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Business viability expert system model for startups in developing economies

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Abstract

Startups in developing economies often lack affordable, scalable tools to validate ideas, leading to high failure rates. This study introduces the Business Viability Score (BVS), an expert system model that automates market validation across four pillars: target user, sector reach, solution design, and venture model. The BVS's structured approach identifies critical risks and opportunities, enabling data-driven decisions. Startup founders confirmed strong alignment between the model's outputs and their expert assessments. This study contributes to the growing discourse on the application of expert systems in entrepreneurial contexts by introducing a structured, low-cost approach to assessing startup viability in developing economies.

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Keywords: Business Viability Model; Expert Systems; Market Validation; Developing Economies; Startups

1. Introduction

Market validation is a critical step for startups, ensuring that their business ideas align with real market needs and customer demands [1, 2]. It helps refine products and business strategies based on practical insights. However, startups

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in developing economies often face significant barriers in accessing effective validation models due to high costs and limited resources [3, 4, 5]. Traditional methods such as focus groups, interviews, and field surveys, though insightful, are labor-intensive, costly, and slow, limiting their practicality in resource-constrained environments [3, 4]. To address these challenges, expert systems present a promising alternative [1, 2, 6-9]. By simulating the decision-making capabilities of human experts, an expert system can guide startups through structured evaluations using established validation frameworks [6-9]. These systems integrate knowledge from business experts and proven methodologies, allowing startups to assess their viability across key dimensions, such as target user, sector reach, solution design, and venture model [7, 9, 10]. Unlike models that require continuous human facilitation or expensive tools, automated expert systems can deliver consistent, accessible, and guided assessments [7, 8, 10]. This approach enables startups to identify gaps, refine strategies, and make informed decisions early in their journey without the need for costly external consultations [7-9, 10]. In developing economies, where entrepreneurial initiatives are vital to combating poverty and driving economic development, [11-14] empowering startups with expert-guided validation tools can help bridge the gap between opportunity and execution [7, 10, 15]. By offering structured, expert-backed assessments, these systems support more sustainable and scalable entrepreneurial growth [10, 15]. The Startup Business Company Validation Methodology (SBCVM) is an established framework designed to support startup teams, particularly those with limited business experience, in systematically evaluating the viability of their ideas [5]. Through targeted, dimension-specific questions, startup founders are guided in identifying potential gaps in their startup ideas and making informed, evidence-based decisions [5]. While the original model has proven effective as a conceptual framework, its manual implementation presents barriers to scalability and accessibility, especially for resource-constrained startups in developing economies [5, 11, 14]. It is hypothesized that enhancing its applicability as an automated expert system model could simulate the knowledge and reasoning of business professionals to support their startup ventures. This study builds upon the existing SBCVM model and transforms it into an expert system, refining its components to create a guided, intelligent tool tailored to early-stage startups. The customized model introduces a rule-based structure that automates assessments, interprets input from founders, and offers actionable insights [5]. The model features a weighted Business Viability Score (BVS) that, through heuristic analysis and logical rules, assigns relevance-based scores to help founders identify and prioritize critical areas for improvement [9, 16, 17]. This expert-guided approach not only reduces the dependency on costly consultations but also equips startups with a cost-effective, scalable, and accessible validation method [16, 17]. Unlike tools such as Startup Genome and Lean Stack, which are subscription-based, expensive, and rely on proprietary algorithms, the proposed BVS model is open-source and transparent. This approach empowers developers, practitioners, and startups to access, understand, and collaboratively enhance the system. Preliminary testing of the model with real startup scenarios is important to assess its reliability and relevance, with startup founders as users who can evaluate its alignment with expert judgment [17]. This validation could reinforce the system's potential to empower startup founders in developing economies with a practical tool for navigating the complex terrain of business viability. Ultimately, this research advances the discourse on market validation models, promoting its broader application as an expert system that supports strategic, data-informed decision-making for emerging startups.

2. Methodology

2.1. Customizing the alternative expert system model for developing economies

This study begins with a comprehensive analysis of the SBCVM to assess its strengths, limitations, and areas for enhancement. The goal is to evolve the original model into an expert system that can more effectively support startups in developing economies [18, 19]. To inform this process, the researchers conducted an exploratory review of relevant literature and the SBCVM framework itself to uncover potential gaps and opportunities for improvement [19]. Exploratory analysis plays a crucial role in the development of intelligent systems, offering insight into how existing frameworks perform in real-world scenarios [20, 21]. Through a SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis, as shown in Table 1 below, the researchers systematically examined which components of the SBCVM should be retained, modified, or expanded.

