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Leveraging Machine Learning Models to Enhance Startup Collaboration and Drive Technopreneurship

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ABSTRACT

In the dynamic and competitive realm of startups, identifying and cultivating effective collaborations is crucial for sustained success. **This research evaluates** how machine learning (ML) technologies can enhance startup collaborations by advancing decision-making processes through the analysis of historical data. **Employing the SmartPLS methodology**, this study collected data from **220** stakeholders, including **207** actively engaged in startups that are either utilizing or integrating ML technologies. The investigation focuses on understanding ML models, the importance of historical data, and the dimensions of collaboration critical to the success of startups. Through analysis with PLS-SEM, it was found that ML models significantly boost inter-startup synergy and the effectiveness of collaborative efforts. **The results** provide vital insights for industry practitioners and strategic decision-makers, offering practical strategies to employ ML in optimizing collaboration and **ensuring sustainable growth** within the technopreneurship arena. This study not only highlights the benefits of ML in fostering cooperative ventures but also **aims** to refine the strategic frameworks essential to the startup ecosystem.

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1. INTRODUCTION

In an era where technological innovation and transformation are driving forces behind economic growth, the startup ecosystem has emerged as a critical contributor to new trends and developments [1]. Startups operate in dynamic and often volatile environments, where agility, innovation, and the ability to collaborate are essential for survival and success. The ability to respond quickly to market demands and challenges allows startups to explore new opportunities, accelerate product development, and establish a competitive edge in their respective industries [2], [3].

The findings of this study align with the United Nations' Sustainable Development Goals (SDGs), particularly SDGs 9: Industry, Innovation, and Infrastructure, by showing that machine learning fosters innovation and operational efficiency, enabling startups to develop resilient infrastructures and contribute to sustainability economic growth. Additionally, the study supports SDGs 17: Partnerships for the Goals, as machine learning enhances the quality and success of startup collaborations [4], [5], [6].

The growing role of digital transformation in industries has further intensified the need for startups to leverage cutting-edge technologies [7], [8]. Among these, Machine Learning (ML) has gained significant traction due to its ability to enhance operational efficiency, foster innovation, and promote sustainability [9], [10], [11]. Startups are increasingly adopting machine learning models not only to automate routine tasks but also to derive valuable insights from vast amounts of data. These insights can inform critical decision-making processes, from product development to market expansion strategies, thus driving long-term growth [12], [13].

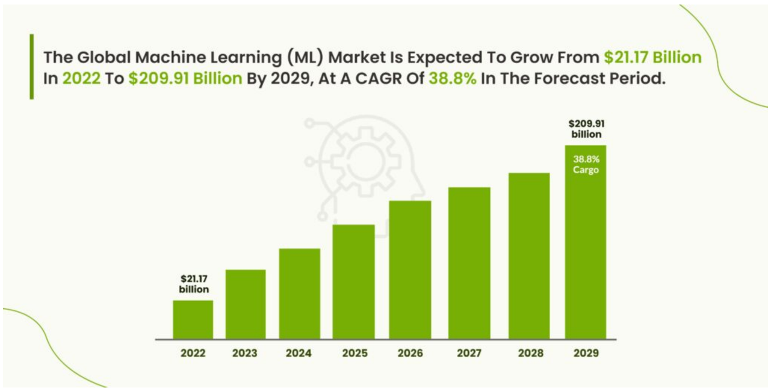

Figure 1. Machine Learning (ML) Market forecast period.
(Source: https://copperdigital.com/blog/machine-learning-trends-you-should-know/)

Machine learning is one of the largest and fastest-growing segments within the artificial intelligence (AI) market, with projections estimating that it will grow from US$140 billion to nearly US$2 trillion by 2030 [14], as shown in figure 1. This underscores the increasing importance of ML in a variety of business contexts, including startup ecosystems.

In this study, we explore the role of machine learning models in enhancing collaboration between startups by utilizing historical data to improve decision-making processes and foster productive partnerships [15], [16]. By facilitating better partnerships through data-driven insights, startups can co-create solutions that address global challenges, furthering the goals of the 2030 Agenda for Sustainable Development [17], [18].

