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# Proposing an Intelligent Competitive Online Network Model Based on Electronic Commerce to Enhance Business Performance Through Online Marketing Capabilities in Media Companies

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## ABSTRACT

The present study was conducted with the aim of systematically explaining and analyzing the role of the intelligent competitive network in improving business performance, with a particular focus on the mediating role of marketing capabilities and competitive advantage in media companies operating in Tehran and Alborz provinces. In the highly turbulent environment of the media industry, competitive intelligence is no longer an option; rather, it constitutes the fundamental infrastructure for survival and sustained profitability. From the perspective of research purpose, the study is applied, and in terms of data collection and analysis, it falls within the category of descriptive–survey research. The statistical population consisted of 500 managers, experts, and senior specialists active in the media ecosystem. Using the Krejcie and Morgan table, a sample of 217 respondents was selected through simple random sampling. The main measurement instrument was a standardized questionnaire containing 28 items measured on a Likert scale, which was distributed among the respondents after confirmation of content validity by subject-matter experts and verification of reliability using Cronbach's alpha. To examine the complex relationships among the constructs of the model, Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) method was employed using SPSS version 21 and SmartPLS version 2. The findings of the structural model indicated that the intelligent competitive network plays a critical role in enhancing business performance through strengthening marketing capabilities. According to the results, although competitive intelligence has a direct effect on performance, the strongest impact is achieved when this intelligence leads to the creation of distinctive competitive advantages and the enhancement of marketing expertise. In essence, intelligence functions as the cognitive input of the organization and transforms its marketing capabilities into tangible business outcomes. Based on the statistical results, it is recommended that media managers accelerate the process of identifying emerging audience needs by deploying advanced and up-to-date monitoring systems. Continuous innovation, identification of creative opportunities in digital markets, and the establishment of strong information networks with suppliers and customers are vital requirements for improving competitive positioning. Furthermore, organizations are advised to replace traditional strategies with models based on competitive intelligence networks in order to demonstrate proactive responses to competitors' actions. The use of predictive analytics not only reduces decision-making risk but also ensures sustainable competitive advantage in the chaotic media environment by creating service differentiation.

**Keywords:** Competitive Intelligence Network; Business Performance; Competitive Advantage; Marketing Capabilities; Media Industry.


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## Introduction

Organizations competing in digitally mediated markets are increasingly shaped by their ability to sense environmental signals, translate them into actionable insights, and mobilize those insights through coherent capability systems that improve performance. This imperative is especially pronounced in sectors characterized by rapid content cycles, platform dependency, and volatile customer attention—conditions that intensify strategic uncertainty and compress decision windows. Across such environments, competitive intelligence and business intelligence have moved from peripheral analytical activities to core strategic infrastructures that support opportunity recognition, threat anticipation, and timely resource reconfiguration (1, 2). At the same time, the diffusion of artificial intelligence is altering the architecture of intelligence work by expanding the scale, speed, and granularity of market sensing and by enabling more adaptive decision processes in dynamic contexts (3, 4). These shifts are not merely technical upgrades; they entail a transformation in how organizations build and orchestrate intelligence capabilities, how they learn, and how they sustain advantage under conditions of digital turbulence (5).

The emerging literature suggests that the performance consequences of intelligence-related initiatives depend less on isolated tools and more on how intelligence is embedded in managerial routines, knowledge flows, and capability development. In competitive intelligence research, the updated perspective emphasizes the link between intelligence activities and strategic decision-making quality, highlighting the importance of systematic collection, interpretation, and dissemination processes that connect environmental scanning to strategic choice (1, 6). Similarly, business intelligence studies show that intelligence systems can enhance financial and operational outcomes when they are integrated with managerial processes and aligned with performance objectives rather than treated as stand-alone reporting functions (2, 7). This process view aligns with broader accounts of knowledge management and innovation, where competitive intelligence activities interact with knowledge processes to shape innovation performance and adaptive outcomes (8). In practice, firms often struggle not with data availability but with converting heterogeneous signals into organizational learning and coordinated responses, a challenge magnified by the velocity and ambiguity of digital markets (5).

