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Data Mining Approaches in Predicting Entrepreneurial Intentions Based on Internet Marketing Applications

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Abstract: Amidst the globalization of markets, there has been a continuous intensification of competitiveness between enterprises. The modern business environment has caused a shift in how business is conducted. Opportunities and challenges arise, which put a tremendous pressure on enterprises regardless of size and industry. Entrepreneurship in enterprises plays an important role in obtaining a competitive edge in the market. Thus, entrepreneurial intentions in enterprises can often shape the future and survival of the enterprise. In this paper, the prediction of entrepreneurial intentions in enterprises through Internet marketing predictors is addressed. For this, several statistical methods in data mining were used. First, simpler approaches such as linear regression, logistic regression were used. Afterward, classifier decision trees QUEST (quick, unbiased, efficient, statistical tree), and CHAID (chi-squared automatic interaction detection) were used. The sample for analysis was 137 enterprises from Serbia. Furthermore, a supervised machine learning algorithm, support vector machine (SVM) was used. Finally, a feed-forward neural network (FNN) was applied. The results varied across the applied approach, thus providing significant insights into the dynamics of data mining for prediction outcomes in an enterprise setting.

Keywords: Internet marketing; entrepreneurship; QUEST; CHAID; support vector machine (SVM); FNN; data mining; algorithm

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1. Introduction

In recent years, the digital revolution has significantly altered the landscape of entrepreneurship and business development, introducing new dynamics that have reshaped how companies operate and grow [1–3]. The advent of digital technologies has not only lowered the barriers to entry for new businesses, but has also expanded the scope of opportunities available to entrepreneurs [4,5]. Digital platforms and tools enable businesses to innovate rapidly, scale efficiently, and compete on a global stage, which was previously accessible only to large, established corporations [6,7]. This shift underscores the importance of understanding and leveraging digital tools and strategies to navigate the complexities of the modern business environment [7]. The integration of digital technologies into business practices has facilitated the democratization of entrepreneurship [8]. Unlike traditional business models that required significant upfront capital investment and physical presence, digital platforms offer low-cost entry points for startups and small enterprises [7,8]. Entrepreneurs can now launch and manage businesses online, utilizing e-commerce platforms, social media, and digital marketing tools to reach their target audiences [9]. This accessibility has led to a surge in entrepreneurial activity, as more individuals are empowered to start and grow their own businesses without the constraints of geographical location or substantial financial backing [10–12].

Innovation in the digital age is heavily driven by the ability to harness data and technology to create value [13]. Entrepreneurs are increasingly turning to big data, artificial intelligence, and machine learning to gain insights into consumer behavior, optimize business operations, and improve customer experiences [14,15]. The use of data-driven decision-making processes allows businesses to tailor their offerings to meet specific customer needs, thereby improving satisfaction and loyalty [16]. This trend toward data-centric business models highlights the necessity for entrepreneurs to develop competencies in data analysis and cybersecurity to safeguard their digital assets and maintain competitive advantage [17]. The global connectivity afforded by the Internet has further amplified the opportunities for entrepreneurs, enabling them to transcend local markets and tap into global supply chains and customer bases [18]. However, this expansion also presents challenges including the need to navigate diverse regulatory environments, understand varied consumer preferences, and manage international logistics [17,18]. The ability to adapt to these complexities is important for entrepreneurs aiming to succeed in a global marketplace, where cultural, legal, and economic differences can impact business operations [19].

In this context, Internet marketing has emerged as an important tool for modern businesses, offering a range of strategies to connect with customers and effectively promote products and services [20]. The Internet allows businesses to reach a vast, global audience, surpassing the limitations of traditional marketing channels [21]. Through precise targeting and personalized marketing campaigns, companies can engage directly with their consumers, building stronger relationships and supporting brand loyalty [22]. The cost-effectiveness and flexibility of Internet marketing further improve its appeal, making it accessible to businesses of all sizes [23]. The rise of mobile Internet usage and the increasing prevalence of the gig economy have influenced how businesses approach marketing and workforce management [24]. Mobile-friendly marketing strategies, coupled with the ability to tap into a flexible and scalable freelance workforce, offer new avenues for growth and innovation [25]. However, these developments also necessitate a focus on cybersecurity, as businesses must protect their digital operations from the growing threat of cyberattacks [26,27].

It is evident that there is a large body of literature that has addressed this topic [1–27]. However, few studies have analyzed the application of data mining approaches on a dataset that was obtained from enterprises in a transitional economy [28–31]. There is a substantial and continuously expanding body of literature examining the use of advanced analytical techniques, such as data mining and machine learning, to enhance decision-making and strategic planning in a range of organizational contexts [32,33]. These techniques have been applied across multiple sectors including finance, manufacturing, healthcare, retail, and telecommunications, and have often focused on enterprises operating in stable, well-established markets. Methodological progress in data mining including more sophisticated algorithms, scalable computing environments, and improved data preprocessing techniques has enabled researchers and practitioners to efficiently derive meaningful insights from large, complex, and multifaceted datasets [34].

Emerging research endeavors have begun to address this gap in the literature by systematically examining the application of data mining tools and techniques in transitional contexts [35,36]. Recent studies have focused on identifying which methods best capture the nuances of organizational behavior and performance in these economies. They have also sought to determine how data mining can support enterprises grappling with uncertainty and constant change.

The main goal of this current research was to analyze the application of multiple data mining approaches for predicting entrepreneurial intentions in enterprises. In the study, linear regression, logistic regression, QUEST decision tree, CHAID decision tree, support vector machine (SVM), and a feed-forward neural network were applied.

Linear regression provides a means to understand how continuous predictors influence a continuous outcome variable. In this paper, it enabled the identification of linear relationships and the estimation of coefficients that highlighted the direction and magnitude of these effects. While it excels in clarity and interpretability, it may struggle when the data exhibit nonlinear patterns or complex interactions among variables [37].

Logistic regression is employed to examine binary outcomes, which allowed us to estimate the probability of events occurring. Its coefficients, expressed in log-odds, provide an interpretable lens through which managers can understand which predictors increase or decrease the likelihood of a particular outcome. However, this method assumes a linear relationship on the log-odds scale and may not fully capture nuanced, nonlinear patterns [38]. The QUEST decision tree analysis in this paper involved creating binary splits in the data to categorize observations and predict outcomes. It was designed to produce simpler, more statistically guided splits, making results more stable than some of the other tree methods. While it can expose meaningful data structures and interactions, the resulting tree may still require careful interpretation and validation to ensure its reliability [39]. Aside from the QUEST decision, a CHAID decision tree was applied. This employs chi-square tests to identify and form multi-way splits, creating distinct, data-driven categories. In the context of this paper, it helped uncover complex, categorical interactions, and groupings that might otherwise have remained hidden. Although CHAID can offer detailed segmentations, the resulting trees may become large and intricate, requiring careful scrutiny to avoid overfitting [40]. SVMs in this paper were applied to detect complex, often nonlinear patterns by using kernel functions to map data into higher-dimensional spaces. This flexibility can lead to strong predictive performance, especially when relationships are not easily described by simpler models [41]. A feed-forward neural network models intricate, nonlinear associations by passing inputs through multiple layers of interconnected nodes. Within this paper, it could identify subtle patterns and interactions that other methods might have missed. While it may enhance predictive accuracy, its "black box" nature limits interpretability, and it often requires significant computational resources and careful training.

The main goals were to determine the differences in predictions/relations of entrepreneurial intentions based on Internet marketing applications. Two main research questions that guided this paper were:

1. How do the distinct modeling assumptions and mechanisms of linear regression, tree-based methods, and support vector machines affect the accuracy and stability of predictive outcomes when applied to enterprise data from transitional economies?
2. In what ways does adapting data mining approaches to the unique characteristics of transitional economies support the reliability and interpretability of predictive insights compared to methods that are not adapted to these contexts?

The paper consists of six main sections: Introduction, Research background, Methodology, Results, Discussion, and Conclusions.

2. Research Background

2.1. Entrepreneurship and Developing Business in the Digital Age

Entrepreneurship in the digital age presents both unprecedented opportunities and unique challenges [42]. The rapid advancement of digital technologies has transformed traditional business models, offering entrepreneurs new avenues for innovation, efficiency, and global reach [42]. The digital landscape has democratized access to resources, enabling even small startups to compete on a global scale [43]. However, this new environment also demands a deep understanding of digital tools, agile strategies, and a strong adaptability to changing market conditions [44]. The digital age has redefined the concept of entrepreneurship by lowering the barriers to entry [44,45]. Traditionally, starting a business required significant capital investment, extensive market research, and a substantial physical presence [46]. Today, digital platforms allow entrepreneurs to launch businesses with minimal upfront costs [47]. For instance, e-commerce platforms like Shopify and Amazon have made it possible for anyone to set up an online store, while social media and digital marketing tools provide affordable ways to reach target audiences [48]. These platforms not only reduce the cost of entry, but also provide scalable solutions that can grow with the business [49]. Innovation in the digital age often revolves around leveraging data and technology to create value [50]. Entrepreneurs are increasingly relying on big data, artificial intelligence, and machine learning to gain insights into consumer behavior, optimize operations, and personalize customer experiences [51]. For example, companies like Netflix and Amazon use data-driven algorithms to recommend products and content to users, improving customer satisfaction and driving sales [52]. This shift toward data-centric business models requires entrepreneurs to develop new skills and understanding, particularly in areas like data analysis and cybersecurity [53].

The global reach of the Internet has expanded the market opportunities for entrepreneurs, enabling them to reach customers beyond their local markets [54]. Digital tools and platforms facilitate international trade, allowing even small businesses to access global supply chains and customer bases [55]. However, this globalization also brings new challenges such as navigating different regulatory environments, understanding diverse consumer preferences, and managing cross-border logistics [56]. Entrepreneurs must therefore be well-versed in global business strategies and be prepared to adapt to different cultural and legal landscapes [57].

In the digital age, the speed of innovation and the rate at which new technologies are adopted can create both opportunities and threats for entrepreneurs [58]. On the one hand, the rapid pace of technological change allows businesses to innovate quickly, bringing new products and services to market faster than ever before [59]. On the other hand, this fast-paced environment can lead to increased competition and shorter product life cycles, forcing businesses to continuously innovate to stay ahead [60]. Entrepreneurs need to be agile, constantly scanning the horizon for emerging trends and technologies that could impact their business [61].

Building a brand in the digital age requires a strategic approach to online presence and reputation management [62]. With consumers increasingly relying on the Internet for information, reviews, and recommendations, having a strong digital footprint is essential for success [63,64]. Entrepreneurs must invest in building a professional website, engaging with customers on social media, and managing their online reputation [65]. Content marketing, search engine optimization (SEO), and influencer partnerships have become important components of brand strategy, helping businesses to connect with their target audience and build trust in a crowded market [66].