This research also employs SmartPLS, a widely recognized analytical tool, to examine key variables such as Machine Learning Models, Historical Data, Startup Collaboration, and Long-term Partnership Success [19]. By using SmartPLS, this study aims to provide valuable insights that can help startups make informed decisions and enhance their collaboration efforts [20], [21]. Therefore, the primary objective is to offer both theoretical and practical contributions that can improve the effectiveness of startup collaborations [22], [23].

Therefore, this study poses the following research questions:

- RQ1: How can machine learning models improve startup collaborations, considering factors like historical data, feature selection, and model training?
- RQ2: What impact does a well-refined machine learning model have on the long-term success of startup partnerships, and how can it help identify collaboration opportunities?
- RQ3: How does the SmartPLS method enhance our understanding of the relationships between key variables in startup collaboration?

1.1. Machine Learning Models and Historical Data

Machine learning models have revolutionized numerous industries by providing data-driven insights that significantly improve collaboration between businesses, including startups [24], [25]. By leveraging historical data, startups can avoid unproductive collaborations and focus on high-potential partnerships. Previous studies have shown that machine learning models have been successfully employed in sectors such as fintech and healthcare to analyze vast datasets and identify potential partners, resulting in more effective business relationships [26], [27].

For instance, fintech startups often use machine learning algorithms to analyze customer behavior, market trends, and transactional data, which helps identify strategic partnerships for co-developing financial products [28], [29]. Similarly, in the healthcare sector, startups have used ML models to collaborate on predictive analytics tools [30], enhancing their ability to innovate in areas like medical diagnostics [31]. These examples demonstrate the practical value of machine learning models in real-world startup environments [32], [33].

H1: Machine learning models that are tailored using feature selection based on historical data significantly enhance the decision-making processes in startup collaborations, leading to more effective partnership strategies.

1.2. Startup Collaboration and Long-term Partnership Success

Collaboration among startups is a crucial factor for sustained innovation and growth, particularly in fast-evolving markets [34], [35]. Long-term partnerships enable startups to pool resources, share expertise, and co-create solutions that address complex challenges [36]. The use of machine learning models can greatly enhance these collaborations by identifying the most promising partners and opportunities based on a thorough analysis of previous collaborations, market data, and partnership outcomes [37], [38].

A notable example is the collaboration between Uber and OpenAI, where machine learning models helped Uber improve its predictive analytics and operational efficiency through AI-driven algorithms. This partnership not only accelerated Uber's technological capabilities but also positioned OpenAI as a leader in applied AI research [39], [40]. Through such collaborations, startups can unlock new levels of innovation and competitiveness.

H2: The refined machine learning model positively impacts long-term partnership success in startups by identifying effective collaboration opportunities and fostering joint innovative solutions.

1.3. SmartPLS

Partial Least Squares Structural Equation Modeling (SmartPLS) has gained prominence as a sophisticated tool for analyzing complex relationships within the startup ecosystem [41], [42]. This method is particularly useful for studies that involve multiple variables and interdependencies, as it allows for a comprehensive examination of both direct and indirect effects [43]. In this study, SmartPLS is used to evaluate key variables such as historical data, machine learning model efficacy, and startup collaboration success [44], [45]. Previous research has highlighted the effectiveness of SmartPLS in uncovering relationships in contexts like business-to-business (B2B) partnerships and technology-driven collaborations [46], [47], [48]. By applying this method, we aim to provide a deeper understanding of the factors that contribute to successful startup collaborations, as well as actionable insights for practitioners and decision-makers.

H3: Utilizing SmartPLS in analyzing the relationships between historical data utilization, machine learning model sophistication, and startup collaboration outcomes provides deeper insights into the factors that drive effective partnerships.