Table 1. Retained, modified, or added areas from the SWOT analysis of the original model.

	Retained	Modified	Added
Strengths	✓		✓
Weaknesses		✓	
Opportunities	✓		
Threats		✓	

This led to the development of a customized version of the model, adapted for integration into an expert system environment. To ensure the reliability and logical consistency of the customized model, both structural and behavioral analyses were performed [21]. The structural analysis focused on the framework's core dimensions, while the behavioral analysis explored how the model responds to different inputs and decision scenarios. This dual approach allowed for a deeper understanding of how changes in structure influence the system's overall behavior [20, 21]. Emergent properties are unexpected outcomes resulting from the interaction of the model's components, were identified and compared between the original and customized versions [21-23]. Figure 1 illustrates the current as-is behavioral model of the SBCVM expert system's assessment process for startups, indicating several processes used to determine startup scores based on the four dimensions [5]. These insights were critical in refining the expert system to better simulate real-world business validation processes [20, 21]. Activity diagrams were used to visually map and compare the workflows of both models, highlighting adjustments made during the enhancement process [23]. Ultimately, this phase of the study ensures that the transition from a manual framework to an expert system is grounded in a clear understanding of both functional structure and behavioral dynamics.

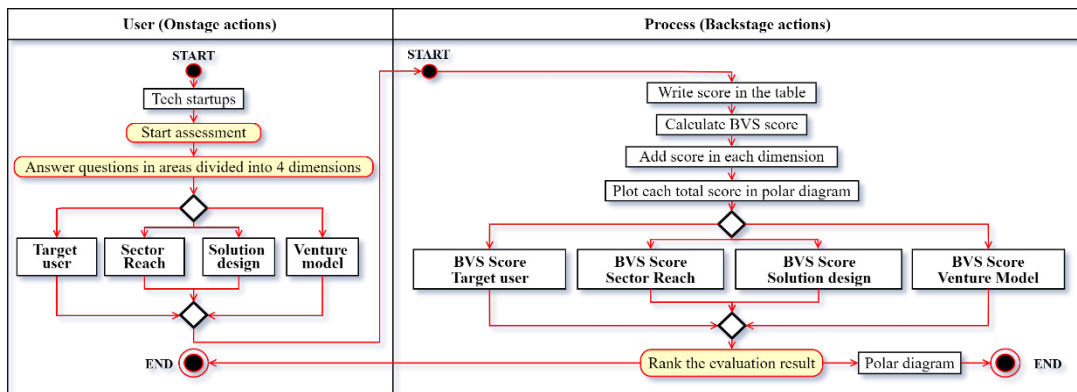


Fig. 1. As-is behavioral model of the original customized Expert System Model

To align the SBCVM with an expert system framework, the researchers analyzed its structural and behavioral components to develop a rule-based scoring method that simulates expert evaluation [21, 22]. The BVS is customized by assigning Key Performance Indicators (KPIs) and scaling indicators to assessment questions under the four SBCVM dimensions [5, 21]. Weights were assigned based on question relevance, determined through SWOT analysis and startup type classification. A rating scale helped calibrate these weights, ensuring they reflect the specific needs of different startup types commonly found in developing economies. The scoring process follows linear mathematical operations to compute average scores per dimension, which are then aggregated to form the overall viability score. This formula-based structure enables consistent, scalable assessments, serving as a foundational component of the expert system. Weight calibration was subjected to validation, which is discussed in the following model testing phase.

2.2. Validation of the customized expert system model

To validate the effectiveness of the customized model as a business viability expert system, the researchers conducted a pilot test involving experienced startup founders from developing economies. The purpose of this phase was to test the model's core logic, assessment criteria, and scoring framework under real-world conditions prior to

