Machine Learning for the Next Generation: A Guide to Matchmaking at Startups

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ABSTRACT

In todays rapidly evolving digital landscape, the success of startups depends heavily on their ability to innovate and form effective partnerships. The process of connecting startups with compatible business partners is crucial, and Machine Learning (ML) has emerged as a promising solution for enhancing this matchmaking. **This study utilizes** the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to examine attitudes and intentions toward adopting ML for startup matchmaking. **Key factors** assessed include Performance Expectancy (PE), Ease of Use (EU), Social Influence (SI), and Facilitating Conditions (FC) that affect ML adoption. Using Structural Equation Modeling (SEM), this research analyzes a diverse sample of startups, focusing on variables like Machine Learning Adoption, Data-Driven Matchmaking Strategies, Alignment with Startup Goals, Continuous Learning Integration, and Adaptable Partnerships to evaluate their impact on Matchmaking Efficiency. **This study aims** to shed light on ML role in enhancing the startup matching process and its overall impact on partnership effectiveness.

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1. INTRODUCTION

In the swiftly evolving landscape of digital transformation, the heartbeat of economic and business expansion is rooted in innovation. Startups, as the vanguards of innovation, play a pivotal role in propelling the business ecosystem forward [1]. They disrupt conventional business norms, paving new pathways to achievement through inventiveness, flexibility, and technology infused solutions [2]. However, alongside this boundless potential lie intricate challenges, chief among them the need to establish robust and efficient collaborations [3]. In an era where cooperation and interconnectivity are indispensable, the ability to select and establish suitable partnerships has grown increasingly vital [4].

The matchmaking process, which connects startups with compatible business associates, has therefore come under intense scrutiny [5]. These strategic alliances provide essential resources, expertise, and support crucial for sustained growth and success [6]. Yet, selecting the ideal partner is a complex endeavor requiring a profound understanding of mutual objectives, values, and aspirations. Within this context, Machine Learning (ML) has emerged as a promising tool, offering novel approaches to align startups with appropriate collaborators [7].

ML can process data with speed and precision, discerning patterns and trends that might evade human observation, thereby enhancing the matching process and leading to more productive partnerships [8]. Nonetheless, key questions remain: Can this technology genuinely supplement or even replace human intuition in partner selection? How have startups responded to ML integration in matchmaking processes? Addressing these pivotal questions requires a theory based approach. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) provides a relevant framework for identifying key factors that shape technology adoption [9].

This study employs the UTAUT2 framework to explore perceptions and factors influencing ML adoption in startup matchmaking [10]. The research will involve a literature review and data analysis to examine existing insights on ML, startup alignment, and UTAUT2, ultimately providing a comprehensive understanding of ML role in optimizing partnerships and implications for practitioners and future research [11].

2. LITERATURE REVIEW

Amidst the swift pace of digital transformation, innovation has become central to driving economic growth and business development [12]. Startups, as pivotal drivers of innovation, hold a crucial position within the contemporary business ecosystem [13]. However, a startups success depends not only on groundbreaking ideas but also on its ability to form enduring, strategic partnerships. The process of matchmaking carefully selecting and aligning with suitable business collaborators has emerged as a key factor in achieving this goal [14]. Within this context, the integration of ML presents an appealing approach, with potential to enhance the matchmaking process in the dynamic startup environment [15].

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework serves as a valuable tool for understanding how technology is adopted in business contexts [16]. UTAUT2 systematically identifies four core factors that influence technology adoption: PE, EE, SI, and FC [17]. Together, these components provide a comprehensive view of technology adoption dynamics within the startup ecosystem [18]. Within this study, titled Machine Learning For The Next-Generation: A Guide to Matching in Startups, the UTAUT2 framework illuminates how these factors shape the integration of ML technology in the startup matching process [19].