Artificial intelligence intensifies both the potential and the complexity of intelligence-driven competition. On one hand, AI enables automated pattern recognition, predictive analytics, and scalable personalization, which can support differentiated customer engagement and operational efficiency. On the other hand, AI adoption introduces governance, capability, and legitimacy challenges, particularly in professional and regulated domains where interpretability, accountability, and stakeholder trust are salient (9). Evidence from public-sector accounting contexts indicates that organizational and contextual factors shape AI adoption, and that adoption is intertwined with perceived implications and constraints rather than being a purely technical deployment decision (9). From a capability standpoint, recent theory-building suggests that competitive advantage through AI is “situated,” meaning that advantage arises when AI is meaningfully embedded within specific organizational contexts, practices, and decision situations, rather than assumed to generalize automatically across firms (4). This perspective reinforces the argument that the performance value of AI-enabled intelligence depends on how organizations align AI tools with strategic priorities, workforce skills, and learning mechanisms (5).

In small and medium-sized enterprises, which frequently operate with resource constraints and less formalized analytics infrastructures, the strategic logic of AI adoption often centers on accelerating innovation and competitiveness while lowering coordination costs. A systematic and bibliometric synthesis indicates that AI adoption is frequently framed as a driver of innovation capability and competitiveness in SMEs, although realized value is contingent on absorptive capacity, skills, and implementation pathways (3). In parallel, empirical modeling work on intelligent competitive online networks highlights how online capabilities can be structured into an integrated model that improves business efficiency, emphasizing the strategic role of digital and online marketing capabilities in translating intelligence into performance outcomes (10). These contributions are consistent with the view that intelligence becomes strategically consequential when it is deployed through capability bundles—such as digital marketing, pricing, and market intelligence routines—that allow organizations to convert insights into market-facing actions (11).

Marketing capabilities are particularly central in digital ecosystems because they provide the operational bridge between market sensing and value capture. When competitive intelligence identifies shifts in customer preferences, platform algorithms, or competitor positioning, marketing capabilities determine whether organizations can respond with speed, coherence, and differentiation across channels. Research on international company performance underscores that product innovation capacities, market intelligence, pricing, and marketing communications can jointly influence performance, with competitive advantage serving as a mediating mechanism that converts capability deployment into superior outcomes (11). In digitally intensive domains, the marketing function is increasingly intertwined with data-driven targeting, content experimentation, and engagement analytics, which raises the strategic importance of intelligence processes that feed marketing decisions with timely and credible insights (1). This linkage suggests that models aiming to explain business performance in contemporary markets should examine not only direct effects of intelligence constructs, but also the mediating roles of marketing capabilities and competitive advantage in shaping performance trajectories (10).

Competitive advantage remains the principal theoretical lens for explaining sustained performance differentials, but its sources are evolving as digital technologies and AI reshape competition. The literature increasingly recognizes that advantage in AI-enabled contexts involves a blend of technological assets, complementary organizational capabilities, and governance arrangements that support responsible and effective use (4, 9). In sustainability-oriented contexts, for example, studies on green artificial intelligence suggest that AI can contribute to green competitive advantage, but the relationship is complex and often dependent on mediated and moderated mechanisms that connect AI deployment to performance outcomes (12). These arguments broaden the competitive advantage construct beyond cost and differentiation to include capability-based, knowledge-based, and legitimacy-based sources of advantage, which may be especially relevant for media and digital service firms operating under heightened reputational and regulatory scrutiny. In parallel, the intellectual capital literature demonstrates that competitive advantage can be linked to intangible resources and is influenced by innovation quality and speed, with business intelligence functioning as an important mechanism in these pathways (13). Collectively, these strands reinforce that intelligence capabilities do not merely inform decisions; they shape the organization's ability to build and renew the sources of advantage that underpin performance.

The operationalization of intelligence and AI is also shaped by cross-domain learning regarding decision modeling and intelligent support systems. Work on intelligent support in manufacturing demonstrates how artificial neural networks, fuzzy logic, and genetic algorithms can be combined to support complex selection decisions, illustrating the broader managerial potential of hybrid intelligent systems for structured decision problems under uncertainty (14). In sports competition contexts, reinforcement learning-based decision modeling highlights how tactical decision-making can be improved through adaptive algorithms, offering conceptual parallels to competitive environments where decisions must be updated rapidly based on feedback and evolving opponent behavior (15). Although these domains differ from media markets, they inform the design logic of intelligent systems that couple sensing, prediction, and action, which is central to the concept of an intelligent competitive online network that integrates intelligence collection with capability deployment.

