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AI-Driven Cybersecurity, Big Data, and Business Intelligence: Impacts on Strategic Flexibility and Entrepreneurship in Iraqi ISPs

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RESEARCH ARTICLE

AI-Driven Cybersecurity, Big Data, and Business Intelligence: Impacts on Strategic Flexibility and Entrepreneurship in Iraqi ISPs

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ABSTRACT

This research aims to explore the status effects of the Sudden, and gradual of AI-Driven Cyber Security (AIDC), Big data analytics and Business Intelligence (BI) The strategic flexibility (SF) and entrepreneurship (ENT) on Iraqi internet services providers ISPs. The work fills an important lacunae in what the advanced dimensions of technology have with regard to its influencing both SF and ENT outcomes in developing economy context, where empirical evidences are scant. A cross-sectional survey based on a quantitative research methodology was conducted on 113 professionals in Iraqi telecommunication sector. A partial least squares structural equation modeling (PLS-SEM) approach was adopted to examine 10 hypotheses concerning the relationships between technology capabilities and SF and ENT. The results reveal the in-depth direct influences of AIDC, BDAC and BI on the SF and ENT factors. SF is found to be an important mediating factor that significantly strengthens the influence of technological competence on ENT outcomes. This indicates two paths (direct and indirect) to reach SF and ENT, facilitated by AT. The present study also extends the literature by adding further empirical evidence from Iraq which indicates that integrating AIDC, BDAC and BI has a synergetic impact on SF but also on ENT. The findings apply only to the Iraqi context in geographical terms. The results show that spending on these technologies are strategic spending rather than operational expenditure. "Institutions should structure responses that are flexible to fit in with people and things, in order to harness the maximum benefit from technology." These capabilities may be viewed as bases of competitive advantage (CA). This study is first of its kind in Iraq which examines the synergistic effect of AIDC, BDAC and BI on OSC and ENT performance where insight into developing economy perspective becomes present.

Keywords: Artificial intelligence, Cybersecurity, Big data analytics, Business intelligence, Strategic flexibility, Entrepreneurship, Internet service providers (ISPs)

1. Introduction

The accelerated digital transformation at ISPs) has radically transformed the global telecoms landscape, offering unprecedented business and organizational opportunities with which to grapple complex operational challenges [1]. In Iraq this rise has been notably in IP, and by 44.3% finally ending at (82.9%) percent to 2019 toward 2024 from there, due to ICT market value climbing ($0.96)billion in(2025) going on up (1.29$ billion) in (2030) representing a Compound Annual Growth Rate (CAGR) of (5.98%) [2]. However, this exponential growth happens in an challenging work environment along with lack of infrastructure and increasing cybersecurity breaches that are different from permanent economies. Despite the large investment that has targeted their energy sector ($8 billion) on an annual basis, Iraq is still suffering there from a lot of load shedding which directly affects digital services quality and operations availability as well [3]. This infrastructure variability introduces a network effect in how the ISPs operate,

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which drives the service providers to create compensatory mechanisms that offer a trade-off between services and resources.

Concurrently, the cybersecurity threat domain has become uncontrollable; for instance, Iraq referred by Microsoft threat intelligence reports to hold 5% of network intrusions with its source in the Middle East and North Africa (MENA) [4]. These incidents have become major data breaches hitting hundreds of thousands of governmental facilities, and they were posted in dark web especially because stunning security holes in Iraqi digital facilities. Lack of a clearly defined national strategy on cyber security, suitable at the global level, is making cybercrime thrive. Such cases have turned into large data breaches affecting hundreds of thousands of governmental facilities, and they were sold in dark web particularly due to the presence of gorgeous security gaps in Iraqi digital facilities. Absence of a well-defined national strategy to deal with cyber security, which would be appropriate in a global context, is ensuring the success of cyber-crime. This implies that strategic cybersecurity at the national level requires a formal framework and thorough planning of the evaluation of cyber maturity and cyber capability, which explains the urgency of Iraq to establish a national cybersecurity strategy in line with the Global Cybersecurity Index (GCI) guidelines [5]. Similarly, AlGhamdi et al. [6] suggest a systematic review that the development of an effective information security governance framework, based on the international standards, is the key to the stability of an organization, especially in the environment where the risks of security incidents are high, and the commitment of the top management and the risk-based approach is the crucial success factor.