2. RESEARCH METHOD

This study employed a survey method, distributing questionnaires to 220 respondents, with 207 of them providing usable responses. Among these respondents, 147 were from startups that had already implemented machine learning (ML) technology, while 60 represented startups currently in the process of integrating it. The questionnaire was designed to capture several key variables, including knowledge of machine learning models, the role of historical data in optimizing collaboration, and the factors contributing to long-term partnership success in startup ecosystems. Each variable was measured on a 5-point Likert scale, where 1 indicated strong disagreement and 5 indicated strong agreement.

2.1. Data Analysis

Partial Least Squares Structural Equation Modeling (SmartPLS) was chosen as the primary analytical tool for this study because of its effectiveness in modeling complex relationships between multiple variables, particularly in exploratory studies like this one. SmartPLS is well-suited for research that involves predictive modeling and theory-building, as it allows for the simultaneous analysis of both measurement models (which assess the reliability and validity of constructs) and structural models (which evaluate the relationships between variables).

In the context of this study, the relationships between historical data, machine learning models, startup collaboration, and long-term partnership success are inherently complex and involve numerous interdependencies. SmartPLS enables the handling of these intricate relationships without requiring large sample sizes, making it particularly effective for studies involving startups, where data collection may be limited due to the early-stage nature of many organizations. Moreover, SmartPLS is robust in handling both reflective and formative constructs, which is important in this study given the diversity of variables—ranging from subjective measures like the perceived success of collaborations to more objective data, such as the extent of machine learning model usage. The method also accommodates non-normal data distributions, which are common in startup environments where the variability of responses can be high due to different stages of technology adoption.

Previous studies have demonstrated the utility of SmartPLS in analyzing business relationships, particularly in contexts that involve emerging technologies and innovation. For example, SmartPLS has been widely used in studies related to business-to-business collaborations, technology adoption, and innovation ecosystems, providing deep insights into how technological tools like machine learning can enhance operational efficiency and strategic decision-making. In this study, SmartPLS provided a comprehensive view of both the direct and indirect effects of machine learning models on startup collaboration and long-term partnership success. This enabled the research team to identify not only the immediate impact of machine learning but also how it influences other factors, such as the use of historical data in decision-making processes.

2.2. Measurement Model Assessment

The evaluation of this model's measurement involves assessments of reliability and validity. For reliability checks, Cronbach's alpha and the composite reliability measure (CR) are used. Both indicators are expected to display values of ≥ 0.70. In terms of validity assessment, convergent and discriminant validity are scrutinized. Convergent validity is assessed based on the Average Variance Extracted (AVE) and factor loadings, with AVE values required to be ≥ 0.50 and factor loadings ≥ 0.70. These criteria exhibit acceptable values, consistent with the outcomes outlined in table 3, thereby confirming convergent validity. Table 5 illustrates that all values fall within acceptable ranges, establishing a foundation for discriminant validity in certain cases.

2.3. Findings

The collected data were then analyzed using SmartPLS software as shown in figure 2, which employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, an effective analytical method for examining the relationships between variables in this study.

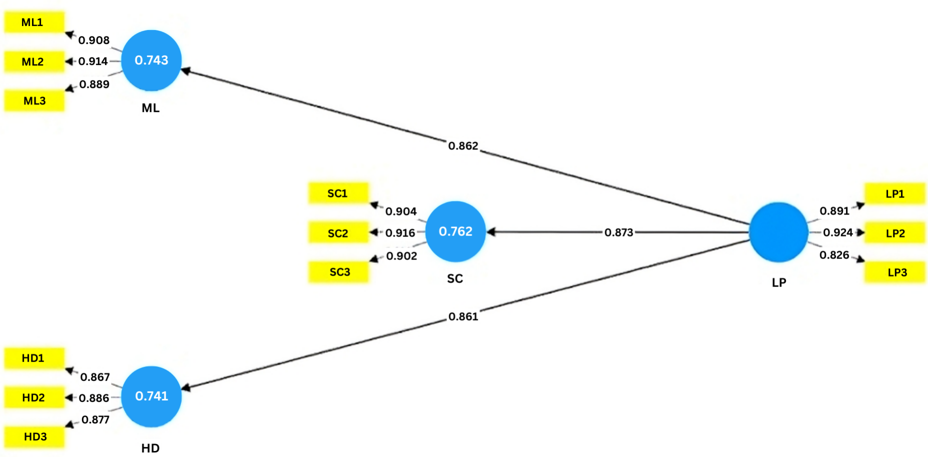

Figure 2. Conceptual Model of the Relationship Between Machine Learning-Historical Data, and Startup Success