Another salient dimension is the institutional and governance layer around AI and intelligence. Standard setting in AI reflects a complex interplay of competition and cooperation, where emergent patterns influence how organizations adopt and operationalize AI systems and how they negotiate interoperability, ethics, and strategic positioning (16). These institutional dynamics matter because intelligence systems often rely on data access, platform interfaces, and algorithmic tools that may be shaped by standards and ecosystem rules. At the organizational level, research on integrating generative AI into learning and development highlights both influence and challenges, suggesting that meaningful value requires intentional capability building, workforce development, and thoughtful governance to manage risks while enabling experimentation and learning (5). These considerations are particularly important in sectors with knowledge-intensive work and fast-paced content production, where generative AI can reshape workflows, role definitions, and performance expectations.

Human capital practices and managerial competencies further condition the effectiveness of intelligence-driven strategies. Talent management has been linked to firm competitiveness by enabling the acquisition, development, and retention of skills needed for adaptive performance, implying that intelligence initiatives are unlikely to deliver sustained value without aligned investments in people and organizational routines (17). Relatedly, research on strategic intelligence among education district managers illustrates how intelligence constructs can be modeled and analyzed in managerial contexts, reinforcing the relevance of leadership cognition, information processing, and organizational sensing in shaping decision outcomes (18). These insights suggest that intelligence capabilities are socio-technical systems in which analytical tools, managerial interpretation, and organizational learning interact to shape performance effects. In digitally intensive markets, where competitive moves are often subtle and rapidly executed, the quality of managerial interpretation and the organization's responsiveness become decisive components of intelligence effectiveness (1, 6).

Despite a growing body of research, important gaps remain in explaining how intelligence, AI-enabled mechanisms, and online marketing capabilities combine to influence business performance through competitive advantage—particularly within digitally dynamic industries and within organizational contexts comparable to media ecosystems. Prior reviews of competitive intelligence in sectoral markets, including insurance, emphasize the breadth of the field while also revealing fragmentation in constructs, measurement, and causal mechanisms, which motivates context-specific empirical modeling and integrative frameworks (19). Moreover, while business intelligence has been linked to operational performance through supply chain ambidexterity, this mediating logic suggests that intelligence systems often influence performance indirectly by enabling organizational capabilities that reconcile exploitation and exploration—an insight that may translate to media firms balancing routine content operations with innovation and experimentation (7). Similarly, studies of AI technologies in digital sports marketing and management signal that AI-enabled marketing is emerging as a strategic arena, but requires clearer models connecting technology use, marketing capability, and performance outcomes (20). Integrating these perspectives supports the proposition that intelligent competitive online networks should be conceptualized as capability orchestration mechanisms that connect intelligence processes with marketing execution and competitive advantage formation (10, 11).

Within this landscape, an intelligent competitive online network can be understood as an integrated configuration of competitive intelligence activities, AI-enabled analytics and decision support, and online marketing capabilities that together enhance responsiveness, differentiation, and value capture. Such a network emphasizes not only the generation and dissemination of market intelligence, but also the organizational capacity to interpret signals, learn, and translate insights into marketing actions that build distinctive competitive advantage (1, 8). It also reflects the increasing importance of platform-mediated interactions and digital touchpoints, where performance depends on the firm's ability to coordinate sensing and responding across channels and stakeholders. At the same time, it recognizes that the value of AI for competitive advantage is contingent on situated implementation and governance, including alignment with professional practices and standards that shape legitimacy and interoperability (4, 16). Finally, it acknowledges that intelligence-driven performance is mediated by organizational capabilities—particularly marketing capabilities—and by the creation of competitive advantage that allows the firm to sustain performance gains rather than realize only temporary improvements (11, 13).

Accordingly, this study aims to develop and test an integrated model explaining how an intelligent competitive online network influences business performance through the mediating roles of online marketing capabilities and competitive advantage.