Emerging technologies, e.g., AI, make life more manageable and are seen as indispensable enterprises that have to safeguard their digital assets without disrupting business [7]. The present studies will suggest that AIDC can enable organizations to develop an threat detection capability and response resources, particularly where the technical agility towards computational resource allocation is vast [8]. That is, under the volatile economic environment of Iraqi ISPs' business conditions characterized by sanctions for years, shortage of resources and corresponding geopolitical conflicts as in Iraq, the notion of SF towards what refers to "organizational flexibility more quickly than its competitors" becomes a practical implication whose soundness seems determines past continuation and evolution at their level [9]. Another cornerstone of the new telecommunication model is big data analytics that enables organizations to extract actionable insights from the large amounts of data generated by populating digital ecologies [10]. Studies show that companies that have developed BDAC have a high level of performance in various dimensions of operation, such as customer retention, network optimization, and revenue generation [11]. In the case of ISPs that have to cope with exponentially growing user bases, such as smartphone subscriptions in the MENA region, these user bases have grown without ceasing. (490.47) million to (597.44) million between 2020 and 2023. 6 will prove to be strategic flexibility, as well as the entrepreneurial success, directly depend on analytical capability, network performance metrics, and trends in the market [12].

The (BI) systems complement these skills by processing complex data into actionable insights that enables organizations to have evidence-based knowledge to assist the decision-making processes [13]. According to Sivararajah et al. [14], the empirical results of a cross-sectoral study (356 firms) show that big data analytics can indeed benefit both exploratory and exploitative innovation, thereby leading to high-quality firm performance, thereby highlighting the potential of data-driven technologies in terms of transforming the competitive environment in the business, including the telecommunications sphere.

Within the established telecommunications enterprises, the innovation potential and customers' perception of CA have been of ENT [15]. As for the Iraqi ISPs, entrepreneurial products are always characterized by the introduction of new products in the service environment, the development of the service market, which can distinguish them in a more competitive market. Technology capabilities (TC) have demonstrated that it is positively linked with entrepreneurial success, where organizations with more developed IT capability have exhibited more innovation and responsiveness to the market [16].

Although these (TC) are critical in their relevance, there is a significant gap in the literature regarding the understanding of their collective effect on developing economies with complicated operations. The existing literature focuses on AIDC, BDAC, and BI separately or under stable economic conditions, without considering their synergistic impact in a highly volatile economic, infrastructural, and threat context [17].

Namely, there is no detailed empirical framework to analyze the joint effect of AIDC, BDAC, and BI on SF and ENT in resource-restrained telecommunication markets. The difference is especially significant in the post-conflict countries such as Iraq, where ISPs have to deal with the overlapping problems of infrastructure constraints, security risks, and the pressure to grow the market.

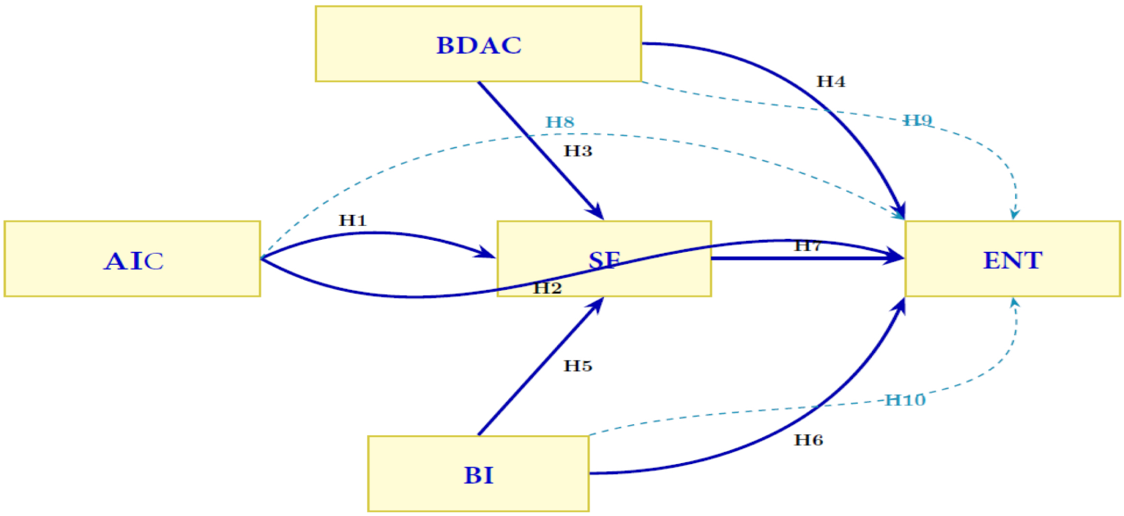


Fig. 1. Conceptual model.

