readiness-score calculation, risk analysis, explainability analysis, benchmarking, semantic similarity processing, and AI-assisted recommendation generation.

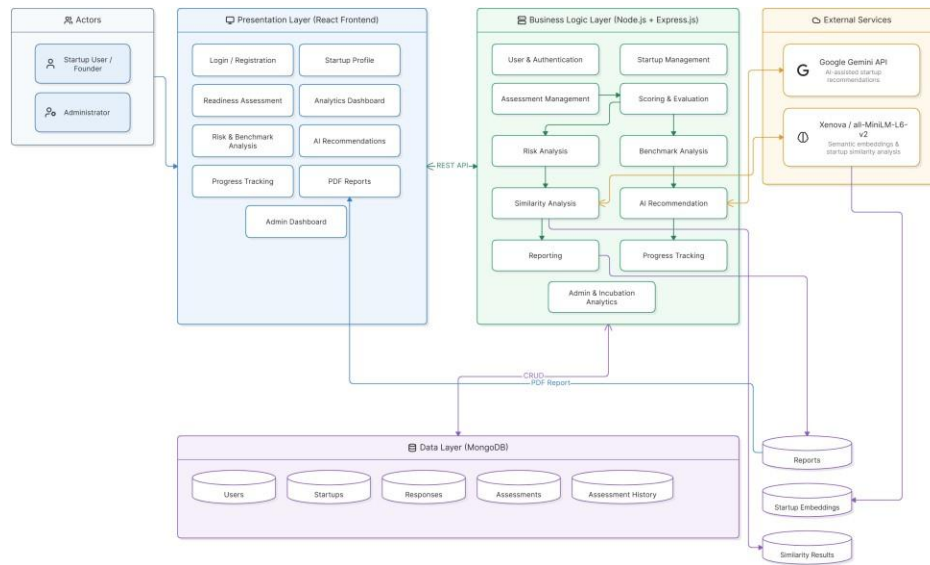


Fig. 2 – System Architecture of the Platform

The Data Layer uses MongoDB for persistent storage of user information, startup profiles, assessment responses, assessment records, assessment history, reports, embeddings, and similarity results. A local JSON-based storage mechanism is also available as a fallback option.

The major functional modules are:

- User and Startup Management
- Readiness Assessment and Scoring
- Analytics and Risk Analysis
- Similarity and Benchmarking
- AI-Assisted Recommendation
- Reporting and Progress Tracking
- Administrative Analytics

Communication between the frontend and backend is performed through REST-based API endpoints. The frontend submits startup and assessment information to the backend, where the data is processed and the resulting scores, risk indicators, similarity outputs, and AI-assisted recommendations are returned for presentation. The processed outputs are displayed through the dashboard and are also incorporated into the consolidated PDF assessment report.

Results and Evaluation

The implemented platform was evaluated by examining the operation of its major functional components, including structured readiness assessment, diagnostic analysis, startup similarity analysis, benchmarking, and AI-assisted recommendation generation. The evaluation focuses on whether the system produces the intended assessment and decision-support outputs from the information provided by the startup user.

1.15. Readiness Assessment Results

The readiness assessment module successfully processes the 20-question SRAF and produces scores for all eight defined dimensions. These dimension-level results are subsequently used to calculate the Startup Readiness Score (SRS), Founder Readiness Score (FRS), and Overall Readiness Score (ORS). The resulting ORS is mapped to the corresponding predefined readiness category.

VentureLens
INCUBATION INTELLIGENCE
AI-Powered Startup Readiness & Incubation Analytics Platform

PLATFORM NAVIGATION

- Startup Profile
- Readiness Assessment**
- Analytics Dashboard
- AI Recommendations
- PDF Report Lab
- Progress Tracking
- Risk & Benchmarks
- General Settings

SYSTEM STATUS

- Database Connection: Connected
- Profile Status: Completed
- Assessment Ready: Ready

VentureLens: Incubation Analytics & Diagnostic Platform
Configure venture credentials and compile multi-dimensional readiness capabilities.

Startup corporate profile saved successfully!

Startup Readiness Assessment
Evaluate key multidimensional domains to quantify venture capability.