wider implementation. According to a recent article published in 2022 by researchers from Oregon State University, pilot testing is a crucial small-scale study that helps ensure the tool's functionality and efficiency [24]. Respondents were selected based on relevant experience in startup incubation, customer discovery, and other market validation practices, ensuring their capacity to provide meaningful feedback. Orientation sessions were conducted to familiarize participants with the original SBCVM model, its four evaluation dimensions, and the customized BVS scoring system. Participants selected a startup type aligned with their business and evaluated the assessment questions according to their relevance, guided by the model's structured framework. During the testing, researchers ensured that participants understood the logic and structure of the model and that each stage of the assessment produced interpretable results. Following the pilot test, respondents evaluated the model using structured feedback forms that collected both categorical and ordinal data on dimensions such as question clarity, scoring relevance, usability, and overall experience, as indicated in Table 2. Special attention was given to assessing the weight assignments per question and the incorporation of different startup types, enhancements that are not present in the original SBCVM model [5]. The collected feedback was used to evaluate the model's reliability, usability, and perceived accuracy in assessing startup viability. By measuring consistency in scoring and respondent feedback across startup types, the researchers were able to validate the model's internal logic and refine areas requiring improvement. This validation process was essential in confirming the model's potential as an expert system capable of supporting data-driven decision-making for early-stage ventures in developing economies.

Table 2. Pre-testing validation metrics and its corresponding data type

Evaluation Metrics	Data Type (Categorical)	
	Ordinal	Nominal
1. Is the spreadsheet model user-friendly and intuitive to navigate?	✓	
2. Are the instructions or guidelines in the model straightforward and easy to follow?	✓	
3. Overall, are the questions in the model clear and understandable?	✓	
4. Out of the 32 questions in the model, which one do you believe doesn't fit well with its intended dimensions, and why?		✓
5. After completing all the questions, what are your observations on the results and conclusions generated?		✓
6. Are there any sections of the model you think should be eliminated or expanded?		✓
7. How would you describe your overall experience using the model?		✓
8. Finally, what are your thoughts on having an automated market validation tool as a website instead of a spreadsheet-based model?		✓

3. Results and Discussions

3.1 Customization results of the alternative expert system model for developing economies

The researchers conducted a comprehensive evaluation of the original model to identify its strengths, weaknesses, scope, and limitations, serving as the foundation for the development of a customized expert system model for business viability [18, 19]. Using the original model as a structural basis, researchers analyzed its capacity to assess startup ventures across four critical dimensions: target user, sector reach, solution design, and venture model. Each dimension comprises targeted assessment questions, linked to a measurable business viability score, providing a structured mechanism for evaluating early-stage ventures [20, 22, 23]. Through exploratory data analysis and behavioral modeling, the researchers retained key components, modified areas needing refinement, and introduced new functions to enhance its relevance [20, 21], particularly for diverse startup types in developing economies as indicated in Figure 2a. The BVS was customized to reflect the varying importance of each question per startup classification. A SWOT analysis guided the redesign, enabling a systematic mapping of components to retain, adjust, or improve [18, 19]. This analysis also led to the inclusion of additional startup types and refined interpretations of the BVS score. Figures 2a and 2b visually represent these modifications, highlighting areas of structural evolution while preserving core

principles from the original SBCVM. This redesigned model advances the SBCVM as a practical and adaptive expert system to support data-driven business validation for resource-constrained startups.

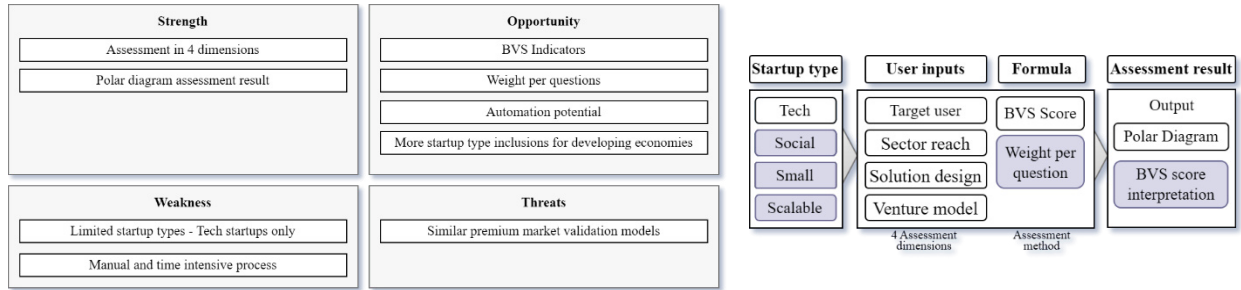


Fig. 2. (a) SWOT analysis of the SBCVM model; (b) Modified SBCVM model assessment process.