The rise of the gig economy and the increasing popularity of remote work have also impacted entrepreneurship [67]. The gig economy, characterized by short-term contracts and freelance work, offers entrepreneurs access to a flexible and scalable workforce [68]. Platforms like Upwork and Fiverr allow businesses to tap into a global talent pool, hiring experts for specific tasks without the need for long-term commitments [69]. This flexibility can be a significant advantage for startups, allowing them to scale their operations up or down as needed [70]. However, managing a remote or freelance workforce presents its own set of challenges including communication barriers, time zone differences, and maintaining company culture [71].

Cybersecurity has become an important concern for entrepreneurs in the digital age [72]. As businesses increasingly rely on digital platforms for operations, sales, and customer interactions, the risk of cyberattacks grows. Entrepreneurs must prioritize cybersecurity, implementing measures to protect their business and customer data. This includes investing in secure payment systems, using encryption, and regularly updating software to protect against vulnerabilities. Failure to address cybersecurity risks can lead to significant financial losses, reputational damage, and legal liabilities.

Entrepreneurship in the digital age offers vast opportunities for innovation and growth, but it also requires a new set of skills and strategies [73]. Entrepreneurs must navigate a rapidly changing technological landscape, leverage digital tools to reach global markets, and prioritize cybersecurity to protect their businesses [74]. The ability to adapt to these changes, continuously learn, and collaborate with others will be the key to success in the digital era [75]. As technology continues to evolve, so too will the landscape of entrepreneurship, offering new challenges and opportunities for those willing to embrace the digital transformation [76].

2.2. Internet Marketing in Modern Business

Internet marketing has become an essential component of modern business strategies, playing an important role in how companies reach, engage, and convert customers [60]. The pervasive use of the Internet in everyday life has shifted the way businesses operate, moving from traditional marketing methods to digital ones. This transformation is driven by the need to meet customers where they are—online [77]. Internet marketing offers businesses a range of tools and platforms to connect with a global audience, improve brand visibility, and drive sales [78,79].

The Internet provides businesses with unparalleled access to a vast and diverse audience [80,81]. Traditional marketing methods, such as print ads and television commercials, are often limited by geography and time [82]. In contrast, Internet marketing allows businesses to reach potential customers anywhere in the world, at any time [82,83]. Social media platforms, search engines, email marketing, and websites enable businesses to communicate with their target audience more effectively and efficiently [84,85]. This global reach is particularly beneficial for small- and medium-sized enterprises (SMEs) that may lack the resources to compete with larger corporations through traditional channels [86,87].

Internet marketing also offers precise targeting and personalization, which are the key to achieving better marketing outcomes [88–90]. Digital tools allow businesses to gather and analyze data on consumer behavior, preferences, and demographics [91]. With theses data, companies can create highly targeted marketing campaigns that resonate with specific segments of their audience [92]. For example, social media platforms like Facebook and Instagram offer advanced targeting options that enable businesses to reach users based on their interests, location, and online behavior [93]. Personalization increases the relevance of marketing messages, making it more likely that consumers will engage with the content and take action, whether it be making a purchase or signing up for a newsletter [94].

One of the most powerful aspects of Internet marketing is its ability to support direct and continuous engagement with customers [95,96]. Unlike traditional marketing, which often involves one-way communication, Internet marketing facilitates two-way interactions between businesses and their customers [97]. Social media platforms, email newsletters, and blogs allow businesses to engage in real-time conversations with their audience, respond to feedback, and build relationships [98,99]. This ongoing interaction not only helps businesses to understand their customers better, but also builds trust and loyalty, which are essential for long-term success [100].

Content marketing is another important element of Internet marketing that emphasizes the importance of providing value to customers [101,102]. Businesses use content marketing to create and share valuable, relevant, and consistent content to attract and engage their target audience [103]. This content can take various forms including blog posts, videos, infographics, and e-books [104]. Effective content marketing not only drives traffic to a business's website, but also positions the company as an authority in its industry [105,106]. Providing valuable content helps build trust with customers, making them more likely to choose the business's products or services [104].

Internet marketing also offers measurable results, allowing businesses to track the effectiveness of their campaigns with precision [107,108]. Digital marketing tools and analytics platforms provide detailed insights into key performance indicators (KPIs) such as website traffic, conversion rates, click-through rates, and customer engagement [109]. This data-driven approach enables businesses to assess the return on investment (ROI) of their marketing efforts and make informed decisions about future strategies [110]. The ability to measure results in real-time allows for continuous optimization, ensuring that marketing efforts are always aligned with the business goals [111].

Internet marketing is an indispensable part of modern business strategy, offering numerous advantages over traditional marketing methods [107–110]. Its ability to reach a global audience, provide precise targeting and personalization, and support direct customer engagement makes it a powerful tool for businesses of all sizes [99]. As the digital landscape continues to evolve, businesses must stay agile and adapt their Internet marketing strategies to remain competitive [96]. With the right approach, Internet marketing can drive significant growth, improve brand visibility, and secure a strong position in the marketplace [96].

2.3. Entrepreneurial Intentions

Entrepreneurial intentions have been examined through a range of theoretical frameworks that highlight the interplay of attitudes, perceptions of control, and social as well as environmental contexts [112–114]. This emphasizes that intentions to launch new ventures do not arise solely from inherent personality traits or isolated preferences. Instead, these intentions develop through complex interactions between the individual's outlook on entrepreneurship, the degree to which that individual believes they can influence outcomes, and the norms and expectations communicated through various social networks. Additional factors, such as the accessibility of financial resources, the presence of supportive mentors, and exposure to entrepreneurial role models, can further shape whether an individual views starting a business as both appealing and achievable [115].

Empirical findings consistently indicate that positive attitudes toward entrepreneurship correlate with greater entrepreneurial intentions. Individuals who see entrepreneurial endeavors as worthwhile, aligned with their values, or capable of delivering personal and professional fulfillment are more likely to consider creating their own ventures. However, a favorable attitude alone does not guarantee that a person will progress toward entrepreneurial action. Perceived behavioral control, understood as the belief that one possesses the knowledge, skills, and resources required to overcome potential barriers, also plays an important role. Individuals who are confident in their ability to navigate administrative hurdles, secure initial funding, and manage early-stage operations tend to express stronger entrepreneurial intentions. Attitudes and perceived control often interact, meaning that the most pronounced intentions emerge when a person both values entrepreneurship and feels capable of achieving entrepreneurial goals [116].

Social and institutional settings likewise influence entrepreneurial intentions. Supportive family members may encourage risk-taking, leading individuals to view entrepreneurship as a legitimate career path. Educational training including courses on venture creation or experiential learning through internships and competitions can provide relevant skills and practical insights that shift intentions toward entrepreneurship [117]. Local entrepreneurial ecosystems, which may include business incubators, startup accelerators, investors, and an important mass of peer entrepreneurs, create environments where aspiring founders are exposed to important knowledge networks and success stories. Even subtle aspects of an institutional setting, such as streamlined legal procedures or community recognition of entrepreneurial achievements, can strengthen or weaken an individual's inclination to transform an idea into a functioning business.

Cognitive processes further refine how entrepreneurial intentions form. Opportunity recognition involves scanning the environment, identifying unmet needs, and envisioning solutions that address those gaps. Individuals who excel at recognizing viable opportunities tend to report stronger intentions, since they perceive a clearer path to successful venture creation. Evaluating risk and reward also matters. While some prospective entrepreneurs are undeterred by uncertainty, others may require convincing evidence that the potential benefits outweigh potential losses. This evaluation process, shaped by experience, feedback from mentors, and information gathered from the external environment, can lead an individual to adjust their intentions over time [117–119].

Longitudinal research has revealed that entrepreneurial intentions are not fixed and can evolve as individuals gain experience through trial and error, refine their business concepts, expand their networks, and adapt to shifting market conditions. Some individuals may begin with minimal interest in entrepreneurship but develop stronger intentions after positive interactions with entrepreneurs, participation in training programs, or exposure to policy changes that lower barriers to entry. Others may start with strong intentions that diminish if they face repeated setbacks or struggle to secure the necessary capital or team members. Cross-cultural comparisons show that the fundamental drivers of entrepreneurial intentions are relatively consistent, however, their relative influence can vary. In some regions, strong family traditions of business ownership or community support create environments where entrepreneurial intentions are more readily expressed. In other contexts, strict regulatory frameworks or social expectations around employment security may reduce the likelihood that individuals translate supportive attitudes into concrete intentions [120]. Understanding these cultural nuances helps explain differences in entrepreneurial activity across geographies.

Taken together, this body of research suggests that entrepreneurial intentions emerge through a multifaceted process shaped by attitudes, perceptions of self-efficacy, and the broader social, cultural, and institutional landscape. Studying entrepreneurial intentions from an interdisciplinary perspective that draws on psychology, sociology, economics, and related fields offers a more nuanced understanding of how individuals decide to pursue new ventures. Such a perspective acknowledges that entrepreneurial intentions do not arise in a vacuum [121,122]. Instead, they result from ongoing interactions between personal outlooks, social influences, opportunity structures, and the evolving circumstances in which potential entrepreneurs find themselves. Through these lenses, the study of entrepreneurial intentions moves beyond simplistic explanations and toward a richer, evidence-based understanding of how entrepreneurship has emerged as a viable and attractive path for many individuals. Integrating predictive analytics into entrepreneurship research moves beyond producing forecasts and encourages the creation of more comprehensive theoretical frameworks that connect individual motivations and abilities with broader institutional, economic, and cultural conditions. Predictive results can inspire new explanations for why certain variable combinations lead to higher entrepreneurial intentions. These explanations can be tested, debated, and refined by researchers, which leads to stronger and more applicable entrepreneurship theories [123–125].

This predictive perspective also supports interdisciplinary collaboration. Combining insights from economics, sociology, psychology, management, information systems, and data science will lead to richer models that account for the complexity of entrepreneurial intention formation. For example, sociologists might focus on norms and social capital, while economists examine resource allocation and market structures, and psychologists analyze personality traits and cognitive styles. Data mining integrates these insights, identifying complex interactions that would remain hidden if each field operated independently.