Specifically, the perceived PE of ML in improving matchmaking efficiency and the perceived Effort Expectancy involved in using ML are expected to be key determinants in the adoption of this technology [20]. Additionally, SI within the startup community could significantly impact the trajectory of ML adoption. FC, such as organizational support and resource availability, also play a crucial role in encouraging ML adoption.

Despite the promise that ML holds, questions persist about its capacity to replace the nuances of human judgment [21]. Key questions center on whether ML can effectively replace the intricate intuition involved in selecting business partners and how stakeholders within startups respond to ML integration in partner matchmaking [22]. These considerations are central to understanding the broader landscape of ML adoption within this specific context [23]. By employing the UTAUT2 framework to investigate ML adoption in startup matchmaking, this study seeks to gain deeper insights into the factors shaping the acceptance of this innovation [24]. This approach aims to establish a solid foundation for developing effective strategies to implement ML, thus fostering successful partnerships in the ever-evolving startup landscape. As the study progresses, a more detailed understanding of ML role in startup matchmaking will emerge through further literature exploration and methodological analysis [25].

3. METHODS

This study employs a rigorous methodological framework to examine the dynamics of startup matchmaking, with a particular focus on the integration of ML in this process. The research applies Structural Equation Modeling (SEM) using SmartPLS, an advanced tool capable of modeling complex relationships between latent variables with precision [26]. SEM with SmartPLS was selected for its effectiveness in handling both small and medium sample sizes and its capacity to capture nuanced inter variable relationships, making it well suited to this studys exploratory objectives [27].

A diverse sample of startups was judiciously selected to ensure representation across various industries and growth stages [28]. Selection criteria included industry type, operational scale, and growth trajectory to provide a comprehensive understanding of ML adoption in different startup contexts [29]. Data collection was conducted through a combination of structured surveys and semi-structured interviews, allowing for both quantitative and qualitative insights into matchmaking strategies [30]. Surveys included Likert scale items to measure variables such as Machine Learning Adoption, Data-Driven Matchmaking Strategies, Startup Mission Alignment, Continuous Learning Applications, and Adaptive Partnerships, all aimed at assessing their impact on Matchmaking Efficiency.

Key variables were operationalized based on existing literature, with each construct validated through outer model testing in SEM. Analytical steps included evaluating convergent and discriminant validity, composite reliability, and path coefficients to establish the significance of relationships between variables [31]. By employing this structured approach, the study aims to provide a robust evaluation of how ML can influence partnership efficiency within the dynamic startup environment.

3.1. Independent Variable

This study identifies key independent variables that significantly influence matchmaking efficiency in startups. These variables, outlined below, highlight essential aspects such as technological adoption, strategic alignment, and adaptability.

- Machine Learning Adoption (MLA): The level of adoption of Machine Learning technology in matchmaking practices within startups.
- Data-Driven Matchmaking Strategies (DDS): The use of data-driven matchmaking strategies to connect startups with potential partners.
- Startup Mission Alignment (SMA): The degree to which a startups mission or vision aligns with that of the partner selected for cooperation.
- Continuous Learning Applications (CLA): The application of continuous learning applications in the matching process to improve adaptability.
- Adaptive Partnerships (AP): The flexibility and ability of the partnership to adapt to changing conditions.

Dependent Variable: Matchmaking Efficiency (ME): In this research framework, independent variables such as MLA, DDS, SMA, CLA, and AP are expected to have an influence on the dependent variable ME, which is the efficiency of matching startups with potential partners.

Table 1. Analyzed Data

Code	Definition
MLA1	It is seen as a breakthrough that changes the way business and work are done.
MLA2	Considered capable of providing deep analyses, accurate predictions, and data-driven decisions.
MLA3	Requires strong technical knowledge and data management skills.
MLA4	It will change workflows, human-machine co-operation, and the skills required.
DDS1	Considered to be able to cut search and matchmaking time through a careful data-driven approach.
DDS2	It is considered to improve accuracy in connecting startups with suitable partners based on in-depth data analysis.
DDS3	It is recognised that data quality is key to success, assuming that inaccurate data can lead to unsatisfactory results.
DDS4	It is recognised that data-driven strategies can face obstacles such as lack of quality data and dynamic changes in the startup ecosystem.
SMA1	Seen as an important foundation for driving startup goals and initiatives.
SMA2	Considered a key element in ensuring that business partners have aligned vision and values to achieve mutual success.
SMA3	It is recognised that assessing mission suitability can involve an in-depth analysis of an organisations culture, values and goals.