The customization of the original SBCVM model followed a structured approach that retained core functionalities, introduced key modifications, and added new components based on insights from a SWOT analysis [18, 19]. As detailed in Table 3, these changes were methodically classified to support the development of a more adaptive and responsive system. Startup classifications includes tech, social, small, and scalable, were added to better represent the overlapping and complex nature of ventures in developing economies as indicated in Table 4. While startups often straddle multiple categories, this classification was simplified to improve clarity for early-stage entrepreneurs and enhance the usability of the expert system [25, 26]. Grounded in the four original viability dimensions such as the target user, sector reach, solution design, and venture model, the model offers a structured pathway for assessing business readiness [5]. Enhancements included the revision of 32 assessment questions, with expert-informed adjustments to their syntax and scope to ensure clarity and eliminate potential misinterpretation, making the model more accessible to novice users [5, 27, 28]. These developments were not merely technical updates but foundational to shaping a practical expert system: one that codifies structured knowledge into an actionable framework, guiding startup founders through early-stage decision-making [28]. By integrating empirical logic with simplified categorization and scoring, the customized BVS-based model positions itself as a functional expert system designed to systematically assess and support the viability of startup ideas in real-world business environments.

Table 3. Outline on the modifications to the customized BVS model

Retained	Modified	Added
4 Dimensions	Business Viability Score (BVS)	BVS score interpretation
Polar diagram	Assessment questions (measurement of confidence level)	Weight per question
Tech startups	32 questions per domain/category	Social startup, small startups, and scalable startups
		Key metrics for assessing confidence levels

Table 4. An overview of the defining features across various types of startups

Startup category	Typical features
Social startup	Nonprofit & social impact startups
Tech startup	Tech & innovation-driven startups
Scalable startup	Acquisition-focused startups (flip businesses)
Small startup	Indie/Solopreneur startups

To systematically evaluate startup viability, the researchers employed the Business Viability Scoring method as a core component of the expert system model. This method assigns a score ranging from 1 to 10, where 1 to 4 indicates very low opportunity, 5 to 8 represents medium opportunity, and 8 to 10 reflects high opportunity [29]. To determine the overall viability across the four dimensions, the researchers adopted Eldin's formula, which averages the scores per dimension [5]. This dimensional analysis enables the expert system to pinpoint areas of strength and identify aspects requiring further development, reinforcing its practical utility in early-stage decision-making. The BVS method draws structural parallels with the Likert scale, a commonly used psychometric approach that captures

subjective judgment through a series of standardized statements [29]. In this study, the Likert format was modified into a five-point scale such as the Very Low, Low, Medium, High, and Very High scales to allow users to select discrete values that reflect their confidence levels more precisely [29]. These indicators, derived from relevant startup literature, ensure contextual relevance and aid in gathering impartial responses from participants. By encoding these human-like judgments into the system, the BVS scoring mechanism operationalizes qualitative insight into quantifiable data, thereby enhancing the model's capability as a business viability expert system. This approach allows the system to function not just as an assessment tool but as a structured, knowledge-based guide that helps founders make informed decisions about their ventures. To support the structured validation process within the expert system model, a simplified mathematical formula was developed based on the SBCVM market validation framework. This formula incorporates weighted inputs from users, adjusted according to startup type, to calculate the BVS score. As outlined in Equation 1, the scoring mechanism enables consistent interpretation across key dimensions and supports the model's role in guiding early-stage entrepreneurs through evidence-based business viability assessments [5].

$$\alpha = \frac{Dtu + Dsr + Dsd + Dvm}{4}, Dn = \frac{(Qs * Stn) + (Qs * Stn) + \dots (Qs * Stn)}{tn} \quad (1)$$

Where α is the weighted BVS score for all dimensions, Dn is the weighted BVS score for each dimension, Qs is the questions multiplied by the weight per questions St , and tn is the total number of questions per dimension

Alpha (α) represents the BVS score for the startup, and Dtu , Dsr , Dsd , and Dvm which are the weighted scores for the target user, sector reach, solution design, and venture model respectively [5]. Users can input values for Qs for each of the 32 questions, where the lowest score value is 1 and the highest is 10, derived from using Likert scale [29]. These values are then multiplied by their corresponding weight, which are assigned based on the selected startup type denoted as Stn , as shown in formula 1 above and derived from Table 5 as St . This models the structure and the denoted unit for the variables indicated in Equation 1. There are a total of 7 assessment questions in sector reach, solution design, and venture model dimensions respectively, and 11 questions in target user dimension [5]. Every question in each dimension has corresponding weights derived from the SBCVM scoring mechanism.