Figure 2 illustrates the conceptual framework used in this study to examine the relationships between Machine Learning Models (ML), Historical Data (HD), Startup Collaboration (SC), and Long-term Partnership Success (LP) within the startup ecosystem. Each variable in the model is represented by a latent construct, measured through multiple observable indicators. For instance, ML is measured by three indicators (ML1, ML2, and ML3), reflecting the extent of machine learning adoption, usage frequency, and its impact on collaboration. Similarly, HD includes three indicators (HD1, HD2, HD3), representing the importance of historical data in collaboration decisions.

The arrows in the figure indicate direct relationships between the variables, quantified by path coefficients. For example, the path coefficient of 0.862 from LP to ML signifies a strong positive relationship, showing that higher adoption of machine learning models leads to more effective collaboration between startups. Likewise, the path from SC to LP (with a coefficient of 0.873) demonstrates that improved startup collaboration directly contributes to long-term partnership success. The R-square values in each circle represent the amount of variance explained by the model for that construct. For instance, ML explains 74.3% of the variance in LP, and HD explains 74.1%, highlighting the significant role both play in enhancing collaboration. Additionally, 76.2% of the variance in LP is explained by SC, emphasizing the importance of strong collaborations in achieving long-term success.

In summary, figure 2 visually represents the complex interactions between machine learning, historical data, and collaboration in determining the success of startup partnerships. The strong path coefficients and high R-square values underscore the pivotal role of data-driven technologies in shaping collaborative outcomes within startup ecosystems.

Table 1. Construct Evaluation

	Item	**Outer loadings**
HD1	How crucial is historical data in guiding decisions concerning collaboration with startups?	0.867
HD2	Historical data plays a pivotal role in identifying novel opportunities and enhancing engagements with startups?	0.886
HD3	Historical data is regarded as a valuable information source for shaping collaboration strategies with startups?	0.877
LP1	The importance of startup collaboration in achieving the company's growth goals and desires?	0.891
LP2	Machine learning that has undergone training and refinement stages to better assist startups in identifying potential collaboration opportunities and increasing their effectiveness in doing so driving co-innovation?	0.924
LP3	To what extent can machine learning models that have gone through the training and refinement stages have a positive impact on the success of long-term partnerships between startups?	0.826
ML1	Has your company gained experience in utilizing machine learning models within the context of startup collaborations?	0.908
ML2	How frequently does your company employ machine learning models in collaborative projects involving startups?	0.914
ML3	Is your company utilizing machine learning models to optimize operations or make decisions in the realm of startup collaborations?	0.889
SC1	Has your company acquired expertise in collaborating with startups on particular projects or initiatives?	0.904
SC2	Does machine learning aid in identifying novel opportunities or changes that can fortify partnerships with startups?	0.916
SC3	Can machine learning potentially incentivize your company to engage in collaborations with startups for product or service development?	0.902

Table 1 presents the constructs used in the study, along with their respective measurement items and outer loadings, which represent the strength of the relationship between each item and its associated construct. Outer loadings above 0.7 shows a strong relationship between the indicators and variables, ensuring that the measurement items accurately reflect their constructs. For example, the outer loading for ML1 is 0.908, demonstrating a strong contribution to the machine learning construct.

Table 2. Convergent Validity Results Which Assure Acceptable Values

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Historical Data	0.850	0.850	0.909	0.769
Long-term Partnership Success	0.856	0.867	0.912	0.776
Machine Learning Models	0.888	0.888	0.930	0.817
Startup Collaboration	0.892	0.894	0.933	0.823

The results of Convergent Validity in table 2 show the convergent validity of the constructs used in the study. Convergent validity is assured if the Average Variance Extracted (AVE) is above 0.5, indicating that more variance is captured by the construct than by measurement error. Cronbach's Alpha and Composite Reliability are also reported, with values above 0.7 indicating that the construct is reliable and internally consistent.