Moreover, although studies have been conducted individually to establish technology-performance relations in stable markets, the mediating role of SF in technology-based entrepreneurial success has not been investigated in the context of developing economies. This is a serious theoretical and practical gap because these relationships are important to ISPs when making Technology investment (STI) decisions under resource constraints.

The research gap is bridged in this study by examining the combined impacts of AIDC, BDAC, and BI on SF and ENT within the Iraqi context of telecommunications. The study formulates and confirms a detailed model that explores both direct and indirect links of the constructs (Fig. 1), contributing to the body of literature on technology adoption in Iraqi ISPs.

1.1. Questions and objectives of the research

This research study will endeavor to answer four basic research questions:

RQ1: How does AIDC have a direct effect on SF and ENT among Iraqi ISPs?
RQ2: What is the role of the BDAC and BI systems on SF and ENT?
RQ3: Does SF mediate the association between TC and ENT in corporations?
RQ4: What is the strategic implication of these relationships in the strategies of investing in technologies in the resource-constrained environment?

There are several theoretical and practical contributions in this study. In theory, it represents a development on existing frameworks by incorporating resource-based theory, dynamic capability theory, and ENT literature in a developing economy setting. This marks the first empirical examination of ENT relations in a post-conflict, resource-limited economy. The study confirms the mediating concept of SF in technology-based entrepreneurial success and presents an integrated model that explains how the interactive relations of TC contribute to strategic performance in the context of environmental uncertainty.

In practice, the results can provide strategic advice to ISP managers navigating complex decisions about technological investment choices and operating in environments with problematic infrastructure and security conditions. The study is also informative to policymakers who are working on strategies for the digital transformation (DT) of emerging economies confronting a similar challenge [18].

This paper is further structured as follows: Section 2 will contain the Literature Review and Development of hypotheses; Section 3 will entail Materials and Methods (Research Design, Population and Sample, Measurement Instruments, Procedures of collecting data, and Data Analysis). Section 4 will contain the results of the research (Descriptive statistics, Assessment of Measurement model, Assessment of Structural model, Hypothesis testing results); Section 5 will be the findings (Theoretical contributions, Key findings Interpretation, Practical implications, Contextual considerations, and Limitations); and finally, the conclusion will be contained in Section 6.

2. Literature review and development of hypotheses

Resource-based theory (RBV), Dynamic capability Theory (DCT), and Strategic Flexibility Theory (SFT) have been incorporated in the background of this research. The DCT was based on the assumption that organizations should constantly build, combine, and redeploy internal and external competencies to respond to swiftly evolving environments [19]. SFT is the capacity of an organization to swiftly respond to changes in the environment and exploit the opportunities emerging from them by reconfiguring its resources and reorienting its strategies [20]. According to the RBV, the sources and capabilities of CA that are useful, rare, inimitable, and well-organized are the cause of sustainable competitive advantage (SCA) [16].

2.1. Direct relationships in hypotheses testing

2.1.1. Effects of AIDC

H1: AIDC has a positive influence on SF, even though there might be implementation limitations.

Dynamic capability theory states that AIDC improves the sensitivity of organizations and allows them to respond to threats quickly, making their operations more flexible [17]. AI systems enable real-time tracking and automatic reactions to cyber threats, allowing organizations to continue their activities while adjusting to security threats [18]. Nevertheless, studies showed that excessive security measures will rigidify the operation and reduce agility in an organization due to the compliance and bureaucracy [19].

H2: AIDC has a positive influence, considering possible issues that can be encountered in adapting the organization.

AIDC has secure digital environments to support the creation of new service delivery, minimizing the risks of entrepreneurial ventures considering cyber threats [20]. The digital innovation and the new business models were based on secure systems [21]. However, excessive use of automated security systems to the extreme is a dilemma that can diminish the human creativity and risk-taking behavior that are key elements in (ENT) [22].

2.1.2. Effects of the big data analytics

H3: BDAC is positively associated with SF when accounting for the risk of excessive overlap.