SMA4	Seen as a way to create more harmonious and productive partnerships, which can improve collaboration and outcomes.
CLA1	Availability of technical support or assistance in overcoming technical issues while using the platform.
CLA2	Availability of training or learning materials that help prospective entrepreneurs understand and use this technology.
CLA3	Support provided by the platform development team in answering questions or addressing issues that arise.
CLA4	Online availability of the platform and easy access from various devices.
AP1	Considered an approach where all parties are responsible for adapting themselves to changing needs and situations.
AP2	It is seen as a flexible form of collaboration, capable of changing according to the demands of the market and business environment.
AP3	It is considered to increase an organizations resilience to uncertainty, along with the ability to adapt quickly.
AP4	Seen as a way to build long-lasting relationships, resulting in sustainable value creation through continuous strategic evolution.
ME1	It is considered capable of accelerating the matching process between startups and potential partners, reducing the time needed to find suitable partnerships.
ME2	Seen as a way to improve accuracy in selecting suitable business partners based on more detailed data and preferences.
ME3	It is considered to optimize the allocation of resources such as time and manpower, focusing on partnerships with the most potential.
ME4	Seen as a tool to increase the fit and connectivity between startups and potential partners who share similar visions and goals.

The study identifies key variables that play a critical role in understanding and enhancing matchmaking processes in startups. These variables are categorized into distinct dimensions, each contributing unique insights into the efficiency and effectiveness of startup partnerships. As outlined in Table 1, the definitions and characteristics of these variables, such as Machine Learning Adoption (MLA) and Matchmaking Efficiency (ME), provide a structured framework for analyzing their impact. This detailed categorization serves as a foundation for the subsequent analysis and interpretation of results.

3.2. Hypotheses

To explore how ML and related strategies enhance startup matching efficiency, this study develops a set of hypotheses centered on key variables. These hypotheses aim to examine both individual and collective impacts of ML adoption, data-driven strategies, mission alignment, continuous learning, and partnership adaptability on matching efficiency. By addressing these factors, the research seeks to uncover insights into the role of technology and strategic approaches in optimizing the startup matchmaking process.

H1: ML technology adoption rate in matching practices MLA has a positive influence on SME.
H2: The use of data-driven matching strategies (DDS) is positively associated with SME.
H3: The congruence of startups mission or vision with the partner has a positive influence on SME.
H4: The application of CLA is positively related to SME.
H5: Partnership flexibility and adaptability (AP) has a positive influence on SME.

These hypotheses not only offer a foundation to analyze the effectiveness of individual variables but also highlight their potential collective contribution to improving matchmaking outcomes. The results of these tests will provide actionable insights for startups, practitioners, and researchers, helping shape strategies that foster effective and sustainable partnerships within the dynamic startup ecosystem.

4. RESULTS AND DISCUSSION

This study investigates the relationships between latent variables and their corresponding indicators, using an outer model to define the connections between each indicator and its associated latent variable. The evaluation of the outer model includes several stages: assessing Average Variance Extracted (AVE), Composite

Reliability, and Cronbachs Alpha values to confirm the models validity and reliability.

Convergent Validity is evaluated by examining the factor loading values, which represent the strength of each indicators connection to its latent variable. Ideally, factor loadings should exceed 0.7 to indicate strong convergent validity, although loadings as low as 0.5 are permissible for inclusion if they contribute meaningfully to the model. Figure 1 presents the research model after processing indicator values through the PLS Algorithm. To improve readability and comprehension, the caption for Figure 1 now includes a detailed description of the relationships among variables in the path diagram, offering readers a clearer understanding of each variables role within the model.