ACTIVE DIMENSION: Problem & Innovation

Question 1 of 20

QUESTION STANDARD BASELINE

Which statement best describes the problem your startup aims to solve?
Please evaluate your current capability under the **Problem & Innovation** criteria. Select the maturity level option that best represents your startup's operational status.

OPERATIONAL MATURITY LEVELS (REQUIRED)

- No specific problem has been identified.
- A general problem has been identified, but there is no supporting evidence.
- The problem has been identified through limited observations or informal discussions.
- The problem has been validated through customer interviews, surveys, or preliminary market research.
- The problem is clearly validated with sufficient evidence from the target market.
- The problem is continuously monitored and strongly supported by customer and market evidence.

Previous Next

Fig. 3 – Startup Readiness Assessment Interface

1.16. Risk and Explainability Results

The analytical component generates risk indicators for five categories: Market, Financial, Execution, Technology, and Business. The system also provides dimension-level contribution information, allowing the influence of individual assessment dimensions on the overall readiness result to be examined. In addition, the Diagnostic Confidence Score is presented as a heuristic indicator of assessment quality.

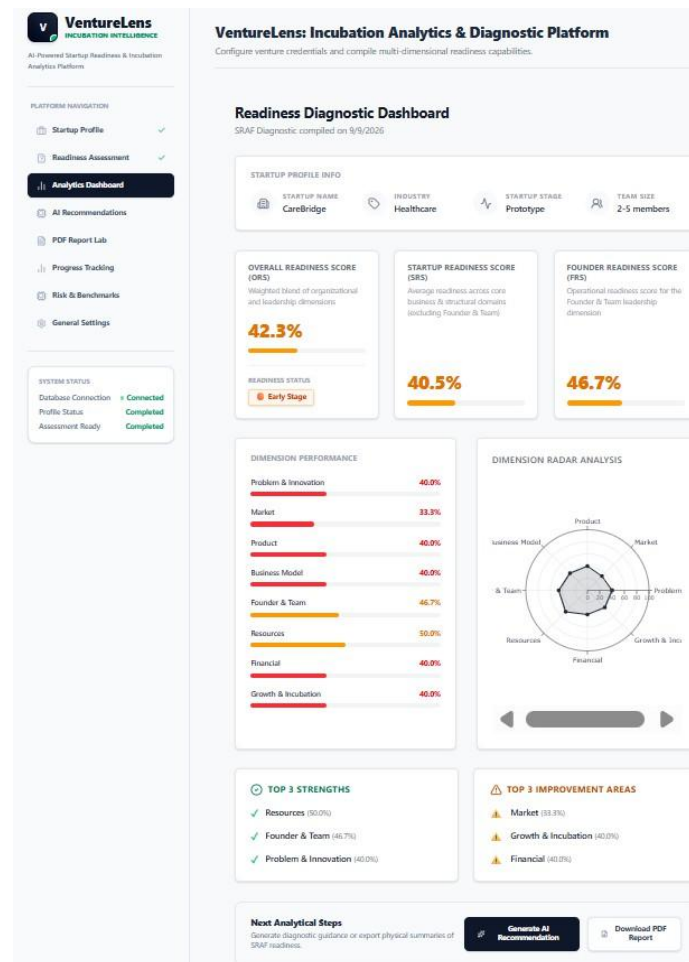


Fig. 4 – Readiness Dashboard

1.17. Similarity and Benchmarking Results

The semantic similarity component converts startup profiles into 384-dimensional embeddings and compares the resulting representations using cosine similarity. The similarity values are used to derive similarity, novelty, and competitive-overlap indicators. The benchmarking component additionally compares assessment results with the available platform and benchmark data.