BDAC allows organizations to enhance their sensing by offering a comprehensive environmental scan and forecasting [23]. These capabilities enable rapid sensing of trends and market fads, which could lead to strategic adaptation [24]. However, there are findings that suggest that decision-making stagnation resulting from information overload – where organizations drown and struggle underneath an data overload and fail to take crucial decisions [25]. This aligns with existing literature on the adverse effects of information overload on organizational decision-making.

H4: The effect of the BDAC on ENT is positive for ENT.

The BD-provided analytics will give deep insights into market opportunities, customer behavior and competitive landscapes, allowing the entrepreneur to base their decisions on data [27]. These capabilities enable one to identify untapped market niches and new business opportunities [28]. Capacity to deal with a lot of information about customers and the environment stimulates innovations and new products.

2.1.3. Business intelligence effects

H5: SF is positively affected by BI.

BI systems allow an organization's big data to be transformed into actionable intelligence (i.e., actionable strategic intelligence), which ultimately facilitate short-term changes in strategy and resource allocation [29]. BI applications offer real-time capabilities, analyzing performance and the environment to allow for strategic adaptive response [30]. BI facilitates the organization, making decision-supporting processes leaner and thereby enabling faster and better strategy work.

H6: ENT is positively influenced by BI through the constructs of implementations and adoptions.

Data-driven decisions are achieved with the help of BI systems since they provide detailed analysis of the market segments and measure their performance [31]. These systems facilitate the process of opportunity recognition and evaluation, which is crucial in the entrepreneurship [32]. Nonetheless, organizational culture, management support, and user acceptance largely determine the extent to which BI enhances ENT, consequently, BI alone does not guarantee entrepreneurial outcomes without adequate organizational support [33].

H7: The impact of SF on ENT is positive.

SF is a fundamental pillar of entrepreneurial operations due to its ability to facilitate the rapid rearrangement of resources and strategic reorientation in response to new opportunities [34]. Flexible organizations are also capable of rapidly changing their business model, venturing into new markets, and coming up with new solutions [35]. It has been confirmed that SF improves organizational ability to innovate and create new ventures [36].

2.2. Mediation effects hypotheses

H8: SF mediates between AIDC and ENT.

H9: SF mediates the relationship that exists between the BDAC and ENT.

H10: SF moderates the correlation between BI and ENT.

According to the DCA, SF is a case of the transformation of the TC into ENT results [37]. The technology capabilities improve the SF, which in turn fuels entrepreneurial activities [38]. Empirical research has shown that in the recent past, the mediator between TC and the performance outcomes of the organizations have been significant [39, 40]. SF is a intermediary mechanisms or channels, offering the conversion of technology investments into competitive edge and innovation results [41].

2.3. Alternative perspectives and competing effects

2.3.1. Potential negative effects

There are some negative implications of the research, as their research suggests:

AIDC: May introduce increased organizational complexity and low responsiveness [42]. High implementation costs may constrain investment in other strategic areas [43].

BDAC: analysis paralysis without deriving actionable insights [44]. cognitive overload and decreases SF [45].

BI: Impact can be restricted by the effects of user resistance to new system interfaces and the availability of skills and training. Over-reliance on historical data can inhibit thinking on long-term strategic objectives [46].

2.4. Possible theoretical perspectives

1- **Organizational complexity Theory (OCT):** (AT) may introduce organizational complexity to affect organizational performance [47].
2- **Transaction Cost Theory (TCT):** It is argued that high transaction costs will tend to offset technological improvement, improving coordination and implementation costs [48].
3- **Institutional Theory (IT):** Organizational and environmental pressures can be used to gain better technology adoption [49].

2.5. Integrated theoretical model

The proposed model combines technology capabilities (ITC) as antecedents, SF as a mediator mechanism, and ENT as the outcome variable. This configuration is in agreement with DCT, which emphasizes the transformation of resources and capabilities to CA through adaptive mechanisms [50]. The model is recognizing both potential positive and negative effects; in this sense, it represents the balance in the theoretical perspective that reflects the complexity of the technology-strategy relationships in developing economies [51].