## Methods and Materials

The present study is classified as applied research in terms of its objective, as the findings can be utilized by senior managers and policymakers in media companies in Tehran and Alborz provinces to improve decision-making processes and enhance business performance. From the perspective of its nature and methodology, this research is a descriptive–survey study. It is descriptive in that it seeks to explain the current status of the research variables (competitive intelligence, marketing capabilities, competitive advantage, and performance), and it is survey-based because it collects data from a statistical sample in order to analyze the relationships among variables and generalize the results to the entire population of media companies in the target regions. According to authoritative sources, a survey is a systematic process of collecting information for the purpose of describing, predicting, and analyzing relationships among research variables.

In this study, to ensure the appropriate selection of statistical tests and to examine the distribution of variables, the Kolmogorov–Smirnov (K–S) test is first employed. If the data follow a normal distribution, parametric tests will be applied; otherwise, non-parametric tests will serve as the basis of analysis. Given the complexity of the conceptual model and the presence of mediating effects, the data analysis process is conducted at two levels: descriptive statistics (examining demographic characteristics) and inferential statistics. In the inferential phase, Structural Equation Modeling (SEM) using the Partial Least Squares (PLS) approach is employed with the assistance of SPSS version 27 and SmartPLS version 4 software. This combined approach enables the simultaneous examination of both direct and indirect (mediating) relationships.

Considering the survey-based nature of the research, the questionnaire was selected as the primary instrument for measuring and collecting primary data. The questionnaire consists of a set of standardized items that assess the knowledge, attitudes, and beliefs of media experts and managers and enable access to their professional experiences. The items of the questionnaire were designed based on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The Likert scale is regarded as the most standard measurement instrument in management and social science research due to its high capacity for measuring perceptual and cognitive constructs.

The statistical population of this study includes all managers, senior experts, and decision-makers in companies active in the media sector (including news agencies, advertising agencies, and digital media organizations) in Tehran and Alborz provinces. The focus on these two provinces is due to the maximum concentration of the country's media infrastructure in this geographical region, which can provide a comprehensive representation of the intelligent competitive network in the media industry. In this study, the validity of the questionnaire is assessed through content validity (expert and faculty evaluations), and its reliability is examined using Cronbach's alpha coefficient and Composite Reliability (CR).

The primary data collection instrument in this research is a structured questionnaire consisting of 28 items, organized into two sections. The first section measures the demographic characteristics of the respondents (gender, age, work experience, and level of education), while the second section evaluates the main variables of the model using a five-point Likert scale. The content validity of this instrument, after necessary revisions, was confirmed by academic supervisors and media experts.

**Table 1. Questionnaire Constructs and Items**

| Variable | Dimension | Item Numbers | Number of Items |
|---|---|---|---|
| Competitive Intelligence Network | Market Intelligence Generation | 1–2 | 6 |
| | Market Intelligence Responsiveness | 2–4 | |
| | Market Information Dissemination | 4–6 | |
| Marketing Capability | — | 7–12 | 6 |
| Competitive Advantage | — | 13–22 | 10 |
| Business Performance | — | 23–27 | 5 |

For the analysis of findings, a combination of descriptive statistics (for data summarization and frequency distribution charts) and inferential statistics (for hypothesis testing) is employed. At the inferential level, the Kolmogorov–Smirnov test is first conducted to determine the data distribution type, followed by the application of Structural Equation Modeling (SEM) and Confirmatory Factor Analysis using SPSS version 27 and SmartPLS version 4 to examine the relationships among variables.

## Findings and Results

The analysis of questionnaire data reflects the composition of the workforce in the studied media companies. Of the 217 respondents, 176 individuals (81.1%) were male and 41 individuals (18.9%) were female. In terms of age distribution, the highest concentration belonged to the 30–40 age group with 122 individuals (56.2%), followed by the 20–30 age group with 80 individuals (36.9%). It is noteworthy that none of the respondents were above 50 years of age, indicating the relatively young executive and managerial structure of modern media organizations in Tehran and Alborz. Regarding educational level, the majority of the sample held a master's degree. In addition, the analysis of work experience revealed that the highest frequency corresponded to individuals with 5–10 years of service (46.1%), suggesting the dominance of a mid-level experienced workforce in this industry.

In this section, after ensuring the accuracy of the data, the hypothesis testing process was conducted in three consecutive stages, including the normality test, evaluation of the variables' status, and finally structural modeling.