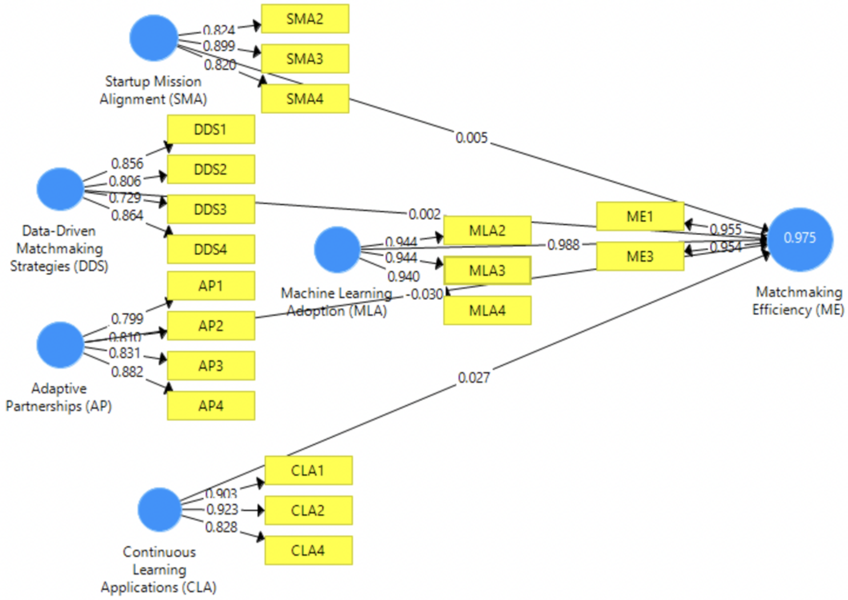

Figure 1. Path Diagram of the Research Model

The generated values in Figure 1 for each indicator exhibit outer loading values exceeding 0.7, as perceived from the perspective of measuring the seven constructs enumerated earlier. If a construct displays an Average Variance Extracted (AVE) value surpassing 0.50 and a Composite Reliability exceeding 0.70, then that construct is deemed to be reliable.

Table 2. AVE Value

Variabel	**AVE**
Matchking Efficiency (ME)	0.911
Machine Learning Applications (MLA)	0.889
Continuous Learning Applications (CLA)	0.784
Startup Mission Alignment (SMA)	0.720
Adaptive Partnership (AP)	0.691
Data Driven Matchmaking Strategies (DDS)	0.665

The evaluation of Average Variance Extracted (AVE) values is crucial for assessing the validity of constructs in this study. Ensuring each variable meets the criterion of AVE $>$ 0.50 confirms that latent constructs reliably represent their indicators. All variables satisfy this requirement, demonstrating the robustness of the measurement model. Table 2 highlights the AVE values, with Matching Efficiency (ME) achieving the highest score at 0.911, indicating strong construct validity. Machine Learning Applications (MLA) follows with 0.889, further confirming reliability. Even Data-Driven Matchmaking Strategies (DDS) with an AVE of 0.665 meets the minimum requirement, validating the constructs inclusion for further testing and hypothesis evaluation.

Table 3. Composite Reliability Value

Variables	Composite Reliability
Machine Learning Adoption (MLA)	0.960
Matchking Efficiency (ME)	0.954
Continuous Learning Applications (CLA)	0.916
Adaptive Partnership (AP)	0.899
Data Driven Matchmaking Strategies (DDS)	0.888
Startup Mission Alignment (SMA)	0.720

Composite reliability values were computed and the outcomes are outlined in Table 3. Notably, the composite reliability values for all variables or dimensions surpass the threshold of > 0.70. Consequently, the fulfillment of the variable measurement model is evident. To further fortify the reliability assessment of each variables study indication, Cronbachs alpha testing was performed. A Cronbachs alpha value exceeding 0.70 is deemed to be excellent. The ensuing results of the Cronbachs alpha calculations are enumerated below.