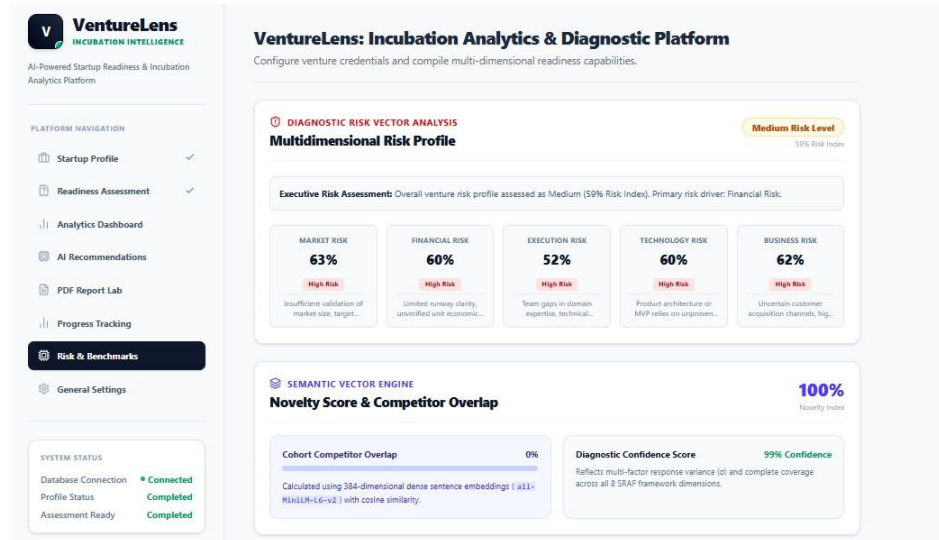


Fig. 5 – Similarity and Benchmarking Results

The interpretation of cohort-level benchmarking depends on the number and representativeness of startup records available within the system. Therefore, the current benchmarking results are treated as contextual comparisons rather than statistically validated industry benchmarks.

1.18. AI-Assisted Recommendation Results

The AI-assisted recommendation module uses the startup's assessment results and diagnostic information to generate personalized decision-support outputs. The generated results include identified strengths, improvement areas, recommended next steps, and suggested incubation support. These outputs extend the assessment beyond numerical readiness scores by providing guidance related to the areas identified during the analysis.