2.4. Synthesis of Literature Review

Entrepreneurship in the digital age has emerged from a landscape reshaped by rapidly advancing technologies, international market access, and changing patterns of consumer behavior [16,19,21,27]. These developments do not simply add new channels for business but introduce ways of thinking, operating, and organizing that differ significantly from those of the past. One of the key differences lies in the reduced barriers to starting a venture. Traditional entrepreneurship often required considerable financial resources, physical infrastructure, and established supply chains. Today, an entrepreneur equipped with a computer, Internet access, and specialized software can establish a new venture and launch products or services without large initial investments. Digital platforms including e-commerce marketplaces, content management systems, and social media channels now allow even small startups to reach audiences that span continents [22,27,30,42]. This unprecedented reach expands competitive possibilities and offers opportunities to test new ideas and refine business concepts at a scale and speed once considered impossible. Entrepreneurs in this environment face persistent difficulties related to understanding complex technologies, keeping pace with market shifts, and maintaining the flexibility needed to pivot their strategies [30,46,49,57]. In addition, the sheer volume of available data, tools, and platforms can be overwhelming. Navigating these complexities demands new competencies such as digital marketing analytics, cybersecurity awareness, and the ability to interpret social media trends. Entrepreneurs must invest time in learning, experimenting, and adapting to ensure that their businesses remain relevant [49,57,112,117]. As technology continues to evolve, entrepreneurs need to remain open to new processes and be ready to adjust their value propositions, communication strategies, and operational frameworks [96,102,110,117]. Success in this context depends on recognizing that the digital age is not simply a new environment but one characterized by continuous change, interconnected markets, and informed customers who have more options and higher expectations than ever before [76,81,96]. Internet marketing is central to the strategies entrepreneurs use to engage with their audiences in this digital space. Rather than broadcasting one-size-fits-all messages, Internet marketing relies on data-driven insights and targeted communication [65,68,80,81]. Analytics tools help entrepreneurs learn who their customers are, what they need, and which channels they prefer. Websites and social media platforms create direct lines of communication, allowing businesses to respond to customer feedback in real-time. Email marketing campaigns can focus on specific customer segments based on their interests, purchasing behaviors, or geographic location. This precision helps businesses make the most of limited marketing budgets, while personalized messaging improves the chances of building trust and loyalty over time [63,68,69,96].

The interactions enabled by digital media go beyond advertising. Content marketing strategies, such as educational videos, blog posts, or white papers, offer ways to engage audiences by providing them with useful information rather than only sales messages [71,77,98,106]. This approach helps establish a company's credibility and long-term relationships with customers who turn to the business as a valuable source of knowledge. The shift toward interactive online communication also supports entrepreneurs in building communities around their brands. Social media conversations, online forums, and virtual events create a sense of belonging and participation, encouraging customers to share their experiences, recommend products, and become advocates [98,106,107]. This community-building aspect of Internet marketing can support sustainability and long-term growth, as satisfied customers help promote the brand to new potential clients. Entrepreneurial intentions, or the motivations and plans that lead individuals to start ventures, arise from a mix of personal and environmental factors. Individuals who view entrepreneurship as aligned with their values and goals often have more inclination to start a business. Similarly, those who feel confident in their abilities to manage challenges, learn new skills, and adapt to uncertainty are more likely to translate their interest in entrepreneurship into concrete steps [73,77,121–126]. This sense of capability, sometimes described as perceived behavioral control, is shaped not only by individual skills, but also by the broader support networks and institutional infrastructures available. Mentorship programs, online training courses, access to funding sources, and policy frameworks that simplify registering and running a business all play important roles in reinforcing the sense that entrepreneurship is both achievable and appealing. The social environment also shapes entrepreneurial intentions [123]. Encouragement from friends, family members, teachers, or professional networks can influence whether individuals feel comfortable with risk-taking. Access to role models and success stories, whether online or in-person, reinforces the idea that entrepreneurship can lead to positive outcomes. On the other hand, restrictive regulations, cultural stigmas against business failure, or the limited availability of startup capital can dampen the transition from intention to action. As a result, entrepreneurial intentions are not static and can shift as individuals gain practical experience, build confidence, and accumulate the resources needed to overcome the initial hurdles. Changes in personal circumstances, economic conditions, or technological landscapes can alter the perceived feasibility and desirability of launching a new venture [124,125].

In this evolving context, predictive modeling and data mining techniques allow researchers and policymakers to better understand and forecast entrepreneurial intentions. Traditional theoretical frameworks have long emphasized the importance of attitudes, subjective norms, and perceived behavioral control [12,125]. Data mining methods, however, open doors to a deeper and more nuanced analysis and can incorporate a wide range of variables, from demographic and economic data to cultural indicators and social network characteristics. Machine learning algorithms can detect patterns and correlations that might remain hidden if researchers only rely on conventional approaches. For example, predictive models might show that certain online resources, such as digital entrepreneurship courses or virtual incubator programs, correlate strongly with increased entrepreneurial intentions in particular regions or demographic groups [32,38,39,121].

These predictive insights not only clarify which factors matter most under specific circumstances, but also guide decision-makers who aim to support entrepreneurship. Policymakers might learn that in certain areas, strengthening the local digital infrastructure and improving Internet access could have a stronger impact on entrepreneurship than offering tax incentives [121]. Educators might discover that implementing hands-on workshops or online simulations that teach entrepreneurial skills can increase the students' confidence in starting their own ventures [121]. Such data-driven guidance helps optimize the allocation of resources and the design of programs intended to encourage entrepreneurial activities. In addition, the continuous updating of predictive models as new information becomes available ensures that these strategies remain relevant in changing market conditions.

The integration of digital entrepreneurship, Internet marketing, and predictive modeling creates a richer theoretical understanding of entrepreneurial intentions. Rather than treating entrepreneurship as a straightforward decision influenced by a limited set of factors, this integrated view acknowledges that individuals and organizations operate in a complex, interdependent system [111,113,114,120]. Entrepreneurs draw on digital platforms to reach new customers while refining their strategies based on real-time feedback and analytics. Their intentions develop not in isolation, but in a social and institutional context that can either support or limit their efforts. Predictive models help illuminate how multiple factors interact, revealing complex patterns that can confirm or challenge existing theories [107,111,119].

Linking these ideas creates a more complete picture of entrepreneurship in a world shaped by digital connectivity. As technology continues to advance, entrepreneurs must keep learning and experimenting, and scholars must remain open to revising theories in light of new evidence. Understanding how entrepreneurs form intentions, how they harness digital marketing tools, and how external conditions influence their paths to venture creation calls for an interdisciplinary approach. Insights from psychology, sociology, economics, information systems, and data science all contribute to this understanding, and combining them leads to more robust theories and better practical applications.

As these perspectives come together, it becomes clear that entrepreneurship in the digital era involves a dynamic interplay between individuals, technology, markets, and institutions. While technology lowers barriers and offers new opportunities, it also introduces complexities and responsibilities. Entrepreneurs must learn to navigate digital security concerns, changing regulatory environments, and emerging trends in consumer preferences. Awareness of these factors and the ability to respond to them effectively can determine whether a new venture thrives or struggles. Internet marketing tools provide entrepreneurs with opportunities to build relationships, gain consumer insights, and adjust their offerings, making continuous learning and adaptation part of the entrepreneurial journey.

2.5. Existing Knowledge Gap and Hypotheses

In this study, the goal was to present the application of statistical methods for data mining through analyzing a relevant topic, which was to predict entrepreneurial intentions based on Internet marketing factors. The dataset included variables of entrepreneurial intentions and the application of Internet marketing. The paper addressed the following knowledge gaps:

- There is a lack of research in the domain of entrepreneurial intentions and the application of Internet marketing in transitional countries. The existing studies in this domain only partly address entrepreneurship intentions and have not been analyzed in the context of Internet marketing [116,119,121,123,125].

- There is not a large body of literature that has analyzed multiple data analysis tools.

This study aimed to fill this gap by analyzing a large dataset comprised from data collected from micro-, small-, medium-sized, and large enterprises that conducted their business in a transitional economic setting. This dataset was analyzed with several data analysis tools including linear regression, logistic regression, QUEST algorithm, CHAID, SVM, and feed-forwards neural networks. This approach will provide a significant insight.

Website optimization (WOPT) refers to the enhancement of a website's structure, content, and functionality to improve the user experience, accessibility, and overall platform efficiency [101]. Recognizing that a well-optimized website can facilitate smoother navigation, faster load times, and more intuitive interactions may lead aspiring entrepreneurs to perceive online business ventures as more feasible and rewarding. The idea that potential customers can locate products or services easily, engage with relevant information, and complete transactions with minimal friction signals a higher likelihood of sustained consumer interest and improved conversion rates. As these outcomes become more evident, individuals are likely to feel more confident about their entrepreneurial prospects, leading to stronger entrepreneurial intentions [105].

- H_1: Website optimization (WOPT) positively affects the entrepreneurship intentions (ENTIN).

Social media marketing (SMM) involves leveraging social platforms to increase brand visibility, support community engagement, and maintain ongoing dialogue with current and prospective customers [11,85]. The awareness that social networks allow entrepreneurs to reach their target audiences efficiently, gather feedback, and tailor their messaging in real-time may encourage individuals to envision entrepreneurship as a more accessible and adaptive pursuit. Observing how social media helps establish brand credibility, amplify outreach efforts, and facilitate cost-effective promotions reinforces the perception that entrepreneurial ventures can gain meaningful traction even in competitive online ecosystems. This understanding, in turn, can bolster one's confidence and interest in initiating entrepreneurial activities [90,94].

- H_2: Social media marketing (SMM) positively affects the entrepreneurship intentions (ENTIN).

E-mail marketing (EMAIL) is characterized by targeted and personalized communication with customers through direct messaging, newsletters, and promotional campaigns. Recognizing the potential of email marketing to nurture leads, retain customers, and build trust in a scalable manner can encourage individuals to see entrepreneurship as more manageable and predictable. The perception that entrepreneurs can maintain consistent contact with their audience, offer tailored recommendations, and promptly address customer inquiries or concerns supports a sense of control and reliability [25,51,63].

- H_3: E-mail marketing (EMAIL) positively affects the entrepreneurship intentions (ENTIN).

Content marketing (CMA) focuses on producing and distributing valuable, relevant, and consistent content that resonates with a well-defined audience. Understanding that high-quality content can attract potential customers, encourage repeat visits, and position the entrepreneur as a knowledgeable source can make entrepreneurship appear both more meaningful and more feasible. Effective content strategies demonstrate that even without large advertising budgets, new ventures can gain audience trust, stimulate interest, and support ongoing engagement. This perceived ability to establish thought leadership, differentiate offerings, and create enduring connections through content enhances the attractiveness of entrepreneurial endeavors [99,100].

- H_4: Content marketing (CMA) positively affects the entrepreneurship intentions (ENTIN).

Customer relationship management (CRM) systems involve collecting, organizing, and analyzing customer data to guide personalized interactions and improve customer satisfaction. Awareness of CRM's capacity to help maintain structured records, track communication histories, and tailor service responses can provide aspiring entrepreneurs with a sense of stability and responsiveness. This reinforces the idea that entrepreneurship is not merely about launching a product, but also about nurturing relationships, anticipating customer needs, and sustaining loyalty [102].