Prior to selecting appropriate statistical tests, it was essential to examine the distribution of the data using the Kolmogorov–Smirnov (K–S) test. In this test, the null hypothesis ($H_0$) indicates that the data follow a normal distribution. The decision criterion is the significance level (Sig); if its value exceeds the 5% error level (0.05), the data distribution is considered normal, and the use of parametric tests (such as regression and factor analysis) is permitted. Otherwise, non-parametric alternatives are employed. Given the use of SmartPLS software in this study, even if the data are not fully normal, structural model analysis can still be conducted with high accuracy due to the non-parametric nature of this software.

**Table 3. Kolmogorov–Smirnov (K–S) Test Results**

| Conclusion | Significance Level | K–S Statistic | Construct |
|---|---|---|---|
| Normal | 0.19 | 1.07 | Competitive Intelligence Network |
| Normal | 0.21 | 1.059 | Competitive Advantage |
| Normal | 0.123 | 1.180 | Marketing Capabilities |
| Normal | 0.18 | 1.09 | Business Performance |

The results of Table 3 indicate that the variables of competitive intelligence network, competitive advantage, strategic marketing capabilities, and business performance follow a normal distribution. Based on these results, a one-sample t-test was used to determine the status of the research variables.

The one-sample t-test is applied to compare the mean of a variable with a hypothetical or expected value. In this study, the test examines whether the status of the research variables is satisfactory. The hypotheses in this section were formulated as follows:

**Table 4. One-Sample t-Test Results**

| Variable | t-value | df | Sig. | Mean Difference | 95% Confidence Interval for Difference (Lower) | 95% Confidence Interval for Difference (Upper) |
|---|---|---|---|---|---|---|
| Competitive Intelligence Network | 26.908 | 216 | 0.000 | 1.11063 | 1.0199 | 1.2025 |
| Competitive Advantage | 25.365 | 216 | 0.000 | 1.14747 | 1.0583 | 1.2366 |
| Marketing Capabilities | 21.943 | 216 | 0.000 | 0.99386 | 0.9046 | 1.0831 |
| Business Performance | 23.904 | 216 | 0.000 | 1.11060 | 1.0190 | 1.2027 |

As shown in Table 4, the significance values (Sig) for all variables are less than 0.05; therefore, at the 5% error level, the null hypothesis is rejected and the alternative hypothesis, representing the researcher's claim, is accepted. Consequently, the mean values of these variables differ significantly from the reference value of 3. Moreover, since both the upper and lower confidence limits are positive and the t-values exceed 1.96, it can be concluded that the mean values of these variables are greater than 3, indicating that the variables are in a favorable condition.

As presented in Tables 5 and 6, the results of Cronbach's alpha coefficient, composite reliability, and convergent validity are reported. Based on the recommended threshold values, the Cronbach's alpha and composite reliability coefficients for all variables exceed 0.70, and the AVE values are greater than 0.50, confirming the adequacy of the measurement model.

**Table 5. Results of Cronbach's Alpha, Composite Reliability, and Convergent Validity**

| Construct | AVE (>0.50) | Cronbach's Alpha (>0.70) | Composite Reliability (>0.70) |
|---|---|---|---|
| Competitive Intelligence Network | 0.52 | 0.82 | 0.93 |
| Competitive Advantage | 0.78 | 0.90 | 0.91 |
| Marketing Capabilities | 0.69 | 0.80 | 0.86 |
| Business Performance | 0.52 | 0.81 | 0.86 |

**Table 6. Reliability and Validity Results for Independent and Dependent Variables**

| Construct | AVE (>0.50) | Cronbach's Alpha (>0.70) | Composite Reliability (>0.70) |
|---|---|---|---|
| Intelligent Competitive Network | 0.65 | 0.94 | 0.95 |
| Business Performance | 0.58 | 0.95 | 0.95 |

Table 7 presents the discriminant validity of the research model. As shown using the Fornell–Larcker criterion, the square roots of AVE for the latent variables, located on the main diagonal of the matrix, are greater than the correlations among constructs. Therefore, the constructs exhibit stronger relationships with their own indicators than with other constructs, confirming acceptable discriminant validity.