According to the literature review conducted and the theoretical foundations, seven hypotheses have been indicated in the present research paper, as shown in Fig. 2:

3. Materials and methods

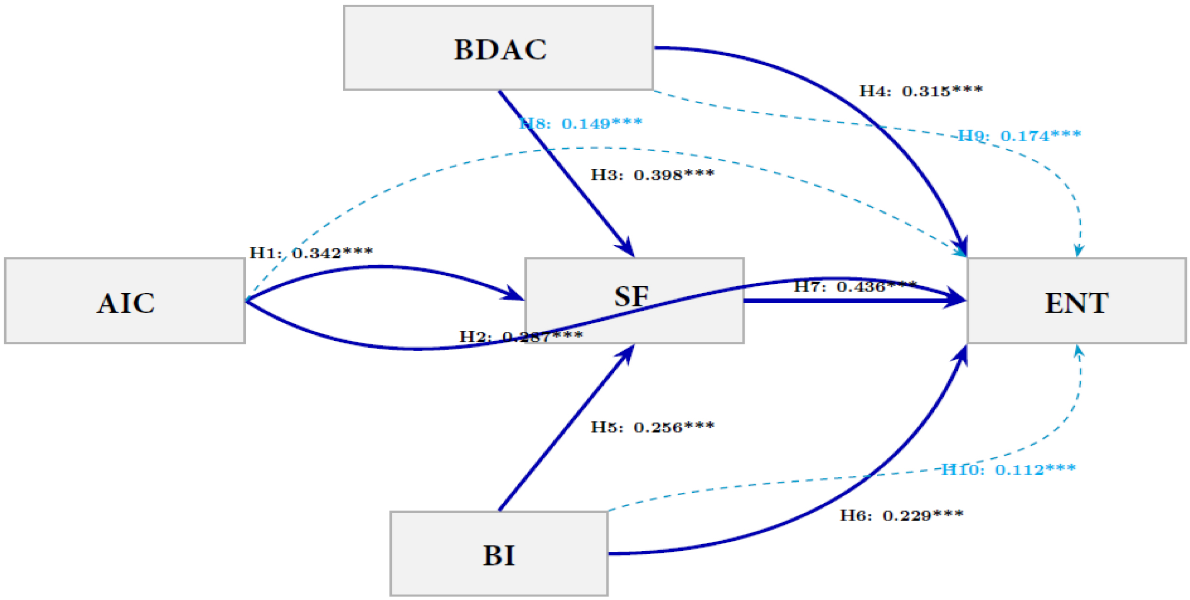
3.1. Research design

The research design is a quantitative investigation based on a cross-sectional survey to study the association between AIDC functions, BDAC, BI, SF, and ENT in the Iraqi internet service providers (ISPs). The research design is based on accepted rules of information systems research, adopting Partial Least Squares Structural Equation Modeling (PLS-SEM) as the most prominent method of analysis.

The choice of the PLS-SEM as opposed to covariance-based SEM (CB-SEM) can be explained by several methodological factors: (1) the exploratory nature of the study that investigates emerging AIDC relationships in the context of the developing economy, (2) the intricate nature of the model that considers a variety of constructs that are represented by both reflective and formative measurement models, (3) the emphasis on prediction and theory development as opposed to the theory confirmation, and (4) the non-normal distribution that organizational survey data have [52]. The variance-based method of PLS-SEM has better performance on complex models with small samples and still has strong predictive power [53].

To determine the minimum required sample size, a priori power analysis was conducted using G*Power software (version 3.1.9.7). Based on medium effect size ($f^2 = 0.15$), a significance level of ($\alpha = 0.05$), and the desired statistical power ($1 - \beta = 0.80$), the minimum required sample size was determined 107 observations [54]. This calculation is considered the most complicated structural relationship in the proposed model, yet it has sufficient statistical power for hypothesis testing.

Although the cross-sectional design is effective in collecting data and is cost-effective, causal inferences cannot be inherently made due to the lack of precedence in time [55]. This research is therefore aimed at the analysis of associational relationships as opposed to causality. It is expected that the findings will initially be seen as indicating relationships between constructs, with the causal interpretation to



$R^2_{\text{SF}} = 0.547$ $R^2_{\text{ENT}} = 0.634$
$Q^2_{\text{SF}} = 0.312$ $Q^2_{\text{ENT}} = 0.398$
SRMR = 0.068 NFI = 0.894