- H_5: Customer relationship management (CRM) positively affects the entrepreneurship intentions (ENTIN).

Online advertising (OAD) encompasses targeted promotional efforts that reach audiences through various digital channels, often with measurable and adjustable parameters. Recognizing that entrepreneurs can selectively display ads to specific market segments, test different messages, and quickly refine strategies based on performance metrics may reduce the perceived uncertainty and risk [89,90]. The sense that online advertising allows for scalable, cost-efficient outreach, and immediate feedback makes entrepreneurial pursuits appear more systematically manageable and scalable. As these conditions become more apparent, individuals are likely to feel more assured that launching and growing a new venture is achievable, thereby solidifying their entrepreneurial intentions [92].

- H_6: Online advertising (OAD) positively affects the entrepreneurship intentions (ENTIN).

Data management and analytics (DMA) involves systematically gathering, processing, and interpreting data to inform business decisions. Understanding that entrepreneurs can rely on empirical insights to identify market trends, measure campaign effectiveness, and adjust product offerings can alleviate concerns over guesswork and misallocated resources [13,50,59]. This evidence-based approach promotes the view that entrepreneurial success is not merely a matter of intuition, but can be guided by concrete, data-driven strategies. When potential entrepreneurs perceive that data analytics can help reduce uncertainties and enhance strategic decision-making, they are more inclined to regard entrepreneurship as a viable and compelling career path, ultimately bolstering their entrepreneurial intentions.

- H_7: Data management and analytics (DMA) positively affects the entrepreneurship intentions (ENTIN).

These hypotheses provide a research framework and guidelines on how to apply the mentioned statistical methods.

While the digital age has revolutionized entrepreneurship and Internet marketing, there remain significant knowledge gaps regarding the factors that predict entrepreneurial intentions and the effectiveness of Internet marketing strategies. Understanding these gaps is important for advancing research and practice in these fields, particularly as the business landscape continues to evolve with rapid technological advancements.

There is a need for studies that explore how digital competencies, exposure to online entrepreneurial communities, and access to digital resources influence an individual's intention to start a business. While it is known that digital marketing can be a powerful tool for startups and small businesses, there is limited research on how entrepreneurial intentions influence the adoption and implementation of these strategies.

3. Methodology

3.1. Research Framework

The framework and methodology of this study followed the best practices typically applied in this type of research [126–129]. The research framework included the following steps:

- Defining the main objective: The goal was to demonstrate how data mining algorithms can be used to predict entrepreneurship intentions based on Internet marketing factors. Various potential predictors were considered.
- Literature review: A concise presentation of the relevant theoretical concepts was provided, focusing on modern business environments.

- Data collection: A structured survey was designed, distributed, and used to gather data. The data were then compiled into a single dataset for analysis using different statistical methods.
- Statistical methods: This study applied a range of statistical techniques including linear regression, logistic regression, QUEST, CHAID, SVM, and FNN.
- Results and discussion: The findings were analyzed to determine whether it is possible to predict entrepreneurial intentions based on Internet marketing factors.

The study was carried out using a structured survey, aligned with the best practices in this field. The dataset comprised responses from 137 enterprises (n = 137). Details on the sample and research methodology summary are provided in Table 1.

Table 1. Summary of the research methodology.

Methodology Aspects	Info
Number of completed surveys	137 (n = 137)
Participants	• Managers at micro-, small-, medium-sized, and large enterprises • 95 male participants; • 42 female participants; • The majority had BSc degrees—62 participants
Enterprise	The majority of enterprises were small (35%) and medium (45,25%). This was expected as the majority of enterprises in the Republic of Serbia are micro and small enterprises.
Study length	3 months (finalized in 2024)
Sample structure	Managers/directors/owners of micro-, small-, medium-sized, and large enterprises
Conducted data analysis	• Regression analysis (linear and binary logistic); • QUEST decision tree algorithm; • Chi-squared automatic interaction detection—CHAID • Classification supervised learning model—support vector machines/support vector networks. • Feed-forward neural network (Python and Tensorflow)
Predictor groups	• Website optimization (WOPT) • Social media marketing (SMM) • E-mail marketing (EMAIL) • Content marketing (CMA) • Customer relationship management (CRM) • Online advertising (OAD) • Data management and analytics (DMA)
Dependent variable	• Entrepreneurship intentions (ENTIN)

The survey items and additional details can be found in Table A1 (Appendix A). Given that most enterprises in Serbia are small- and medium-sized enterprises (SMEs), it was anticipated that the majority of survey data would come from SMEs, with a few contributions from larger companies. The data collection took place in 2024, and the dataset included information about website optimization, social media marketing, email marketing, content marketing, and customer relationship management. The dataset was comprehensive and suitable for applying data mining algorithms.

The research was conducted in three primary phases. The first phase involved developing a structured survey and thoroughly reviewing existing studies in this area. After the surveys were distributed, the dataset was prepared for data collection. Literature sources were reviewed, leading to the establishment of a theoretical framework. The surveys were anonymous, and respondents had one month to complete them. Following the survey period, the collected data were integrated into a dataset for statistical analysis.

The second phase focused on data analysis and data mining. Statistical methods ranged from simple to more advanced techniques, linear regression, logistic regression, QUEST classification tree algorithm, support vector machines (SVM), CHAID, and feed-forward neural networks. These methods were applied using WPS Spreadsheets and MPlus 7.11 software.

In the third phase, the results were analyzed and evaluated. The goal was to emphasize the study's significance as well as its limitations and strengths.

3.2. Applied Tools and Techniques

3.2.1. Reliability Test

In order to assure that there was no strong correlation between the independent variables, a variance inflation factor analysis was conducted. The results are presented in Table 2.

Table 2. Multicollinearity test.

	WOPT	SMM	EMAIL	CMA	CRM	OAD	DMA
Tolerance	0.566	0.457	0.746	0.793	0.691	0.594	0.460
VIF	1.802	2.172	1.304	1.219	1.567	2.002	2.231

Based on the obtained results presented in Table 2, it can be seen that there was no significant correlation between the observed independent variables, as the VIF values were under 2.500. Therefore, the reliability of the experimental results was not compromised.

3.2.2. Linear and Logistic Regression Approach

With linear regression, the goal was to predict this outcome based on one or more independent variables. The method assumes a linear relationship between the variables, where changes in the independent variable(s) lead to proportional changes in the dependent variable. The objective of linear regression is to find the line of best fit that minimizes the differences between the observed and predicted values [130].

In this paper, the dependent variable was entrepreneurship intentions (ENTIN), while the independent variables where website optimization (WOPT), social media marketing (SMM), email marketing (EMAIL), content marketing (CMA), customer relationship management (CRM), online advertising (OAD), and data management and analytics (DMA).

For the logistic regression, there was a loss of information as the ordinal data were converted to categorical data such as 0 or 1. Instead of predicting a continuous outcome, logistic regression estimates the probability that a particular event will occur. The model transforms the relationship between the independent variables and the probability of the outcome using a specific function that confines predictions within a range of 0 to 1 [131]. Similarly to the regression analysis, the dependent variable was entrepreneurship intentions (ENTIN), while the independent variables where website optimization (WOPT), social media marketing (SMM), email marketing (EMAIL), content marketing (CMA), customer relationship management (CRM), online advertising (OAD), and data management and analytics (DMA).

The Likert-scale responses, which were originally on an ordinal scale, were combined and processed to create variables that approximated interval-scale measurements. This was conducted through a series of steps that grouped multiple related survey items into composite indices, allowing for more traditional statistical analyses such as regression.

The first step involved identifying sets of items that measured the same underlying concept or dimension. For each such dimension, responses from multiple Likert-scale items were aggregated, typically by taking their arithmetic mean. Before aggregation, the items were examined to ensure that they reflected a consistent underlying factor. This often involved evaluating internal consistency, commonly through methods such as Cronbach's alpha. Items that demonstrated acceptable reliability and measured the same latent construct were then combined into a single indicator. In some cases, items that were negatively phrased were reverse-coded, ensuring that all items within a set aligned in their interpretation, with higher scores consistently indicating more agreement or a stronger presence of the concept being measured.

After confirming that the items formed a coherent scale, their values were averaged. The mean of these multiple Likert items was treated as an interval-scale variable, allowing for the application of regression and other parametric analyses. While the resulting measures still originated from the ordinal responses, the aggregation of several items helped approximate a continuous distribution. This practice of combining several ordinal indicators into a single composite score is common and presents a more stable variable. This, in turn, supports more robust statistical modeling and interpretation.

3.2.3. Quick, Unbiased, Efficient, Statistical Tree—QUEST

The QUEST algorithm, short for quick, unbiased, efficient, statistical tree, is a classification tree induction method designed to provide more reliable and statistically sound decision trees. It addresses some limitations found in earlier tree algorithms, particularly the tendency of certain methods to favor variables with many potential split points. QUEST aims to produce smaller, more interpretable trees while maintaining efficiency and accuracy. The algorithm uses binary splits and a two-step procedure for selecting the best splitting variable and the best split point. First, it chooses the variable to split on by using significance tests that help avoid bias toward variables with multiple categories or a wide range of values. It evaluates candidate variables based on statistical tests of association (for categorical predictors) or correlation (for continuous predictors) with the target variable. Variables that show stronger evidence of a relationship with the outcome are considered for the next phase, while those that do not are excluded.

After identifying a candidate variable, QUEST determines the exact split point differently for categorical and continuous predictors. For a categorical variable, it uses statistical procedures to find the grouping of categories that best separates classes. For a continuous variable, it often uses a linear discriminant analysis-based approach to identify a split that effectively divides the data into two groups that differ in their class distributions. This approach helps reduce selection bias and leads to splits that reflect the true underlying structure in the data, rather than being driven by the sheer number of possible cut points. The QUEST algorithm implements several additional features to support reliable and interpretable trees and includes methods to handle missing values, often by using surrogate splits or imputation-like strategies. Pruning procedures are applied to avoid overfitting and to produce trees that do not grow unnecessarily large. Furthermore, QUEST's computational efficiency makes it possible to handle moderate to large datasets without excessive computational cost.

The QUEST (quick, unbiased, efficient statistical tree) algorithm was chosen due to several key advantages [132]:

- Speed and accuracy: Its accuracy remains stable even at higher processing speeds, making it efficient without sacrificing precision.
- Handling missing values: Unlike the CART (classification and regression tree) algorithm, which uses surrogate splits for missing data, QUEST applies imputations, offering a more robust approach.