**Table 7. Discriminant Validity Results**

| Constructs | Intelligent Competitive Network | Competitive Advantage | Marketing Capabilities | Business Performance |
|---|---|---|---|---|
| Intelligent Competitive Network | 0.83 | | | |
| Competitive Advantage | 0.72 | 0.69 | | |
| Marketing Capabilities | 0.75 | 0.71 | 0.63 | |
| Business Performance | 0.80 | 0.71 | 0.71 | 0.57 |

Another assessment of the measurement model is the evaluation of its quality using the cross-validated communality index (Cv Com). This index measures the model's ability to predict observed variables through their corresponding latent constructs. A positive value indicates adequate measurement quality. The results presented in Table 8 show positive values for all constructs, with an overall mean of 0.63, demonstrating desirable measurement model quality.

**Table 8. Measurement Model Quality Assessment**

| Construct | Cv Com |
|---|---|
| Intelligent Competitive Network | 0.78 |
| Competitive Advantage | 0.69 |
| Marketing Capabilities | 0.52 |
| Business Performance | 0.57 |

Based on the values reported in the above tables, all criteria used to evaluate the measurement model indicate its adequacy.

According to the results of Table 9, the t-values for all paths exceed 1.96 and are statistically significant at the 95% confidence level. Furthermore, Figure 1, representing the main research model, shows that the t-values for most paths exceed 1.96 and even 2.58, indicating the correctness of the structural relationships among the model variables. As shown in Table 9, the $R^2$ values for the main endogenous variables exceed 0.67, reflecting strong explanatory power. Moreover, since the $R^2$ values of the endogenous constructs exceed 0.33, the model demonstrates strong predictive power and confirms the structural model fit.

**Table 9. $R^2$ Coefficients of Research Variables**

| Construct | $R^2$ | Interpretation |
|---|---|---|
| Intelligent Competitive Network | 0.884 | 0.19, 0.33, 0.67 indicate weak, moderate, and strong levels |
| Competitive Advantage | 0.719 | |
| Marketing Capabilities | 0.796 | |
| Business Performance | 0.712 | |

**Table 10. $Q^2$ Predictive Relevance of Research Variables**

| Predictor Construct | $Q^2$ | Interpretation |
|---|---|---|
| Intelligent Competitive Network | 0.433 | 0.02, 0.15, 0.35 indicate weak, moderate, and strong predictive relevance |
| Competitive Advantage | 0.365 | |
| Marketing Capabilities | 0.412 | |
| Business Performance | 0.300 | |

The overall model includes both the measurement and structural components. After confirming their fit, the goodness-of-fit of the complete model is assessed using the GOF index, introduced by Tenenhaus et al. (2004). The GOF index is calculated based on the average communality and the average $R^2$ values. The thresholds of 0.01, 0.25, and 0.36 indicate weak, moderate, and strong fit, respectively. In this study, the mean communality was 0.63 and the mean $R^2$ was 0.76. Using the GOF formula, the resulting GOF value was 0.69, indicating a strong overall model fit.

**Table 11. Overall Model Fit Using the GOF Criterion**

| GOF | Interpretation |
|---|---|
| 0.69 | 0.01 = weak, 0.25 = moderate, 0.36 = strong |

To test the hypotheses, the structural model was re-estimated using SmartPLS software, as illustrated in Figure 1. In this model, Cronbach's alpha, AVE, and composite reliability values all exceeded the threshold levels. The GOF value for the hypothesis model (Figure 1) was 0.66, indicating high model fit.