Table 3 presents the results of the discriminant validity assessment using the Fornell-Larcker Criterion. This criterion is employed to establish discriminant validity, ensuring that a latent variable is better represented by its own indicators than by the indicators of other latent variables. To meet this benchmark, the diagonal values, which represent the square root of the Average Variance Extracted (AVE), must be greater than the correlation values between other latent variables in the same column.

Table 3. Fornell-Larcker Discriminant Validity

	Historical Data	Long-term Partnership Success	Machine Learning Model	Startup Collaboration
Historical Data	0.877			
Long-term Partnership Success	0.861	0.881		
Machine Learning Model	0.896	0.862	0.904	
Startup Collaboration	0.909	0.873	0.865	0.907

The study's findings reveal that the correlations among distinct latent constructs are higher compared to the correlations between diverse latent constructs. Consequently, it can be concluded that within the scope of this research, each variable achieves a heightened level of precision and validity.

Table 4. R-Square

Construct	R-square
Historical Data	0.741
Machine Learning Model	0.743
Startup Collaboration	0.762

Table 4 presents the R-square values, which reflect the explanatory power of the model in predicting the variance in startup collaboration and long-term partnership success. The R-square value for Historical Data is 0.741, indicating that 74.1% of the variation in startup collaboration can be explained by the effective use of historical data. This highlights the critical role that historical data plays in driving collaboration, as startups that leverage past data are better equipped to make informed decisions and identify promising partners.

Similarly, the R-square value for Machine Learning Models is 0.743, showing that 74.3% of the variance in startup collaboration can be attributed to the adoption of machine learning models. This finding underscores the importance of machine learning in optimizing collaborations by enabling startups to use predictive analytics and data-driven decision-making processes. Finally, the R-square value for Startup Collaboration is 0.762, meaning that 76.2% of the variance in long-term partnership success is explained by strong startup collaboration. This suggests that well-established collaborations are key drivers of long-term success, as they foster sustained growth and innovation

2.4. Hyphothesis Testing

Table 5 outlines the results of the hypothesis testing, confirming the statistical significance of the relationships between the variables. For Hypothesis 1 (H1), the path coefficient of 0.861 and p-value of 0.000

indicate that the success of machine learning models has a strong, positive impact on startup collaboration. This result implies that startups that effectively implement machine learning models are more likely to engage in successful collaborations. Hypothesis 2 (H2) also holds, with a path coefficient of 0.862 and a p-value of 0.000. Suggesting that machine learning models have a significant positive impact on long-term partnership success.

Table 5. Summary of the Results Btained from Statistical Hypothesis Testing

Hypothesis	Original Sample (O)	P values	Decision
Machine Learning Models Success has a significant and positive impact on Startup Collaboration	0.861	0.000	Supported
Machine Learning Models has a significant and positive impact on Long-term Partnership Success	0.862	0.000	Supported
Startup Collaboration Success has a significant and positive impact on Long-term Partnership Success	0.873	0.000	Supported

This finding indicates that refining and applying machine learning not only enhances collaboration but also contributes to sustainable, long-term partnerships. Lastly, Hypothesis 3 (H3), with a path coefficient of 0.873 and a p-value of 0.000. Confirms that successful startup collaborations significantly improve long-term partnership outcomes. This demonstrates that startups capable of establishing strong collaborative relationships are more likely to achieve lasting partnerships, which in turn supports continuous innovation and competitive advantages.

3. RESULTS AND DISCUSSION

The results from testing H1, H2, and H3 show a significant and positive impact, as indicated by p-values of 0.000 for all three hypotheses, which are well below the 0.05 threshold, confirming statistical significance at the 95% confidence level. As displayed in table 4, the R-square value for Historical Data is 0.741, which implies that 74.1% of the variance in startup collaboration can be explained by the use of historical data. This underscores the critical role that historical data plays in enabling startups to make more informed decisions regarding partnerships and collaboration.