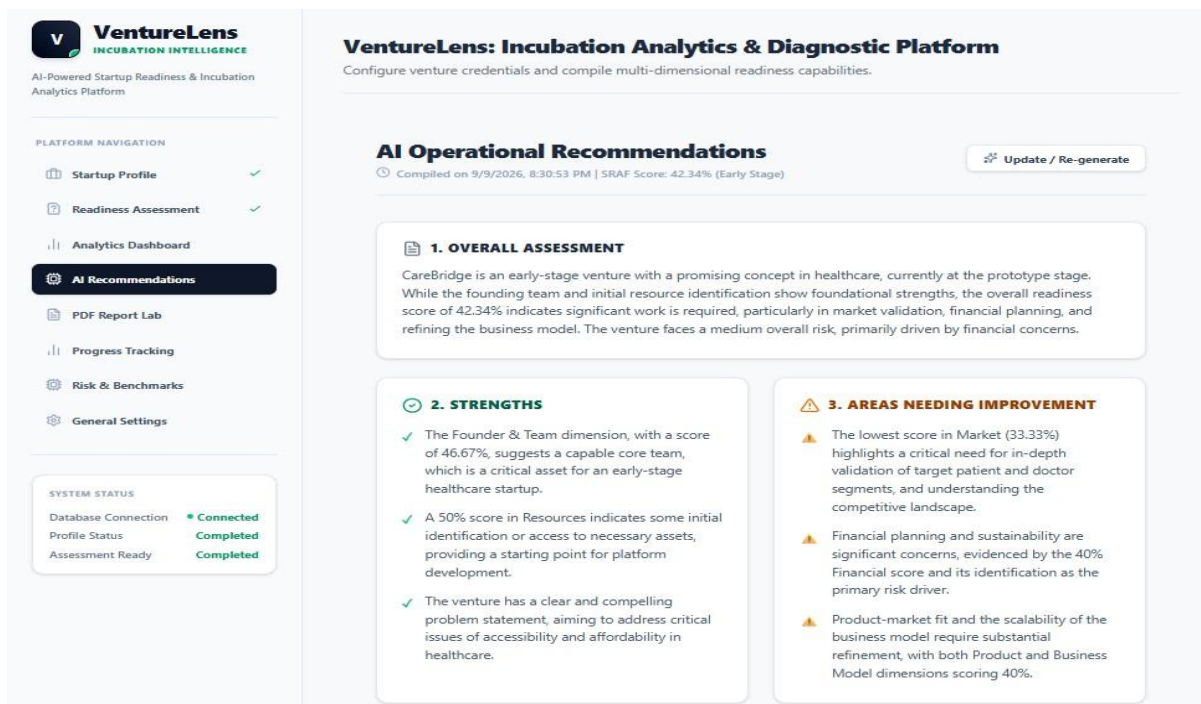


Fig. 6 – AI-Assisted Recommendations

4. RECOMMENDED NEXT STEPS & IMPACT MATRIX

PROBLEM: INSUFFICIENT MARKET VALIDATION AND UNDERSTANDING OF TARGET USER NEEDS WITHIN THE HEALTHCARE SECTOR. HIGH PRIORITY

Reason: The low Market score (33.33%) indicates a lack of empirical data on specific patient pain points, doctor requirements, and competitive differentiation, which is crucial for product adoption.

Action: Execute a comprehensive market validation study, including qualitative interviews with at least 20-30 potential users (patients and doctors) and quantitative surveys to identify key feature priorities and pricing sensitivities.

Expected Impact: A significantly improved understanding of market demand, leading to a more targeted product roadmap and a higher Market dimension score.

PROBLEM: INADEQUATE FINANCIAL PLANNING AND A HIGH PRIMARY FINANCIAL RISK PROFILE. HIGH PRIORITY

Reason: The 40% Financial score and identified 'Financial Risk' as the primary risk driver suggest a lack of detailed financial projections, funding strategy, and cost management, which is critical for securing investment and operational stability.

Action: Develop a detailed financial plan encompassing startup costs, operational expenses, revenue projections, and a clear funding roadmap (e.g., seed, grant applications) for the next 18-24 months.

Expected Impact: Reduced financial risk, increased investor confidence, and a clearer path to financial viability and sustainability.

PROBLEM: UNREFINED PRODUCT-MARKET FIT AND POTENTIAL MISALIGNMENT OF THE PROTOTYPE WITH USER EXPECTATIONS. MEDIUM PRIORITY

Reason: A 40% Product score at the prototype stage suggests that the current offering may not fully address validated market needs or provide an optimal user experience, hindering future adoption.

Action: Implement an iterative product development cycle, conducting usability testing and A/B testing with target users to gather feedback and refine the prototype's features, interface, and overall value proposition.

Expected Impact: Enhanced product usability, stronger product-market fit, and improved user engagement metrics, leading to a higher Product dimension score.

PROBLEM: UNDEVELOPED OR UNVALIDATED BUSINESS MODEL FOR SUSTAINABLE REVENUE GENERATION IN THE HEALTHCARE INDUSTRY. MEDIUM PRIORITY

Reason: The 40% Business Model score indicates that the current revenue streams and value capture mechanisms may not be fully optimized or validated for the complex and regulated healthcare market.

Action: Refine the business model by exploring and validating various revenue streams (e.g., subscription for premium features, transaction fees, B2B partnerships) and testing different pricing strategies with potential customers and partners.

Expected Impact: A more robust and sustainable business model, increasing the venture's attractiveness to investors and ensuring long-term viability.

5. SUGGESTED INCUBATION SUPPORT

Mentorship in healthcare technology and business strategy, Business Validation, Product Development guidance, Funding Guidance, Market Research support, and Networking opportunities with healthcare professionals and investors.

6. FINAL RECOMMENDATION

CareBridge is at a critical juncture, possessing a strong concept and team but requiring focused effort on foundational elements. The immediate path forward necessitates rigorous market validation to ensure product-market fit and the development of a comprehensive financial strategy to mitigate the identified primary risk. By systematically addressing these core areas, CareBridge can significantly enhance its readiness for product refinement, secure necessary funding, and establish a sustainable and impactful presence within the competitive healthcare landscape.