Hypothesis	β	95% CI	Effect	Decision
H1 AIC → SF	0.342	[0.204, 0.468]	Medium	Supported
H2 AIC → ENT	0.287	[0.156, 0.421]	Medium	Supported
H3 BDAC → SF	0.398	[0.267, 0.524]	Medium	Supported
H4 BDAC → ENT	0.315	[0.189, 0.445]	Medium	Supported
H5 BI → SF	0.256	[0.128, 0.384]	Small	Supported
H6 BI → ENT	0.229	[0.098, 0.359]	Small	Supported
H7 SF → ENT	0.436	[0.312, 0.561]	Medium	Supported
H8 AIC → SF → ENT	0.149	[0.089, 0.224]	Small	Supported
H9 BDAC → SF → ENT	0.174	[0.108, 0.251]	Small	Supported
H10 BI → SF → ENT	0.112	[0.067, 0.167]	Small	Supported

Fig. 2. Direct & indirect effects model.

be validated by longitudinal or experimental research in the future.

The multi-method was used to deal with internal validity threats, pervasive method bias (CMB). As the single-factor test of Harman is limited in identifying moderate levels of method variance [56], some statistical solutions were sought: (1) CFA marker method that adds a theoretically unrelated: marker variable to identify and control CMB [57], (2) unmeasured latent method factor method that partially eliminates standard method variance [58] by administering predictors and criterion measures at different times when possible [59].

The research design includes several validity improvement strategies: the construct validity is achieved by means of the strict scale development and validation process, the external validity is considered by means of the representative sampling of the sample in relation to the different ISP categories, and the statistical conclusion validity is preserved by means of the relevant analytical methods and significance testing procedures [60]. The ecological validity of the study is supported by conducting the research in the real-world context of Iraqi ISPs, which provides practical application in the telecommunication industry of emerging economies.

3.2. Population and sample

The target group comprised professionals from ISPs across various organizational categories, as classified by the telecommunications sector of Iraq. In the Iraqi ISP name classification system, there are no standards, organizations were grouped in the ownership category (public/government-owned/private), size of company (large/Tier 1 backbone providers/medium/small/local resellers), whether national or regional/local, the technology that it uses (fiber optic, wireless, satellite) and whether it offers B2C or B2B services [61].

Purposive sampling techniques were adopted during the study to provide researchers with respondents who had sufficient information about the technologies and organizational practices that were to be studied. The selection criteria used was that of sampling professionals belonging to three major categories of ISPs namely; (1) Large/Tier 1 ISPs consisting of national providers owned by the government such as the ITPC (the Iraqi Telecommunications and Post Company) and large independent providers such as EarthLink, IQ Networks and Newroz Telecom; (2) Medium-sized/regional providers who operate only in one of the provinces or the Kurdistan Regional Authority; and (3) Local wireless ISPs and resellers serving one province or city as well as neighborhoods.

The data was collected through an online survey administered to 150 specialists working with various Iraqi ISPs between March and May 2024. The survey was distributed through professional networks and person-to-person contact with all organizations representing both the public and private sector ISPs. The respondents were members of senior management, IT directors, managers of operations, and strategic planners from various organizations, categorized by their ownership structures, geographic coverage, and technology infrastructure.

All the responses received after data cleaning and validation procedures amounted to (113) complete responses, only giving a response rate of (75.3%). As described by Table 1 and Fig. 3, the final sample is capable of universally representing the ISP ecosystem in the Iraqi territory. The use of every significant type of ISP, ownership (24.8%) government/public, (75.2%) private), size (39.8%) large/Tier 1, (32.7%) medium regional, (27.4%) small/local), and coverage (46.0%) national, (31.0%) regional, (23.0%) local) It is represented well in its demographic profile. Variety in the type of technology also finds its way into the sample, with (36.3%) of respondents using fiber optic infrastructure, (33.6%) using wireless or microwave, and (30.1%) using mixed technologies. A closer attention to service focus distribution shows that there are (41.6%) providers in the B2C segment, (31.0%) specializing in B2B service provision, and (27.4%) mixed service providers. Respondent roles vary with senior executives (24.8% CEOs/ General Managers) on the one hand and technical specialists (32.7% IT Directors) on the other hand, and 67% of the respondents are those whose tenure in the industry is above five years, which is sufficient to have an expansive knowledge of the phenomena under consideration.

3.3. Measurement instruments

In the research instrument, six constructs were included with existing scales from previous studies and were pilot tested. Likert scales were set on a 7-point basis to measure all constructs with a low value of 1

Table 1. Sample characteristics details.