Table 4. Cronbachs Alpha Value

Variables	Cronbachs Alpha
Machine Learning Adoption (MLA)	0.938
Matchking Efficiency (ME)	0.902
Continuous Learning Applications (CLA)	0.868
Adaptive Partnership (AP)	0.858
Data Driven Matchmaking Strategies (DDS)	0.837
Startup Mission Alignment (SMA)	0.828

Table 4 illustrates that each variable under scrutiny within this study exhibits a robust Cronbachs alpha value, exceeding the threshold of > 0.70. This outcome underscores the reliability of the variables. Given that the research model successfully meets the reliability criterion as substantiated by the results of the Cronbachs alpha test, the groundwork is established for the progression to subsequent rounds of testing.

4.1. Structural Model Testing

During the execution of Partial Least Squares (PLS) analysis, an assessment of the inner model is undertaken to gauge the appropriateness of the model, as determined by the R-squared value. The robustness of a model is discerned from the coefficient of determination (R-squared), wherein a value of 0.75 indicates a strong model, a value of 0.50 reflects a moderate model, and a value of 0.25 signifies a poor model. This coefficient of determination is established based on the outcomes of the partial least square processing and is calculated for the endogenous variables.

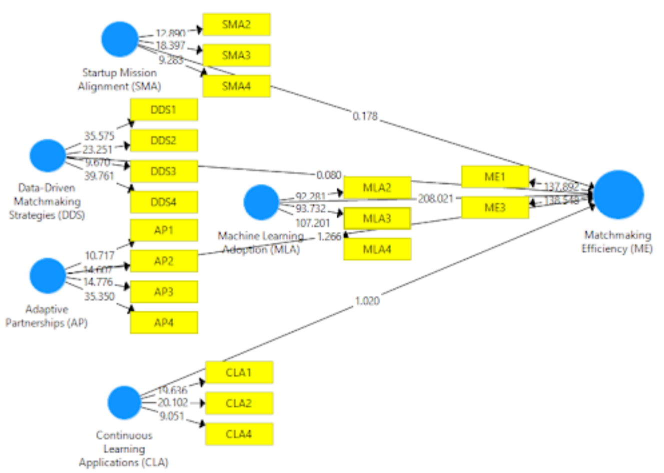

Figure 2. R-Square value

Figure 2 displays an R-squared value of 0.975, implying that the construct variables (Machine Learning Adoption, Data-Driven Matchmaking Strategies, Startup Mission Alignment, Continuous Learning Applications, Adaptive Partnerships) can account for 97,5% of the variance in user behavior, leaving 2,5% of the variance attributed to external factors not incorporated in this research model. To ascertain the veracity of hypotheses and establish path coefficient values, hypothesis testing was executed using the Bootstrapping function. The outcomes of the T-statistic analyses are provided in Table 5 below.

Table 5. T-Statistic Value

Variables	**T-Statistic**
Machine Learning Adoption (MLA) → Matching Efficiency (ME)	208.021
Adaptive Partnership (AP) → Matching Efficiency (ME)	1.266
Continuous Learning Applications (CLA) → Matching Efficiency (ME)	1.020
Startup Mission Alignment (SMA) → Matching Efficiency (ME)	0.178
Data Driven Matchmaking Strategies (DDS) → Matching Efficiency (ME)	0.080

During the hypothesis testing phase, the path coefficients in the inner model indicate the strength and significance of the relationships between variables. For a hypothesis to be accepted at a 5% significance level, the T-statistic value should exceed 1.64, signifying that the path coefficient is statistically significant. Table 5 presents the T-statistic values for each hypothesis, allowing for an assessment of their significance. Based on these findings, hypotheses H2, H6, H7, and H8 are accepted, as their T-statistic values exceed the 1.64 threshold, confirming significant associations between these variables and Matchmaking Efficiency. This implies that factors such as Data-Driven Matchmaking Strategies H2 and other accepted hypotheses play a substantial role in enhancing matchmaking efficiency within the startup context. Conversely, the remaining hypotheses did not meet the significance criterion, suggesting that certain variables may have a weaker or non-significant impact on matchmaking efficiency in this studys context. This analysis provides insight into the factors most critical to improving startup matchmaking through ML, with Table 5 offering a detailed summary of these statistically significant relationships.