1.19. Reporting Results

The platform presents the assessment and analytical outputs through an interactive dashboard and generates a consolidated PDF assessment report. The report brings together the principal readiness, risk, similarity, benchmarking, and recommendation results into a single document.

Discussion

The implemented platform addresses the gap between startup idea evaluation and broader startup readiness assessment by examining the current state of a venture across multiple dimensions. Rather than concentrating only on idea validation or future success prediction, the system provides a structured assessment of the startup's present readiness.

The Startup Readiness Assessment Framework provides a standardized structure for examining different aspects of startup preparedness. The calculation of SRS, FRS, and ORS produces an overall readiness indication while retaining dimension-level information that can be used to identify areas requiring further attention.

The inclusion of risk analysis and explainability extends the assessment beyond a single numerical score. The system identifies relevant risk categories and provides information about the contribution of individual dimensions to the overall readiness result. This gives users additional context for interpreting the factors associated with their assessment.

Semantic similarity adds another layer of contextual information by identifying startup profiles with related representations. Benchmarking similarly allows assessment results to be examined against the available cohort data. However, the usefulness of these comparative outputs depends on the availability, size, and quality of the underlying startup records.

The generative-AI recommendation component uses the assessment and analytical outputs to produce personalized improvement guidance. Consequently, the platform combines deterministic scoring, diagnostic analysis, semantic comparison, benchmarking, and AI-assisted recommendations within a unified decision-support workflow.

Overall, the implemented system demonstrates how startup readiness assessment can be structured as an integrated analytical process rather than being limited to a questionnaire or a future-success prediction model. The platform is intended to support decision-making, while its results should be considered alongside expert evaluation and entrepreneurial judgment.

Limitations and Future Work

Although the implemented platform provides an integrated approach to startup readiness assessment and decision support, several limitations should be considered.

The current assessment framework uses a predefined set of 20 questions and associated scoring rules. Consequently, the quality of the assessment depends on the accuracy and completeness of the information supplied by the startup user. The reliability of the benchmarking component is also influenced by the number and representativeness of startup records available for comparison.

The semantic similarity module compares available startup profiles using embedding-based representations. Therefore, the resulting similarity values indicate semantic relatedness between startup profiles and should not be treated as a definitive measure of direct market competition.

The AI-assisted recommendation module generates guidance from the assessment and analytical outputs. These recommendations are intended to support decision-making and should not replace expert assessment, incubation-committee evaluation, or investment decisions.

Future work can extend the assessment framework using larger and more diverse startup datasets, improve benchmark reliability through larger cohorts, and validate the assessment framework against evaluations performed by domain experts. Further research can investigate domain-specific embedding models, additional startup analytics, longitudinal analysis of readiness changes, and systematic evaluation of recommendation quality.

These extensions could improve the reliability, generalizability, and practical applicability of the platform for founders, incubators, and other organizations involved in startup support.

Conclusion

This paper presented an AI-Assisted Startup Readiness Assessment and Decision Support System for evaluating the current readiness of early-stage startups across multiple dimensions. The implemented platform uses a structured 20-question Startup Readiness Assessment Framework together with deterministic scoring to calculate dimension-level scores, Startup Readiness Score (SRS), Founder Readiness Score (FRS), Overall Readiness Score (ORS), and the corresponding readiness classification.

The platform extends the assessment process through risk analysis, explainable assessment insights, benchmarking, semantic similarity analysis, and generative-AI-assisted recommendations. These capabilities provide founders with information about their current readiness, areas requiring improvement, contextual similarity with available startup profiles, and potential next steps. The system also incorporates assessment history, progress tracking, administrative analytics, interactive dashboards, and consolidated PDF reporting.

The main contribution of the work is the integration of structured startup-readiness assessment and AI-assisted decision support within a unified platform. In contrast to approaches primarily concerned with startup idea validation or prediction of future startup success, the proposed system focuses on diagnosing the startup's current readiness and translating the assessment results into actionable improvement guidance.

The implementation demonstrates the potential of combining structured data analysis, natural language processing, semantic embeddings, and generative AI for startup evaluation and decision support. However, the platform is intended to complement rather than replace expert assessment and real-world evaluation by founders, incubators, and other startup-support organizations.

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