Table 5. BVS Scoring mechanism of questions with its weights per startup type.

Dimension (Dn)	Questions (Qs)	Startup type (St)			
		Social	Tech	Scalable	Social
Target user (Dtu)	Q1: How directly does your product/service reduce unemployment?	n	n	n	n
	Q2 Q10	...	...	...	...
	Q11: How easily can your target customers adopt your product/service?	n	n	n	n
Sector reach (Dsr)	Q12: What's the estimated size of your target market?	n	n	n	n
	Q13 Q17	...	...	...	...
	Q18: How well do your marketing efforts reach your ideal customers?	n	n	n	n
Solution design (Dsd)	Q19: How innovative is your product/service compared to existing solutions?	n	n	n	n
	Q20 Q24	...	...	...	...
	Q25: How clearly can you articulate your UVP (Unique Value Proposition) to stakeholders?	n	n	n	n
Venture model (Dvm)	Q26: How well-defined do you think your business model?	n	n	n	n
	Q27 Q31	...	...	...	...
	Q32: How strong are your IP protection strategies?	n	n	n	n

The researchers utilize Google Spreadsheets as the primary tool for conducting the market validation remotely. The tool was chosen because of its ability to be shared with respondents remotely and its capacity to perform arithmetic operations through its functions and cell configuration [15, 23]. The researchers noted that although Microsoft Excel has better plugins and commands, Google Spreadsheets' ability to collaborate with multiple users simultaneously made it a more suitable tool for conducting guided validation with remote participants [15]. To integrate the customized

BVS model, the researchers created a new document and encoded the model's formulas into the platform using a computer. These formulas were then integrated into the platform digitally, adjusting each cell layout and configuration, and encoding appropriate logical and arithmetic functions including Formula 1, BVS scoring metric, 32 questions in the 4 dimensions, and their corresponding weights that follows the structure of scoring mechanism highlighted in Table 5. Building on the concepts discussed above, this configuration sets the groundwork for testing and validating the customized BVS model with ten startup founders using a Google spreadsheet. To provide a clearer understanding of how the alternative expert system model has been tailored, Figure 3 below presents the system framework, which outlines the process these founders will follow in the next stage of testing and validation.

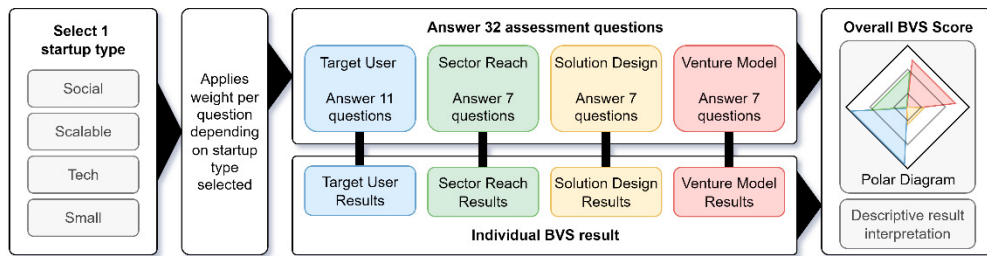


Fig 3. System framework of the Business Viability Scoring Process

3.2 Validation results of the alternative expert system model for developing economies

The evaluation of the modified SBCVM model involved the selection of 10 respondents who had experience in the field of startups. These respondents were tasked with validating the model and provide feedback while testing their own startup. To ensure a thorough evaluation, the researchers conducted an orientation through Google Meet video conferencing website for virtual meetings, a popular validation method when surveying is conducted through computer-aided applications [30, 31]. The respondents were acquired through social media, and their background information was collected after signing their informed consent forms. The selection of respondents was based on their proactive participation and willingness to critique the customized model, as well as their eligibility to have already sustained their startup and possess relevant experience in similar market validation processes [23]. The results of the selection process are presented in Figure 4a, which shows the number of testers per startup type, and Figure 4b, which shows the corresponding type of market validation experience prior to model testing. By selecting respondents with relevant experience, the researchers were able to assess whether or not the respondents had a clear understanding of how to answer the assessment questions that are targeted around startup concepts.