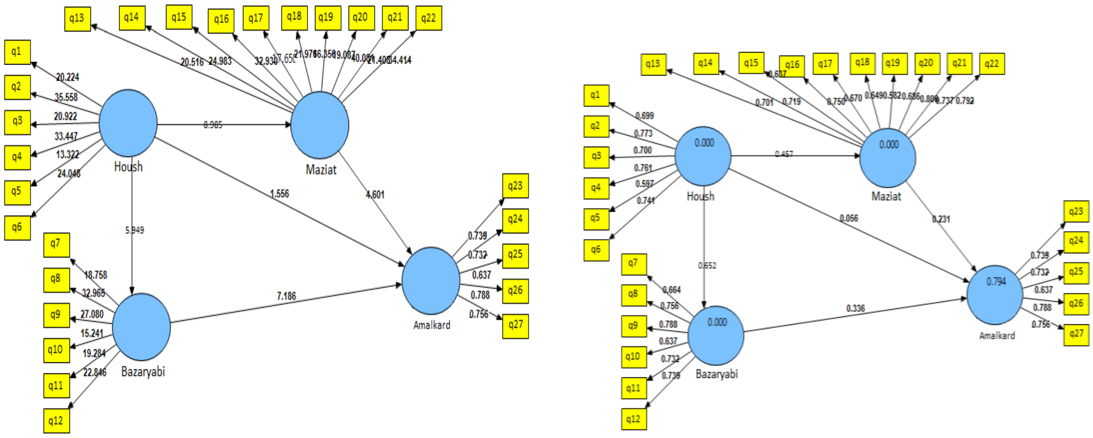


**Figure 2. Standardized Factor Loadings and t-Values of the Structural Model**

## Discussion and Conclusion

The findings of the present study provide strong empirical support for the proposed intelligent competitive online network model and confirm the central proposition that competitive intelligence, when systematically integrated with online marketing capabilities, leads to superior business performance through the creation of sustainable competitive advantage. The structural model results demonstrated that the intelligent competitive online network exerts a significant direct effect on business performance, while also exerting substantial indirect effects through marketing capabilities and competitive advantage. These results are fully consistent with the contemporary strategic management literature that positions intelligence and analytics as core dynamic capabilities rather than peripheral technical tools (1, 10). The high explanatory power of the model suggests that in digital and media-intensive environments, performance outcomes are increasingly determined by how effectively organizations sense, interpret, and act upon market intelligence rather than by traditional resource endowments alone.

One of the most important contributions of this study lies in demonstrating the mediating role of marketing capabilities in transforming intelligence into measurable performance outcomes. The results indicate that competitive intelligence alone does not automatically generate superior performance unless it is embedded in operational marketing routines that allow firms to translate insights into customer-facing actions. This aligns closely with the capability-based view advanced by Alizadeh and Tavan (11), who showed that market intelligence and innovation capacity influence firm performance primarily through competitive advantage. Similarly, Huang et al. (2) found that business intelligence improves financial performance of start-ups only when it becomes part of managerial and operational decision-making processes. The present study extends this logic by explicitly modeling marketing capabilities as the key transmission mechanism that connects intelligence inputs with strategic outcomes in the context of digital media firms.

The strong relationship observed between the intelligent competitive online network and competitive advantage further reinforces the argument that advantage in contemporary markets is fundamentally capability-driven. The findings support Kemp's theory of situated artificial intelligence, which emphasizes that AI-based advantage emerges only when technology is meaningfully integrated into specific organizational practices and strategic contexts (4). In the present model, intelligence systems function not merely as analytical instruments but as strategic infrastructures that reshape how firms coordinate market sensing, content production, customer engagement, and competitive positioning. This is also consistent with the work of Niwash et al. (13), who demonstrated that business intelligence strengthens competitive advantage through the enhancement of innovation quality and speed. In media organizations operating under extreme environmental turbulence, this integration of intelligence and capability appears to be the decisive mechanism through which firms stabilize and extend performance.

The empirical strength of the mediating effect of competitive advantage suggests that performance improvements are not immediate or mechanical consequences of intelligence adoption. Rather, firms must deliberately convert intelligence into differentiated value propositions that competitors find difficult to replicate. This observation is in line with Salehzadeh et al. (12), who showed that artificial intelligence contributes to green competitive advantage only through mediated and moderated pathways rather than through direct effects alone. The present study generalizes this insight beyond sustainability contexts and demonstrates that in media and digital markets, intelligence-driven strategies produce lasting benefits only when they systematically reinforce the firm's unique market position.

Another notable implication of the findings concerns the role of artificial intelligence and digital technologies as amplifiers of intelligence effectiveness. While the study did not isolate specific AI tools, the conceptualization of the intelligent competitive online network inherently reflects AI-enabled data processing, predictive analytics, and real-time market monitoring. The positive effects observed in the model are consistent with Yesuf's systematic review, which identified AI adoption as a major driver of innovation and competitiveness in small and medium-sized enterprises (3). Moreover, Alhusban et al. (5) emphasized that the successful integration of generative AI into organizational learning and development significantly enhances firms' adaptive capacity. The current results suggest that such adaptive capacity is especially valuable in media industries, where rapid shifts in audience behavior, platform algorithms, and content formats require continuous recalibration of strategic priorities.