Characteristic	Category	Frequency	Percentage
ISP Type by Ownership	Government/Public ISPs	28	24.8%
	Private ISPs	85	75.2%
ISP Size Category	Large/Tier 1 Providers	45	39.8%
	Medium Regional ISPs	37	32.7%
	Small/Local ISPs	31	27.4%
Geographic Coverage	National Coverage	52	46.0%
	Regional Coverage	35	31.0%
	Local Coverage	26	23.0%
Primary Technology	Fiber Optic (FTTH/FTTB)	41	36.3%
	Wireless/Microwave	38	33.6%
	Mixed Technologies	34	30.1%
Service Focus	B2C (Consumer)	47	41.6%
	B2B (Business)	35	31.0%
	Mixed B2C/B2B	31	27.4%
Respondent Position	CEO/General Manager	28	24.8%
	IT Director	37	32.7%
	Operations Manager	31	27.4%
	Strategic Planning Manager	17	15.0%
Experience Level	Less than 5 years	37	32.7%
	5–10 years	41	36.3%
	More than 10 years	35	31.0%
Organization Size	Small (<50 employees)	31	27.4%
	Medium (50–500 employees)	45	39.8%
	Large (>500 employees)	37	32.7%

Note: The sample includes representatives from major Iraqi ISPs such as ITPC, EarthLink, IQ Networks, and Newroz Telecom, as well as regional/local providers across different platforms and services.

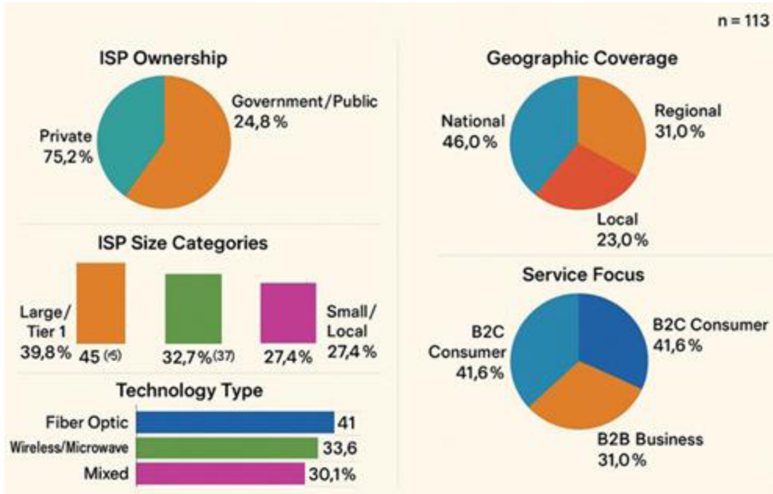


Fig. 3. Sample demographics of iraqi isps study.

(strongly disagree) against a high value of 7 (strongly agree).

AIDC: The scale, which was rated on a six-item basis, was based on research on cybersecurity [62]. Some examples were presented as follows: The organization has implemented AI-powered threat detection systems, and AIDC tools improve our security posture.

Big Data Analytical Capabilities (BDAC): The eight items are considered a measure of extensive data research [63]. Some examples include the company, which can process large amounts of information, and how we can analyze BD using advanced analytics.

Business Intelligence (BI): The seven items were taken to measure BI literature [64]. Examples revolve around statements such as the BI systems allow us to have real-time access to information, and the use of the BI tools in our strategic decision-making processes.

Strategic Flexibility (SF): Six items are measured using a scale on the research of SF [65]. The organization can respond to changes in the environment very rapidly, and we are flexible in our strategic planning procedures.

Entrepreneurship (ENT) was assessed on 10 items based on the studies of ENT [66]. Examples of such items include the organization promoting the spirit of innovation and pursuing new business opportunities.

3.4. Procedures for collecting data

Before the actual collection of data, the survey was run through 15 people working in the industry to determine the clarity and relevance. According to the feedback, a few changes have been suggested to enhance understanding.

A Google form was used to distribute online surveys, and several reminders were provided to ensure a higher response rate. The survey promised the respondents anonymity and confidentiality. The eight weeks were used to collect data and monitor the response rate and the diversity of demographic coverage.