Similarly, the Machine Learning Model achieves an R-square value of 0.743, meaning that approximately 74.3% of the variance in startup collaboration is driven by machine learning adoption. This finding emphasizes the power of machine learning in enhancing collaboration, allowing startups to analyze data and optimize partnerships based on predictive insights. Furthermore, the R-square value for Startup Collaboration is 0.762, indicating that 76.2% of the variability in Long-term Partnership Success is accounted for by the strength of startup collaboration efforts. This highlights the importance of effective collaboration in ensuring sustained success for startup partnerships.

These results not only benefit the startup ecosystem but also align with the United Nations' Sustainable Development Goals (SDGs). Specifically, the findings contribute to SDG 9: Industry, Innovation, and Infrastructure, by showing that machine learning fosters innovation and operational efficiency, enabling startups to develop resilient infrastructures and contribute to sustainable economic growth. The study also supports SDG 17: Partnerships for the Goals, as machine learning enhances the quality and success of startup collaborations.

4. MANAGERIAL IMPLICATION

Based on the findings of this study, there are several key managerial implications. First, managers can optimize startup collaborations by leveraging machine learning (ML) models. By utilizing historical data, ML can help identify the most promising collaborative partners and steer startups away from unproductive partnerships. Second, ML enables data-driven decision-making, which significantly contributes to long-term partnership success. It helps in identifying new collaboration opportunities and refining more innovative and effective collaborative business models. Third, using analytical tools like SmartPLS allows managers to gain deeper insights into the relationships between key variables in the startup ecosystem, such as historical data, ML adoption, and collaboration success, enabling a more comprehensive assessment of the models in use. Additionally, while ML adoption is more prevalent in tech-driven industries, other sectors, such as healthcare, finance, and education, can also benefit from ML integration to optimize their collaborative decisions through predictive analysis. Lastly, ML adoption not only enhances short-term collaboration outcomes but also fosters long-term innovation and success, boosting the competitiveness of startups in dynamic markets.

5. CONCLUSION

Machine learning (ML) is becoming an essential pillar of innovation, collaboration, and sustainable growth within the startup ecosystem. As businesses increasingly adopt ML technologies, their capacity to analyze data comprehensively, make informed decisions, and create efficient, collaborative strategies improves substantially. This study has shown that ML plays a critical role in enhancing collaboration between startups by enabling data-driven insights and fostering long-term partnerships. The findings highlight how ML adoption not only improves immediate collaboration outcomes but also contributes to sustained innovation and success in highly competitive and dynamic markets.

Despite the promising potential of ML in startup ecosystems, this study is not without its limitations. One notable **limitation** is the sample size and scope of startups included. While 207 responses provide a solid foundation for analysis, the sample is concentrated in sectors where ML adoption is relatively high, such as tech-driven industries. As a result, the findings may not fully represent startups from less technologically mature sectors, which may face different challenges when adopting machine learning. Moreover, the geographic focus of the study is limited, with most respondents likely representing startups from regions with robust technological infrastructures, which may not apply to startups in less developed areas.The study's emphasis on startups that have either adopted or are in the process of integrating ML technologies also presents a scope limitation, as it does not account for startups that have yet to embrace ML or that face significant barriers to adoption. These barriers could include limited resources, lack of access to talent, or infrastructural constraints, which future research could explore.

Future research should consider expanding the scope by including a broader range of industries and geographic regions. Studies could investigate how ML is applied in industries such as agriculture, education, or healthcare, where AI adoption is still emerging but holds great potential for innovation and collaboration. In addition, conducting comparative studies across developed and developing economies would offer valuable insights into how regional differences affect ML adoption and collaboration dynamics.

6. DECLARATIONS

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6.2. Author Contributions

Conceptualization: NL; Methodology: SW; Software: NA; Validation: UR and HD; Formal Analysis: UR and NL; Investigation: NL; Resources: SW; Data Curation: SW; Writing Original Draft Preparation: NA and UR; Writing Review and Editing: NA and HD; Visualization: SW; All authors, NL, SW, UR, HD, and NA, have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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