The strong relationship between intelligence and marketing capabilities in the model also reflects broader transformations in the marketing function itself. Marketing in digital media environments is no longer limited to communication and promotion; it has become a complex analytical and technological system involving personalization algorithms, engagement analytics, content experimentation, and platform optimization. Nalbant and Aydın (20) highlighted how AI technologies are reshaping digital sports marketing and management, creating new forms of customer engagement and competitive differentiation. The present findings indicate that similar dynamics are at work in media organizations, where intelligence-driven marketing capabilities serve as the primary operational vehicle through which strategic insights are converted into economic value.

Furthermore, the results resonate strongly with the knowledge-based perspective on competitive intelligence articulated by Zuochun (8), who demonstrated that competitive intelligence activities enhance innovation performance by improving knowledge management processes. In the present study, the intelligent competitive online network can be interpreted as an institutionalized knowledge system that enables organizations to continuously refresh their understanding of market conditions and competitor behavior. This continuous learning loop is essential for sustaining performance under conditions of rapid technological and competitive change.

The empirical support for the overall model fit also contributes to the ongoing discourse on intelligence governance and standardization. Ingersleben-Seip (16) argued that competition and cooperation in AI standard setting create emergent patterns that shape how organizations implement and benefit from AI systems. The strong structural relationships observed in this study imply that firms that succeed in aligning intelligence practices with emerging standards and institutional expectations are better positioned to extract performance benefits from their intelligence investments. This insight is particularly relevant for media firms operating within highly regulated information environments, where legitimacy and compliance are critical components of competitive success.

The present findings further support the notion that intelligence effectiveness is deeply intertwined with human capital and managerial capabilities. Rahmat et al. (17) demonstrated that talent management plays a crucial role in enhancing organizational competitiveness. Similarly, Miri Rami et al. (18) showed that strategic intelligence among managers significantly influences organizational effectiveness. The results of the current study implicitly confirm that intelligence systems yield maximum value when managerial interpretation, decision-making competence, and organizational learning processes are sufficiently developed to exploit the insights generated by these systems.

Finally, the results reinforce the strategic logic proposed by Ghasemi and Kazemi (10), who argued that intelligent competitive online networks represent a new generation of business models capable of enhancing efficiency and competitiveness through integrated digital capabilities. The present study empirically validates this proposition in the context of media organizations and demonstrates that such networks function as high-level strategic architectures that coordinate intelligence generation, marketing execution, and competitive positioning in a coherent and mutually reinforcing manner.

Despite the robustness of the findings, several limitations should be acknowledged. The study relied on self-reported survey data, which may be subject to perceptual bias and common method variance. The cross-sectional design also limits the ability to draw strong causal inferences about the dynamic relationships among intelligence, capabilities, and performance over time. In addition, the empirical context was confined to media companies within specific geographic regions, which may constrain the generalizability of the results to other industries or national settings.

Future studies could employ longitudinal designs to examine how intelligent competitive online networks evolve over time and how their effects on performance unfold across different stages of organizational development. Comparative studies across industries and countries would further enhance understanding of contextual contingencies. Researchers could also integrate objective performance indicators and digital trace data to complement perceptual measures and reduce potential response bias. Finally, deeper qualitative investigations could explore the micro-level processes through which intelligence is interpreted and enacted within organizations.

Managers should view intelligent competitive online networks as strategic infrastructures rather than isolated technological projects. Investments in intelligence systems must be accompanied by continuous development of marketing capabilities, managerial competencies, and organizational learning mechanisms. Firms should establish formal routines for transforming market intelligence into marketing actions and competitive positioning. Leadership teams must also ensure that intelligence practices are aligned with corporate strategy and supported by appropriate governance structures. By institutionalizing intelligence-driven decision-making and capability development, organizations can significantly enhance their long-term competitiveness and performance.

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## Authors' Contributions

All authors equally contributed to this study.

## Declaration of Interest

The authors of this article declared no conflict of interest.

## Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

## Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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