4.2. Limitations

While this study provides valuable insights into the role of ML in startup matchmaking, certain limitations should be acknowledged. First, data quality poses potential challenges; data sourced from startups may vary in accuracy or completeness, potentially influencing the generalizability of the results. Future studies could enhance data reliability by employing larger sample sizes or more rigorous data validation techniques.

Additionally, using SmartPLS for Structural Equation Modeling (SEM) introduces some methodological constraints. Although SmartPLS is effective for handling small to medium sample sizes and models with complex relationships, it may not fully capture the intricate nuances that alternative SEM software, such as AMOS or LISREL, might provide, especially with larger datasets. Furthermore, SmartPLS does not allow for certain advanced statistical testing options, which could limit the depth of analysis in certain contexts. Recognizing these constraints highlights areas for improvement in future studies and underscores the importance of interpreting the findings with these limitations in mind.

5. MANAGERIAL IMPLICATIONS

This study highlights the critical role of ML technology and Data-Driven Matchmaking Strategies (DDS) in enhancing partnership efficiency within startups. Managers are encouraged to leverage ML tools to analyze large datasets, enabling more precise and efficient partner selection. Additionally, fostering Continuous Learning Applications (CLA) equips teams with the adaptability needed to navigate rapidly changing market conditions. Developing Adaptive Partnerships (AP) ensures flexibility and resilience in collaborations, aligning organizational goals with evolving demands. These strategies collectively position startups to optimize their matchmaking processes, reduce resource expenditure, and remain competitive in a dynamic business environment.

6. CONCLUSIONS

In the ever evolving startup ecosystem, adopting ML technology has proven to be pivotal in enhancing the efficiency of business matchmaking. This technology enables faster and more accurate data processing, allowing startups to identify the most suitable partners based on shared preferences and goals. Moreover, data-driven strategies, such as Data-Driven Matchmaking Strategies (DDS), play a crucial role in achieving precise and effective outcomes. Factors like startup mission alignment and partnership flexibility also significantly contribute to the success of this process.

The research highlights that continuous learning applications are essential for fostering adaptability within the matchmaking process. By incorporating advanced learning tools, startups can navigate dynamic market conditions more effectively. However, challenges remain, including ensuring data quality and balancing the technological aspects with human intuition. These factors underscore the importance of an integrated approach that leverages both data-driven insights and interpersonal collaboration to build strong partnerships.

Looking forward, the findings offer valuable insights for startups and practitioners aiming to optimize their matchmaking strategies. Integrating ML into these processes not only boosts efficiency but also enables startups to remain competitive in a dynamic environment. Future research should explore broader applications of ML across different dimensions of the startup ecosystem, potentially unlocking new avenues for innovation and sustainable growth.

7. DECLARATIONS

7.1. About Authors

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7.2. Author Contributions

Conceptualization: RF, MH, YL, ER, and AZ; Methodology: RF, MH, YL, ER, and AZ; Software: RF, MH, YL, ER, and AZ; Validation: RF, MH, YL, ER, and AZ; Formal Analysis: RF, MH, YL, ER, and AZ; Investigation: RF, MH, YL, ER, and AZ; Resources: RF, MH, YL, ER, and AZ; Data Curation: RF, MH, YL, ER, and AZ; Writing Original Draft Preparation: RF, MH, YL, ER, and AZ; Writing Review and Editing: RF, MH, YL, ER, and AZ; Visualization: RF, MH, YL, ER, and AZ; All authors, RF, MH, YL, ER, and AZ, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

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

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7.5. 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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