- Categorical predictors: It effectively handles categorical predictor variables with multiple categories, providing flexibility across different data types.
- Lack of bias in variable selection: The algorithm avoids bias in variable selection prior to splitting, ensuring fairer and more accurate decision-making processes.
- Data types: QUEST is applicable to nominal, ordinal, and continuous values. It uses ANOVA for ordinal and continuous values, and Pearson's χ^2 for categorical values, making it adaptable across various datasets.
- Pruning via cross-validation: The use of cross-validation in pruning ensures that the resulting model is both generalizable and efficient.
- Flexibility with split types: QUEST supports variate splits as well as combinations of linear splits, improving its versatility in different scenarios.
- These features make QUEST a suitable algorithm for the given data structure and classification objectives.

The QUEST algorithm begins by selecting the primary variable and subsequently determines the optimal split point. This approach helps the algorithm avoid any bias toward categorical variables. Additionally, quadratic discriminant analysis (QDA) is applied to consolidate multiple variable classes into two larger super-classes, followed by a binary split process. When two potential binary split points are available, the algorithm selects the one closest to the sample mean. The construction of the QUEST algorithm involves selecting an independent variable for splitting and determining the corresponding split point, after which the process halts.

3.3. Chi-Squared Automatic Interaction Detection—CHAID

Chi-squared automatic interaction detection (CHAID) is a decision tree technique used primarily for identifying significant relationships between categorical variables. It is commonly applied in areas like market research, social science, and other fields where classification tasks are involved. CHAID works by repeatedly splitting the data into mutually exclusive subsets based on the most significant independent variable, measured by the chi-square statistic [132].

The process starts by evaluating all potential splits for each predictor variable. For each predictor, the algorithm assesses whether the relationship between the independent variable and the target variable is statistically significant. It merges categories of the predictor variable that do not significantly differ in relation to the target variable. The merging continues until all significant differences are accounted for, with the chi-square test determining the statistical significance. Once the best predictor is selected, the dataset is split accordingly, and the process is repeated for each branch of the tree. Unlike other decision tree algorithms such as CART or C4.5, CHAID can produce trees with more than two branches at each node, making it a multiway split approach. This is particularly useful when dealing with categorical variables with multiple levels, as it allows for more nuanced classifications. Additionally, CHAID is non-binary and can handle missing data, which adds to its flexibility [132].

3.4. Support Vector Machine

Machine learning represents a major advancement in algorithm development and is considered a transformative trend across multiple fields. It encompasses various approaches including clustering (unsupervised learning), classification (supervised learning), and dynamic programming (reinforcement learning). Among these, classification is particularly important for predictive modeling. Decision trees, such as the previously mentioned QUEST algorithm, are one of the many machine learning classification methods. Another widely used classification technique is support vector machine (SVM), which has applications in a variety of domains [133,134].

SVMs operate by separating training data into two distinct classes, determining the hyperplane that best divides the data. The hyperplane's position is defined by a subset of vectors known as support vectors. For problems that are nonlinear, SVM uses kernel functions to map the data into higher-dimensional spaces.

3.5. Feed-Forward Neural Network—FNN

In addition to the above applied algorithms and statistical approaches, a feed-forward neural network was applied on the dataset. The neural network was trained on the dataset that included the dependent variable and the independent variables. To test the hypotheses, the trained network was used with different combinations of values for the independent variables. From here, the relationship between each independent variable and the dependent variable were analyzed. Python (v3.12) and Tensorflow (https://www.tensorflow.org, accessed on 5 October 2024) was used for the feed-forward neural network.

4. Results

4.1. Linear and Logistic Regression Results

The results of the linear regression analysis are presented in Table 3.

Table 3. Results of the linear regression analysis.

Independent Variables (Predictor Groups)	Dependent Variable	Standardized Coefficients	p
Website optimization (WOPT)	Entrepreneurship intentions (ENTIN)	0.271	0.000
Social media marketing (SMM)		0.214	0.214
Email marketing (EMAIL)		−0.062	0.000
Content marketing (CMA)		0.366	0.000
Customer relationship management (CRM)		0.219	0.621
Online advertising (OA)		0.058	0.057
Data management and analytics (DMA)		0.137	0.004

In Figure 1, a graphical presentation of the linear regression analysis plot is presented.

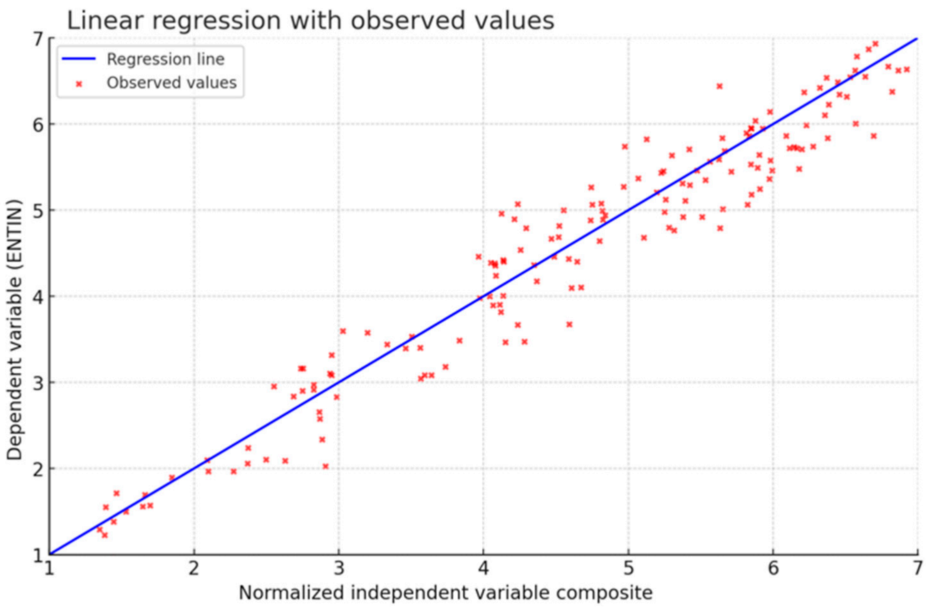

Figure 1. Graphical presentation of the linear regression model.

For the linear regression, website optimization (WOPT), social media marketing (SMM), email marketing (EMAIL), content marketing (CMA), customer relationship management (CRM), online advertising (OA), and data management and analytics (DMA) were observed as independent variables, while entrepreneurship intentions (ENTIN) was observed as a dependent variable.

The results indicate that several factors influence entrepreneurship intentions, with varying levels of significance. Website optimization (WOPT) showed a strong positive relationship with entrepreneurship intentions (ENTIN), reflected by a standardized coefficient of 0.271 and a highly significant p-value of 0.000. This suggests that optimizing websites is a key factor in supporting entrepreneurial intentions among individuals.

Social media marketing (SMM) also demonstrated a positive influence on entrepreneurship intentions, with a standardized coefficient of 0.214. However, its p-value of 0.214 indicates that this relationship may not be statistically significant. In contrast, email marketing (EMAIL) presented a negative effect on entrepreneurship intentions, with a coefficient of -0.062 and a p-value of 0.000 showing a significant and negative association. This suggests that email marketing might deter entrepreneurship intentions or could be less effective in promoting entrepreneurial behaviors.

Among all of the factors, content marketing (CMA) emerged as the most significant predictor, with a standardized coefficient of 0.366 and a p-value of 0.000. This strong positive relationship highlights the importance of content marketing in shaping and improving entrepreneurial intentions. On the other hand, customer relationship management (CRM) showed a positive coefficient of 0.219, but its p-value of 0.621 indicates that this relationship was not statistically significant.

Online advertising (OA), with a small positive coefficient of 0.058 and a p-value of 0.057, showed marginal significance, suggesting a weak association with entrepreneurship intentions. Data management and analytics (DMA), however, exhibited a notable positive relationship, with a standardized coefficient of 0.137 and a p-value of 0.004, pointing to its significance in influencing entrepreneurship intentions. Overall, content marketing and website optimization were important drivers, while email marketing may have a counterproductive impact on entrepreneurial intentions.

Next, a logistic regression was conducted. A stepwise regression was used to automatically select the significant predictor variables. The results are presented in Table 4.

Table 4. Results of the logistic regression.

Predictor	Dependent Variable	β	p	95% CI	
Website optimization (WOPT)	Entrepreneurship intentions (ENTIN)	0.82	0.000	0.97	1.47
Social media marketing (SMM)		0.94	0.001	0.78	0.84
Email marketing (EMAIL)		0.91	0.001	1.11	1.74
Content marketing (CMA)		0.95	0.000	0.73	0.98
Customer relationship management (CRM)		0.79	0.001	0.84	1.11
Online advertising (OA)		0.90	0.000	0.98	1.24
Data management and analytics (DMA)		0.77	0.188	0.73	0.97

The results indicate that several key factors significantly influence the likelihood of achieving the desired outcome. Website optimization (WOPT) showed a strong positive effect, with a coefficient of 0.82 and a highly significant p-value of 0.000. The 95% confidence interval for this predictor ranges from 0.97 to 1.47, confirming the robustness of its impact. This suggests that optimizing websites plays an important role in influencing the outcome.

Similarly, social media marketing (SMM) is another significant predictor, with a coefficient of 0.94 and a p-value of 0.001. The 95% confidence interval for SMM falls between 0.78

and 0.84, further supporting its substantial contribution. This highlights the importance of effective social media strategies in driving positive outcomes.

Email marketing (EMAIL) also demonstrated a significant positive relationship with the outcome, with a coefficient of 0.91 and a p-value of 0.001. The 95% confidence interval, ranging from 1.11 to 1.74, underscores the strong influence of this factor. This finding suggests that email marketing efforts can considerably improve the likelihood of success.

Content marketing (CMA) proved to be another important contributor, with a coefficient of 0.95, a p-value of 0.000, and a confidence interval between 0.73 and 0.98. This result highlights the role of content marketing in driving outcomes. In addition, customer relationship management (CRM) showed a significant effect, with a coefficient of 0.79, a p-value of 0.001, and a confidence interval from 0.84 to 1.11, emphasizing the importance of maintaining strong customer relationships.

Online advertising (OA) also had a notable impact, with a coefficient of 0.90 and a p-value of 0.000. The confidence interval, ranging from 0.98 to 1.24, points to the effectiveness of online advertising strategies. However, data management and analytics (DMA) did not show a significant effect, as indicated by a p-value of 0.188, suggesting that this factor may not be as important in influencing the outcome, despite having a coefficient of 0.77.

4.2. QUEST and CHAID Decision Trees

The QUEST classification decision tree was used to attempt to predict the entrepreneurship intentions. The tree had a yes/no structure. Cross-validation was also applied. The main predictors noted were:

- Social media marketing (SMM);
- Email marketing (EMAIL);
- Customer relationship management (CRM);
- Online advertising (OA);
- Data management and analytics (DMA).