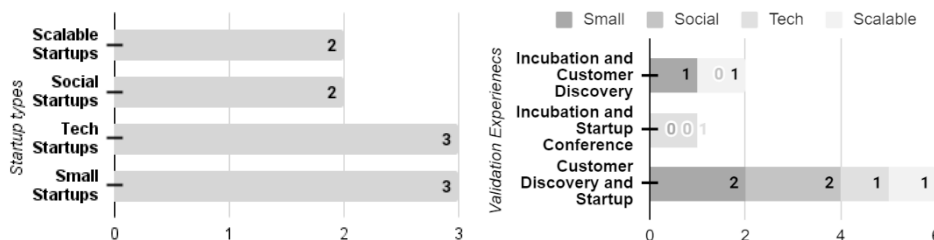


Fig. 4. (a) Number of pre-testers per startup type; (b) Startup founders prior experiences to similar market validation models per startup type.

A virtual meeting using Google Meet was conducted to train the 10 respondents individually, each of them being briefed in a separate meeting about the process for answering and the evaluation of the customized BVS model [30–32]. During testing, the 10 respondents were observed and guided through the customized BVS model. The model successfully generated individual assessment results for each respondent's startup, which were consolidated to calculate their individual weighted business viability score and the average results per dimension as shown in Table 6. The model's functionality, including the calculation of the weighted BVS score and the formula behind generating the average BVS score per dimension, was tested without any noticeable errors. Furthermore, the researchers emphasized that model testing is a crucial step in the development process [32, 33]. It aids in the selection of the

model to represent the data and the prediction of how well the chosen modifications of the model perform in the future.

Table 6. Pre-testers average BVS score results per startup with their corresponding startup names

Pre-testers' startup names	4 Assessment dimensions			
	Target user	Sector reach	Solution design	Venture model
Startup A	7.24	4.63	7.66	5.07
Startup B	7.18	6.77	7.14	8.9
Startup C	4.8	6.03	5.63	4.87
Startup D	8.11	7.09	6.34	5.2
Startup E	5.35	5.49	3.09	2.63
Startup F	6.04	6.57	6.4	4.67
Startup G	6.78	7.91	8.43	7.93
Startup H	7.49	8.14	8.43	9.9
Startup I	5.11	7.46	6.69	6.13
Startup J	6.69	4.77	9.29	5.17

The evaluation of total average results across different dimensions was conducted to determine the relative performance of the four types of startups. Figure 5 provides a comparative analysis of startup type scores based on their weighted equivalence to the 32 assessment questions. The research findings reveal distinctive patterns in the scores obtained by each startup type across various dimensions. Within the venture model dimension, scalable startups and tech startups exhibit higher average scores. This outcome aligns with the nature of business-related questions that focus on a startup's capacity to expand and secure patents for their products or services [25, 26]. Conversely, small and social startups face inherent limitations in achieving such milestones, contributing to comparatively lower scores in the venture model dimension. Regarding the target user dimension, all startup types demonstrate nearly identical average scores. This outcome stems from the shared objective among startups to develop products or services that align with perceived customer demand, emphasizing their customer-centric approach [3, 5, 13, 14, 25]. In the sector reach dimension, all startups exhibit similar average scores, except for social startups. This disparity can be attributed to the distinctive purpose of social startups, which revolves around fulfilling a social mission or goal. [3, 11, 13, 26] Consequently, their target market or market reach tends to be more focused or limited, leading to variations in their average scores within this dimension. Finally, in the solution design dimension, social startups achieve the highest average scores. This result can be attributed to the unique nature of social startups, leveraging their Minimum Viable Product (MVP) or Unique Value Proposition (UVP) to create innovative and impactful products [11, 13, 14, 26]. These findings provide valuable insights into the performance of different startup types across multiple dimensions, highlighting the diverse challenges and opportunities that each startup type encounters within specific areas of assessment. Understanding these dynamics allows startup founders to make informed decisions and leverage their strengths in pursuit of success [5].

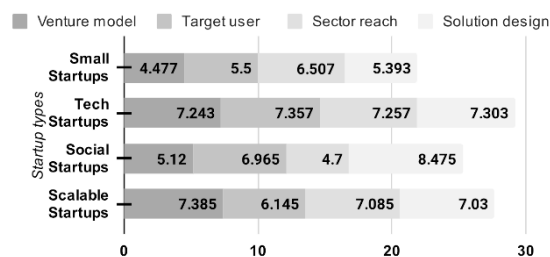


Fig. 5. Pre-testers average BVS score results comparison per startup types.