In Figure 2, the QUEST classification decision tree is presented.

The rules explaining the QUEST algorithm are as follows:

N1: Social Media Engagement

- If the business regularly updates its social media with relevant content, then the probability of considering entrepreneurship is high:
- Class yes = 75.26% (those who said yes to entrepreneurship);
- Class no = 24.74% (those who said no to entrepreneurship).

N2: No Social Media Updates

- If the business does not update its social media, then the likelihood of considering entrepreneurship drops slightly:
- Class yes = 70.00%;
- Class no = 30.00%.

N3: Content Aligned with Audience Interests

- If the social media content is aligned with the target audience's interests and needs, the likelihood of entrepreneurship remains high:
- Class yes = 75.34%;
- Class no = 24.66%.

N4: Content Not Aligned

- If the content is not aligned with the audience but the business still updates its social media, the likelihood of entrepreneurship is still strong:
- Class yes = 75.00%;
- Class no = 25.00%.

N5: CRM Strategies Focused on Retention and Acquisition

- For businesses without regular social media updates, if they have strong CRM strategies focused on both customer retention and acquisition, the likelihood of entrepreneurship remains high:
- Class yes = 78.57%;
- Class no = 21.43%.

N6: No Strong CRM Strategies

- If the business lacks CRM strategies focused on retention and acquisition, the likelihood of entrepreneurship decreases:
- Class yes = 50.00%;
- Class no = 50.00%.

N7: Creative Online Advertising

- If the business's online advertising campaigns are creative and attention-grabbing, there is a high likelihood of considering entrepreneurship:
- Class yes = 78.95%;
- Class no = 21.05%.

N8: No Creative Advertising

- If the online advertising is not creative, the likelihood of entrepreneurship is slightly lower but still significant:
- Class yes = 77.76%;
- Class no = 22.24%.

N9: Use of Analytics in Marketing

- For businesses with creative advertising, if they effectively use analytics to improve their marketing strategies, the likelihood of entrepreneurship remains high:
- Class yes = 75.00%;
- Class no = 25.00%.

N10: No Use of Analytics

- If businesses with creative advertising do not use analytics, the likelihood of considering entrepreneurship is still relatively strong but slightly higher:
- Class yes = 85.71%;
- Class no = 14.29%.

The CHAID decision tree helps to determine how different Internet marketing factors are associated with the entrepreneurship intentions, showing how each factor contributes to predicting different levels of intention. The nodes of the decision tree are as follows:

Root Node (EMAIL)

Email Marketing (EMAIL): This is the most important factor influencing entrepreneurship intentions.

Lower EMAIL usage: For people or projects with low engagement in email marketing, the tree leads to outcomes of lower to medium entrepreneurship intentions in many cases.

Higher EMAIL usage: Projects or people with higher email marketing usage tend to have higher entrepreneurship intentions. The branches lead to a mix of medium, high, and very high entrepreneurship intentions.

Left Branch of Node 1: Lower EMAIL Engagement

Data Management and Analytics (DMA): For those with lower email engagement, data management becomes the next important factor.

Lower DMA usage: If there is low use of data management and analytics, it generally leads to lower entrepreneurship intentions, especially when combined with other factors like low content marketing and low customer relationship management.

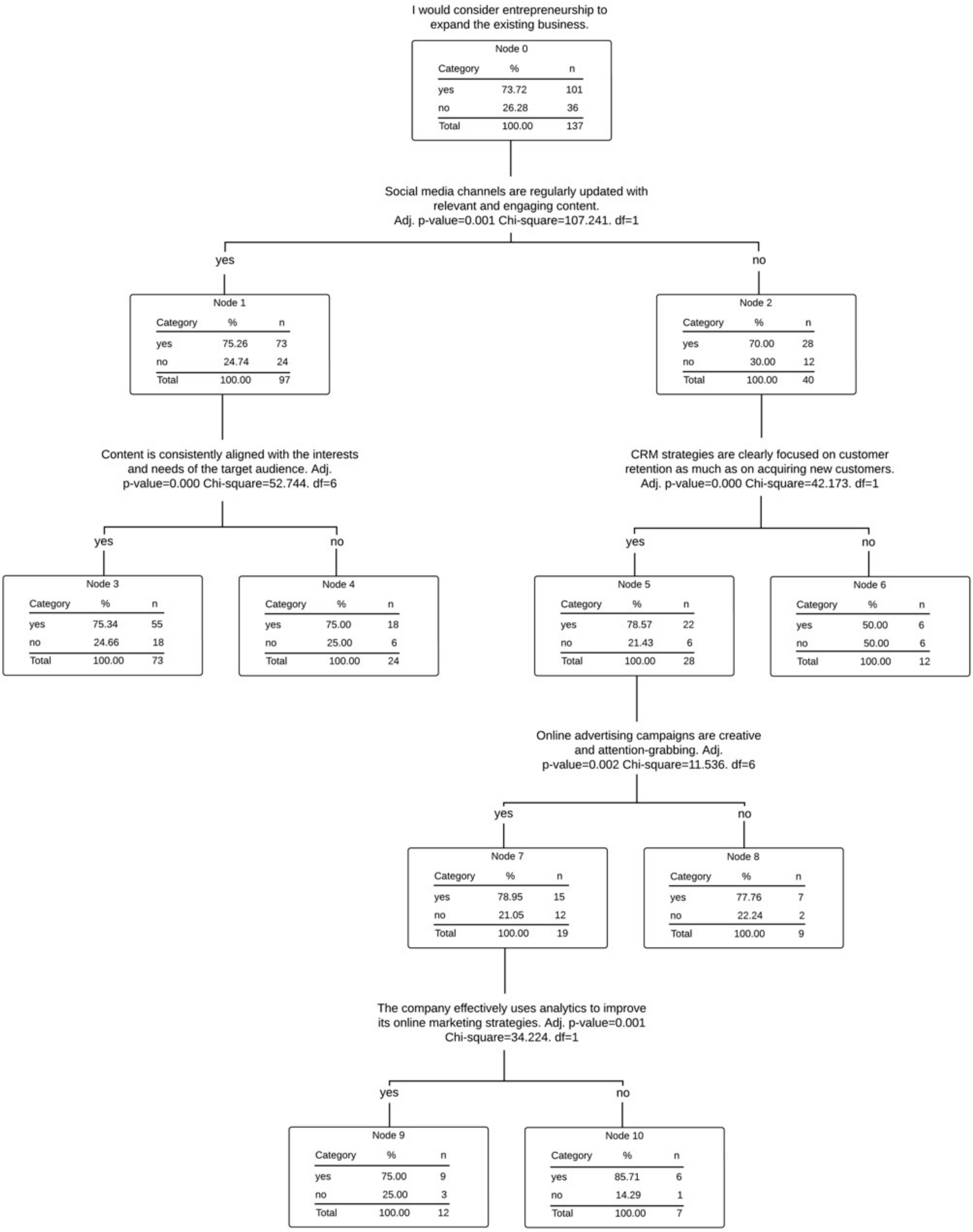

Figure 2. QUEST decision tree algorithm for predicting the entrepreneurship intentions.

Higher DMA usage: For those with better data management practices, the tree starts to show more potential for high or very high entrepreneurship intentions.

Lower DMA Engagement

Content Marketing (CMA): If the data management is low, the tree checks the content marketing usage.

Lower CMA usage: If the content marketing is also low, it predicts low entrepreneurship intentions. This suggests that without effective content marketing, the potential for entrepreneurship intentions decreases significantly.

Higher CMA usage: If the content marketing is high, it boosts the potential for higher entrepreneurship intentions.

Higher CMA Engagement

Customer Relationship Management (CRM): When the content marketing is high, customer relationship management comes into play.

Lower CRM usage: If CRM is low, social media marketing becomes important.

Low SMM leads to medium entrepreneurship intentions, meaning that without high social media marketing, the intentions are moderate.

High SMM leads to very high entrepreneurship intentions, suggesting that combining strong content marketing, CRM, and social media marketing greatly increases the entrepreneurship intentions.

Higher CRM usage: If CRM usage is higher, it starts to show a decline in entrepreneurship intentions, predicting low intentions when online advertising is low.

Higher DMA Engagement

CRM: For those with better data management, CRM has a strong influence.

Lower CRM usage: This predicts very high entrepreneurship intentions, showing that low CRM, combined with strong data management, may focus efforts on other areas, boosting intentions.

Higher CRM usage: If CRM is higher, content marketing again becomes a decisive factor.

Low CMA tends to lead to low entrepreneurship intentions.

High CMA leads to high entrepreneurship intentions, showing that strong content marketing and CRM can increase intentions.

Right Branch of Node 1: Higher EMAIL Engagement

Website Optimization (WOPT): For projects with high email engagement, website optimization is the next key factor.

Lower WOPT usage: If website optimization is low, social media marketing (SMM) becomes important.

Low SMM tends to lower entrepreneurship intentions, predicting low intentions.

High SMM increases the entrepreneurship intentions to very high, showing that social media can offset the effects of lower website optimization.

Higher WOPT usage: If website optimization is high, the tree checks the CRM usage.

Lower CRM usage: Predicts medium intentions, showing that a balance of high website optimization and low CRM can moderate intentions.

Higher CRM usage: Leads to further splits on email marketing and data management.

Lower EMAIL tends to predict medium intentions.

Higher EMAIL increases the intentions if the data management is also high, predicting very high entrepreneurship intentions.

EMAIL was the most influential factor overall. When email engagement was low, the success of the project depended heavily on other factors like data management and content marketing. When email engagement was high, factors like website optimization, CRM, and social media marketing became more important. Each split in the tree refined the predicted entrepreneurship intentions based on how these factors interacted.

The CHAID decision tree model demonstrated an overall accuracy of approximately 0.75, meaning that it correctly classified entrepreneurship intentions in 75% of cases. In terms of precision, the model achieved a score of about 0.70. This indicates that 70% of the cases where the model predicted a high likelihood of entrepreneurship intentions were accurate. The recall score, which measures how well the model identified actual instances of entrepreneurship intentions, was around 0.65. This means that the model successfully recognized 65% of the true cases where entrepreneurship intentions were present, pointing to a moderate ability in capturing relevant instances. The F1 score, which provides a balance between precision and recall, was approximately 0.67. This suggests a balanced performance, reflecting the model's overall capacity to predict and correctly identify the entrepreneurship intentions in various cases. The ROC-AUC score was around 0.80, indicating the model's effectiveness in distinguishing between individuals with and without entrepreneurship intentions. This score highlights the model's ability to separate the two groups with 80% accuracy across different thresholds, making it a robust tool for classification tasks.

4.3. SVM and FNN

The details of the SVM classifier is presented in Table 5.

Table 5. Details of the SVM classifier.

Positive class	1
Number of observations in the training set	137
Bias	0.000
Number of support vectors	65
Features used (independent variables)	Website optimization (WOPT) Social media marketing (SMM) Email marketing (EMAIL) Content marketing (CMA) Customer relationship management (CRM) Online advertising (OA) Data management and analytics (DMA)

Next, the confusion matrix of the SVM analysis is presented in Table 6.

Table 6. Confusion matrix of the SVM.

From/To	0	1	Total	% Correct
0	18	9	28	86.74
1	8	6	14	73.55
Total	15	8	23	76.44

The area under the curve (AUC) value was 0.854. This indicates that the model had a 85.4% chance to classify the observation in accordance with the positive class. More precisely, the model had a probability of 85.4% to correctly classify the entrepreneurship intentions.

Furthermore, regarding the feed-forward neural network decision tree, the dependent variable in this analysis was entrepreneurial intentions, classified as a binary outcome. A binary cross-entropy function was utilized as the loss function, with the Adam optimizer used to compile the model. Categorical variables were encoded using one-hot encoding, and feature values were standardized through StandardScaler. The feed-forward neural network consisted of two hidden layers containing nine and eighteen neurons, respectively, and used a sigmoid activation function in the output layer. The model was trained with a batch size of 30 over 100 epochs. The model achieved an accuracy of 87.41%, a precision of 93.2, a recall of 84.5, and an F1-score of 83.5.

5. Discussion

5.1. Assessing the Results

Each technique offers unique strengths and limitations, and different methods may be more appropriate depending on the specific needs and contexts faced by corporate decision-makers. Statistical methods often focus on hypothesis testing and the identification of clear causal relationships, while data mining approaches emphasize pattern recognition and the discovery of hidden structures within the data.

Statistical methods, such as regression analysis, are often grounded in well-established theoretical frameworks and offer interpretable, transparent models. They excel at testing hypotheses, inferring causal relationships, and providing confidence intervals that help assess the reliability of the findings. These characteristics can make statistical methods well-suited to situations where understanding the underlying mechanisms is important. However, these methods sometimes struggle with capturing complex, nonlinear relationships and may require strong assumptions about the data distribution. They can be sensitive to outliers and may not perform as effectively when working with very large or unstructured datasets.

Data mining methods including techniques such as decision trees, neural networks, and clustering algorithms tend to focus on revealing hidden structures, patterns, and associations within the data. They do not typically require strict assumptions about the underlying distributions and can handle more complex, large-scale datasets. These methods are often more flexible and can uncover insights that traditional statistical techniques might miss. At the same time, data mining approaches can be more difficult to interpret, which can create challenges for decision-makers who need to understand the rationale behind a recommendation. Additionally, some data mining techniques may require extensive fine-tuning and computational resources, and their results can vary depending on the hyper parameter settings and data preprocessing steps.

Optimally, an integrated approach that combines the strengths of both statistical and data mining methods can yield more comprehensive insights. Such a strategy might involve using statistical methods to establish reliable baselines, validate core assumptions, and ensure interpretability, while simultaneously applying data mining techniques to detect patterns and relationships that might not be captured otherwise. The results of these complementary methods can be combined, weighted, or merged into a unified framework or ensemble model that incorporates interpretability, robustness, and pattern recognition capabilities. This hybrid methodology can enhance both the reliability and practical utility, offering decision-makers a more thorough understanding of the data's characteristics and trends.

A balanced, integrated approach would likely be the most appealing choice. Statistical methods alone offer clarity and theoretical grounding, but they sometimes fail to capture the complexity and hidden relationships within large, diverse datasets. Purely data-driven techniques can reveal unexpected patterns and adapt well to complex environments, but they often lack transparency and may pose difficulties for understanding the reasoning behind specific findings. Integrating both approaches can provide a solid interpretive foundation while also embracing complexity and flexibility. This combination ensures not only that patterns are recognized, but also that the insights are interpretable and supported by established theoretical underpinnings. As a manager, relying on a hybrid strategy increases confidence in the results, supports informed decision-making, and ultimately contributes to a more robust, practical understanding of the data's implications for strategic planning.

If combining methods is not feasible, selecting a single approach would depend largely on the decision-making context and the specific goals at hand. If a manager needs to understand the underlying causes and justify decisions with a clear, theoretically grounded explanation, statistical methods would be the better choice. They provide a robust framework for inferring relationships, testing hypotheses, and ensuring that decision-makers can communicate the reasoning behind certain recommendations to stakeholders. This interpretability is often essential in environments where accountability and transparency are paramount.

A practical choice might be a decision-tree-based ensemble method such as a random forest. This approach offers a balance between complexity and interpretability. Random forests are capable of handling large datasets, complex feature interactions, and nonlinear patterns. They typically do not require strict assumptions about the data distribution and tend to be robust against outliers and noise. While less transparent than simple statistical models, random forests still provide more interpretability than many other data mining methods such as deep neural networks. For example, feature importance rankings and partial dependence plots can help managers understand which factors are most influential, even if the model itself is relatively complex.

5.2. Hypotheses Assessment

Based on the results of the linear regression analysis, the proposed hypotheses can be assessed as follows:

- *H_1: Website optimization (WOPT) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_2: Social media marketing (SMM) positively affects the entrepreneurship intentions (ENTIN).* Did not gain support.
- *H_3: Email marketing (EMAIL) positively affects the entrepreneurship intentions (ENTIN).* Did not gain support.
- *H_4: Content marketing (CMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_5: Customer relationship management (CRM) positively affects the entrepreneurship intentions (ENTIN).* Did not gain support.
- *H_6: Online advertising (OAD) positively affects the entrepreneurship intentions (ENTIN).* Did not gain support.
- *H_7: Data management and analytics (DMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.

Additional insight was provided by conducting a logistic regression analysis. From this, the proposed hypotheses were evaluated as follows:

- *H_1: Website optimization (WOPT) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_2: Social media marketing (SMM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_3: Email marketing (EMAIL) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_4: Content marketing (CMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_5: Customer relationship management (CRM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_6: Online advertising (OAD) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_7: Data management and analytics (DMA) positively affects the entrepreneurship intentions (ENTIN).* Did not gain support.

Furthermore, based on the QUEST decision tree results, the proposed hypotheses were assessed as follows:

- *H_1: Website optimization (WOPT) positively affects the entrepreneurship intentions (ENTIN).* Did not gain support.
- *H_2: Social media marketing (SMM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_3: Email marketing (EMAIL) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_4: Content marketing (CMA) positively affects the entrepreneurship intentions (ENTIN).* Did not gain support.
- *H_5: Customer relationship management (CRM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.

- *H_6: Online advertising (OAD) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_7: Data management and analytics (DMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.

Next, the CHAID decision tree results provided insights, and had an 80% accuracy of predicting the entrepreneurial intentions. Based on this, the hypotheses were addressed as follows:

- *H_1: Website optimization (WOPT) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_2: Social media marketing (SMM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_3: Email marketing (EMAIL) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_4: Content marketing (CMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_5: Customer relationship management (CRM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_6: Online advertising (OAD) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_7: Data management and analytics (DMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.

Based on the SVM classifier, none of the proposed hypotheses were rejected. The classifier included all predictors, yielding a moderately high accuracy rate of 85.4%. As a result, the hypotheses were assessed as follows:

- *H_1: Website optimization (WOPT) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_2: Social media marketing (SMM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_3: Email marketing (EMAIL) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_4: Content marketing (CMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_5: Customer relationship management (CRM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_6: Online advertising (OAD) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_7: Data management and analytics (DMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.

The modeled feed-forward neural network (FNN) was used to analyze the proposed hypotheses. The FNN had an accuracy of 87.41%, thus the hypotheses were addressed as follows:

- *H_1: Website optimization (WOPT) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_2: Social media marketing (SMM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_3: Email marketing (EMAIL) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_4: Content marketing (CMA) positively affects the entrepreneurship intentions (ENTIN).* is failed to be rejected.
- *H_5: Customer relationship management (CRM) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.
- *H_6: Online advertising (OAD) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.

- *H_7: Data management and analytics (DMA) positively affects the entrepreneurship intentions (ENTIN).* Failed to be rejected.

It is interesting to note that different statistical methods obtained different results, with variations in the details. It is important in data mining to avoid bias and set the parameters correctly. Different analytical techniques produce divergent results because their foundational assumptions, computational procedures, and data processing strategies differ. Each method interprets the underlying patterns, relationships, and noise within a dataset in a unique manner, which can lead to variations in prediction accuracy, stability, and general usability. Understanding these differences can support better decision-making when selecting an approach for a given problem, especially when the data characteristics or research objectives require careful consideration.

Linear models assume a direct, proportional relationship between the predictor variables and the outcome. This assumption can make linear approaches sensitive to data points that deviate substantially from the expected trend. Even a small set of outliers, values that lie far from the bulk of the data distribution, may shift the regression line, influencing the predicted outcome for many observations. Such sensitivity arises because linear regression methods attempt to minimize a global error measure, often the sum of squared residuals. Tree-based methods, such as decision trees and their ensemble variants, rely on splitting the data repeatedly into subgroups that are more homogeneous with respect to the target variable. This process involves choosing variables and split points that separate the data into subsets with increasingly similar outcomes. Although this approach can support modeling complex relationships and interactions without requiring linearity, it introduces variability linked to how the splits are chosen. Early splits in a tree have a substantial impact on subsequent partitions, shaping the entire modeling structure. Support vector machines (SVMs) introduce another layer of complexity through the choice of kernel functions. Instead of attempting to fit a direct relationship between the predictors and the outcome in the original feature space, SVMs map the data into a higher-dimensional space where a clear separation may be easier to achieve. The kernel defines how this mapping occurs. A linear kernel attempts to find a simple dividing boundary, similar in spirit to a linear model, while more flexible kernels, such as the radial basis function (RBF), consider nonlinear transformations. The kernel choice influences which patterns are captured and how the model generalizes. If the kernel is too simple, the model may fail to capture complex patterns. If it is too flexible, the model might overfit the training data and produce less reliable predictions. This dependence on kernel selection means that even with the same dataset, different SVM setups can produce widely varying results. Small changes in kernel parameters, such as the bandwidth of an RBF kernel, can alter the shape of the decision boundary and the model's sensitivity to noise and outliers, resulting in divergent predictive outcomes.