This phase presents the evaluation results obtained through online platforms, specifically using Google forms for data collection [34]. Table 7 provides an interpretation of the pilot testers' feedback regarding the market validation model. Through the utilization of a four-point Likert scale, it was observed that the majority of respondents strongly

agreed with the model's ease of navigation and clear instructions. Notably, 87 percent of the 10 respondents expressed their strong agreement that the assessment tool effectively generates results for their startup. These findings signify the successful implementation and development of the customized BVS model using a spreadsheet, indicating its readiness for further validation by a larger pool of respondents through a web-based application.

Table 7. Feedback of the custom BVS model usage

Rating	Number of testers (raw response count)				Results	
	Strongly Agree	Agree	Disagree	Strongly Disagree	Average Mean	Overall Interpretation
Easy to navigate	9	1	0	0	3.9	Strongly Agreed
Clear instructions	6	4	0	0	3.6	Strongly Agreed
Satisfactory overall results	6	4	0	0	3.6	Strongly Agreed

The assessment of question complexity plays a crucial role in evaluating the respondents' ease of understanding the jargon used in the web-based market validation tool as it may distort the meaning or perception among the users with different background if complex or technical phrases were used. [32, 33, 34]. Figure 7 presents the pilot tester assessment results, highlighting the percentage of respondents' perceptions regarding question complexity within the market validation model. Notably, 50 percent of the pilot testers agreed that some questions require a basic level of understanding for effective response. Additionally, 30 percent of the respondents noted that most questions necessitate a basic understanding, while the remaining 20 percent indicated that certain questions are too complex to answer. Based on these findings, it is evident that startup founders possess diverse background and experiences when it comes to establishing a startup and highlights the need to use easily readable phrases and jargons to better understand the questions and remove potential bias in the results later on [32-24]. Consequently, in order to respond to the assessment tool questions accurately, a foundational knowledge of the terms utilized within the tool is deemed necessary. Furthermore, the data suggests the importance of configuring the structure of the 32 questions in a manner that ensures easy comprehension, potentially by eliminating overly technical or complex terminology. These insights underscore the significance of catering to the varying levels of familiarity and expertise among startup founders, ensuring that the assessment tool is accessible and understandable to a wider range of users [32-34]. By addressing question complexity and refining the language used, the customized BVS model can enhance its usability and effectiveness in facilitating data-driven decision making for startup founders.

3. Conclusion

This study introduces the Business Viability Score (BVS) Expert System, an innovative solution addressing the critical challenge of startup validation in developing economies. By transforming the SBCVM framework into an intelligent, rule-based expert system, we demonstrate how expert systems can be made accessible and practical for resource-constrained entrepreneurs. The BVS uniquely integrates the analytical rigor of expert systems with the simplicity of spreadsheet implementation, delivering a low-cost, customized validation model. Results suggest that majority of startup scores is aligned with the BVS model expert judgments using cost effective tools compared to traditional methods, highlighting that sophisticated business intelligence does not require complex or expensive infrastructure. Despite the promising insights gained, this study has certain limitations. The pilot test was conducted with a relatively small sample of ten startup founders, and the results primarily reflect subjective evaluations. Future research will involve larger and more diverse samples to validate and refine the customized BVS model and enhance its generalizability. Designed as a Google Sheets-based model, the BVS overcomes two critical barriers: accessibility and scalability. It requires only basic digital literacy while performing weighted calculations across four validation dimensions. This lightweight approach bridges the technology gap in developing economies, where expensive, labor-intensive validation solutions are often unfeasible. As a rule-based expert system, the BVS simulates human decision-making through weighted KPIs and startup-type classifications. Pilot tests confirmed its effectiveness in identifying strengths and weaknesses, particularly for social and scalable startups undergoing critical validation checks. Future development may involve transitioning the BVS system into a web or mobile application to improve accessibility beyond Google Sheets. Machine learning integration could also be explored to dynamically adjust question weights

based on training data. Once the system is ready, broader testing across diverse startup ecosystems and various developing economies could proceed. Additionally, integration with lean validation methods and the design of an interactive tool to enhance engagement and assess creative viability may be explored to further differentiate the system. These directions could potentially strengthen the system's long-term value and practical relevance.

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5. Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

6. Declaration of generative AI and AI-assisted technologies in the writing process

In preparing this manuscript, the authors utilized OpenAI ChatGPT and Deepseek to proofread, enhance grammar, language, and overall readability. All content generated with this tool was carefully reviewed and revised by the authors, who accept full responsibility for the final published work.

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