Another important factor underlying these differences involves how each technique handles data preprocessing and variable selection. Linear models often require careful feature engineering, removing, or transforming outliers and ensuring that predictors follow a suitable distribution. Tree-based methods are more tolerant of varying scales and do not necessarily require explicit transformations, but they may still suffer if irrelevant variables are present or if influential variables are measured with noise. SVMs, on the other hand, can work effectively with standardized variables but rely heavily on choosing parameters that affect how the data are represented in the transformed feature space. Thus, differences in preprocessing strategies and parameter tuning can further explain why distinct methods yield different results.

Each modeling technique has its strengths and limitations, which shape the outcomes it produces. These differences highlight why no single method consistently outperforms all others across every possible scenario. Instead, analysts often compare multiple techniques, tune their parameters, and examine performance metrics to identify which approach best supports the task at hand. Understanding the reasons behind divergent results can improve the selection process, guide data preprocessing steps, and inform parameter tuning strategies. Applying domain knowledge and examining the data properties can indicate which assumptions are more likely to hold, making it possible to choose a method that aligns better with the nature of the problem.

5.3. Research Questions

Based on the analyzed literature and the results, the research questions can be assessed as follows:

RQ1: The results suggest that variations in modeling assumptions across different techniques can influence the predictive performance in significant ways. Linear models are sensitive to data points that deviate substantially from the expected pattern, which can shift the overall model fit. Tree-based methods divide the data into segments, but the positions of these divisions depend on the initial splits, leading to potential instability in predictions. Support vector machines, in contrast, rely on the choice of kernel functions, which can either support discovering complex nonlinear patterns or restrict the model to simpler boundaries. Together, these findings indicate that the assumptions and choices made by each method have important consequences for predictive accuracy and stability in transitional contexts.

RQ2: The findings also indicate that adapting data mining approaches to the conditions in transitional economies can support improved reliability and interpretability of the results. Adjusting methods to address irregular data distributions, changing market conditions, and evolving institutional frameworks can lead to better alignment between the model assumptions and observed data. This alignment supports more consistent predictions that reflect the unique challenges faced by enterprises in these environments. As a result, an approach that considers local conditions, tuning procedures, and data characteristics can improve the practical usefulness of predictive analytics in transitional economies.

6. Conclusions

This study investigated the relationship between Internet marketing factors and entrepreneurial intentions within enterprises in Serbia, providing valuable insights into the role that digital tools play in shaping business outcomes. The findings confirm that website optimization, social media marketing, content marketing, and customer relationship management are significant predictors of entrepreneurial intentions. These digital marketing strategies allow businesses to engage more effectively with customers, optimize their online presence, and manage relationships, all of which contribute to supporting an entrepreneurial mindset.

The study's application of various statistical and data mining methods including linear regression, logistic regression, decision trees (QUEST and CHAID), support vector machines (SVM), and feed-forward neural networks (FNN) demonstrated a robust analysis of the data. The findings suggest that content marketing and website optimization are particularly influential in driving entrepreneurial intentions, while email marketing may have a less positive impact. These results highlight the importance of adopting targeted digital marketing strategies to improve business competitiveness.

The findings indicate that entrepreneurial behavior arises from multiple influences including individual traits, social environments, educational backgrounds, and prevailing market conditions. The data mining techniques applied in the analysis uncovered subtle patterns and nonlinear relationships, demonstrating that certain combinations of factors may significantly enhance the likelihood of entrepreneurial engagement. These insights offer important implications for both theory and practice. From a theoretical perspective, the study illustrates the value of advanced analytical methods in predicting entrepreneurial intentions.

The findings have several practical implications for entrepreneurs and managers who seek to strengthen their organizations. Understanding which variables exert the strongest influence on outcomes can support more informed decision making. For example, if the study identifies certain behavioral factors, resource allocation practices, or strategic orientations as having a significant effect on performance or innovation, managers can tailor their initiatives and strategies accordingly. Entrepreneurs who are navigating the challenges of new ventures can draw on these insights to guide resource investments and prioritize activities that are likely to improve their chances of long-term success. Managers in established firms can use this information to improve training programs, refine marketing strategies, or reorient product development efforts to align with the variables shown to contribute to better results. In a competitive environment, having a clearer sense of which elements matter most can improve the selection and development of talent, direct investments toward more productive areas, and support organizational changes that yield more favorable outcomes.

In practice, understanding these relationships can also guide managers in communicating priorities throughout the organization. If the model highlights the importance of certain capabilities or processes, managers can focus on reinforcing these aspects. For example, knowing that a particular managerial practice is associated with better performance may lead to adapting internal guidelines, reshaping leadership training, or changing the incentive structures. Entrepreneurs might use these insights to shape their business models, focusing on the attributes that customers value most or improving supply chain arrangements that directly affect their competitiveness. Overall, these practical implications help managers and entrepreneurs identify where to concentrate their efforts so that interventions lead to tangible, positive results.

Although this study provides valuable insights into how Internet marketing factors influence entrepreneurial intentions, there were a few limitations. One of the main limitations is that the study focused on businesses in Serbia, which may not fully represent how Internet marketing works in other countries or regions. Future research should look at a wider range of countries, especially those in different stages of economic development, to better understand how these strategies work in various contexts.

Another limitation is that this study used cross-sectional data, meaning that the data were collected at one point in time. This limits the ability to see how Internet marketing strategies affect businesses in the long run. Future research could use a longitudinal approach, tracking businesses over time to see how the ongoing use of digital marketing impacts entrepreneurial success.

The focus on a single geographical area and the cross-sectional nature of the data could also have been a limitation. Future research could expand on these findings by exploring additional regions and incorporating a longitudinal approach to better understand the long-term effects of Internet marketing on entrepreneurship.

The study also focused on specific Internet marketing tools like website optimization, social media marketing, and CRM. While these are important, future studies could explore how newer technologies, like artificial intelligence (AI) and automation tools, affect entrepreneurship. These technologies are becoming more common in marketing, and understanding their impact on entrepreneurial behavior could provide useful insights. In terms of implications, the findings suggest that businesses, especially small- and medium-sized enterprises (SMEs), should focus on developing strong Internet marketing strategies to improve their chances of success. Digital tools like CRM and content marketing are particularly important for reaching customers and improving business performance. Policymakers and business organizations should support entrepreneurs by offering training programs that help businesses develop their digital marketing skills. This could help businesses, especially in transitional economies, compete more effectively in the global market.

Future research can extend these findings in several ways. One line of research might involve conducting longitudinal studies to track how relationships among variables evolve over time. This would provide additional insights into the stability of the identified patterns as well as how strategic initiatives introduced by managers might alter the outcomes in the long run. Another area for future inquiry could involve testing the model in different cultural or industry contexts to see whether certain findings are region-specific or if they apply more broadly. This could improve the generalizability of the conclusions and help managers from different backgrounds understand whether the insights are relevant to their specific settings.

Further research could also incorporate more nuanced performance metrics, exploring not only financial indicators, but also non-financial ones such as employee well-being, environmental sustainability measures, or customer satisfaction. Doing so would yield a more comprehensive picture of organizational success. Additional variables might be introduced to understand how external factors, such as regulatory changes, technological shifts, or macroeconomic trends, affect the relationships identified in the current study.

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Appendix A

For every survey item, labels/codes where introduced to present them in pseudocodes. There were seven predictor groups. The attributes, survey items, and variables are presented in Table A1.

Table A1. Survey items, predictors, and item codes.

First Predictor: Website Optimization (WOPT)		
Label	**Variable**	**Available Answers**
WONAV	The enterprise's website is easy to navigate.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
WOSEO	The website is optimized for search engines (SEO).	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
WOUP	The content on the website is regularly updated to reflect current offers and information.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree

Table A1. *Cont.*

First Predictor: Website Optimization (WOPT)		
Label	**Variable**	**Available Answers**
WOCH	The website offers a seamless checkout process for online purchases.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
Second Predictor Group: Social Media Marketing (SMM)		
Code	**Attribute**	**Available Answers**
SMUP	Social media channels are regularly updated with relevant and engaging content.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
SMROI	The company effectively measures the return on investment (ROI) of its social media marketing efforts	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
SMFI	Financial goals are easily achieved.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
SMRES	The company responds quickly and appropriately to customer inquiries and comments on social media.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
SMIN	The company engages with influencers or brands that align with its values for broader reach.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
Third Predictor Group: Email Marketing (EMAIL)		
Code	**Attribute**	**Available Answers**
EMPE	The company's email marketing campaigns are personalized and relevant.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
EMAC	Emails that are frequently sent are acceptable to consumers.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree

Table A1. *Cont.*

Third Predictor Group: Email Marketing (EMAIL)		
Code	**Attribute**	**Available Answers**
EMCO	The company effectively uses email marketing to communicate offers, news, and updates.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
EMSEG	Email segmentation is effectively used to tailor messages to different audience segments.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
Fourth Predictor Group: Content Marketing (CMA)		
Code	**Attribute**	**Available Answers**
CMVAL	The content provided by the company (e.g., blogs, videos, infographics) is informative and valuable.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
CMAL	Content is consistently aligned with the interests and needs of the target audience.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
CMSAL	The company effectively uses content marketing to generate sales and leads.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
CMPR	Content is effectively shared and promoted across various channels.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
Fifth Predictor Group: Customer Relationship Management (CRM)		
CODE	**Attribute**	**Available Answers**
CRPE	The company offers personalized recommendations based on previous interactions and consumer preferences.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
CROS	Online support channels (e.g., chatbots, live chat) provide quick and efficient solutions to problems.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree

Table A1. *Cont.*

Fifth Predictor Group: Customer Relationship Management (CRM)		
CODE	**Attribute**	**Available Answers**
CRCR	CRM strategies are clearly focused on customer retention as much as on acquiring new customers.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
Sixth Predictor Group: Online Advertising (OAD)		
CODE	**Attribute**	**Available Answers**
OAREV	The company's online ads are relevant to consumers.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
OACRE	Online advertising campaigns are creative and attention-grabbing.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
OATAR	The company effectively uses targeted advertising to reach its audience.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
OAPER	The company tracks and analyzes the performance of its online advertising campaigns.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
Seventh Predictor Group: Data Management and Analytics (DMA)		
CODE	**Attribute**	**Available Answers**
DMIM	The company effectively uses analytics to improve its online marketing strategies.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
DMPER	Data collected online are used to personalize the experience with the company.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
DMTR	The company is transparent about the data it collects and how they are used.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree

Table A1. *Cont.*

Seventh Predictor Group: Data Management and Analytics (DMA)		
CODE	Attribute	Available Answers
DMFOR	The company uses predictive analytics to forecast trends and adjust marketing strategies accordingly.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree
Dependent Variable: Entrepreneurship Intentions (ENTIN)		
CODE	Attribute	Available Answers
ENTEX	I would consider entrepreneurship to expand the existing business.	○ Agree ○ Mostly agree ○ Don't know ○ Mostly disagree ○ Disagree

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