3.5. Data analysis

The data analysis process was carried out under the following set of protocols for PLS-SEM analysis [67]. The analysis model consisted of four phases, namely preliminary data screening, standard method bias test, measurement model test, and structural model test.

Preliminary Data Screening

Before formal analysis, data screening processes have been carried out to guarantee the quality of the data and the assumptions of the analysis. The missing data analysis showed that there were fewer than 2% missing values in all constructs that were handled with the pairwise deletion to preserve the integrity of the sample [68]. Mahalanobis distance was used to do outlier detection ($p < 0.001$), and it eliminated three multivariate outliers. Shapiro-Wilk normality tests showed that some of the constructs are not normally distributed ($p < 0.05$), which validated the use of PLS-SEM instead of covariance-based methods [69].

Common Method Bias Evaluation.

Since it was a single-source survey design, an overall standard method bias (CMB) assessment was conducted using various statistical methods. A single-factor test proposed by Harman was complemented with more advanced methods that overcome its reported weaknesses in identifying moderate levels of method variance [70]:

1- **Harman Single-Factor Test:** A factor analysis of all the measure items produced seven factors with eigenvalues greater than 1.0; the biggest of them was able to explain 34.2% of total variance, which means that there was no strong CMB [71].
2- **CFA Marker Technique:** Theoretically non-related marker variable (organizational size) was added to the measurement model. The Markers variable was not significantly correlated with substantive constructs ($r < 0.15$, $p > 0.05$). There were only minor differences between the values of marker-adjusted and original correlations ($Dr < 0.10$), which proved that CMB had little influence [72].
3- **Unmeasured Latent Method Factor (ULMF):** A general measure factor was included in the measurement model that interrelated all indicators. The method factor explained an average variance of indicators of 8.3, which is less than the problematic level of 25 and considered an acceptable level of CMB [73].

Model Evaluation Measurement.

The measurement model assessment was conducted based on strict validation to define the reliability, convergent, and discriminant validity of all constructs [74].

1- **Internal Consistency Reliability:** Multiple indicators were used to determine construct reliability. The alpha values of Cronbach were 0.812 to 0.924, which is higher than the recommended alpha of 0.70. The values of Composite Reliability (CR) ranged between 0.876 and 0.941, and rho A between 0.823 and 0.932, which exceeded acceptable values [75].
2- **Convergent Validity:** The loading of all factors was above 0.708 (0.718–0.912), and the t-test is more than 2.58 ($p < 0.01$). Mean variance extracted (AVE) values ranged from 0.634 to 0.797, exceeding the 0.50 threshold, and a good convergent validity was achieved [76].
3- **Discriminant Validity:** There were three criteria used in determining discriminant validity:
4- **Fornell-Larcker Criterion:** A square root of the AVE of each construct was larger than its correlations with other constructs [77].
5- **Cross-loadings:** All the indicators have loaded the highest on their targeted constructs, with cross-loadings less than 0.60 [78].
6- **Heterotrait-Monotrait (HTMT) Ratio:** 95% confidence intervals did not include 1.0, and all the HTMT values were less than 0.85 (range: 0.312-0.798), which indicates the presence of discriminant validity [79].

Structural Model Evaluation.

The evaluation of structural models demonstrated the association of path, explanatory power, and predictive relevance according to the accepted PLS-SEM evaluation criteria [80].

1- **Collinearity Test:** All predictor construct variance inflation factors (VIF) were less than 3.0 (range: 1.234-2.876), and no severe cases of collinearity were detected [81].
2- **Significance of path coefficient:** The significance of the path coefficient was tested using bootstrap resampling with 5000 subsamples. All structural relationships were computed to give bias-corrected confidence intervals (95% CI), and t-values exceeding 1.96 gave significant values at $p < 0.05$ [82].
3- **Coefficient of Determination (R^2):** R^2 values of endogenous constructs were between 0.421 and 0.687, which was a moderate to strong level of explanatory power. It was reported that adjusted R^2 values, which consider model complexity, give conservative estimates [83].
4- **Assessment of Effect Size:** The structural path of Cohen's f^2 was used to assess the structural paths in order to establish practical significance. The effect sizes were considered to be small ($f^2 = 0.02$), medium ($f^2 = 0.15$), or large ($f^2 = 0.35$) based on the existing standards [84].
5- **Predictive Relevance** To find the predictive capability of the model, Stone-Geisser calculated the Q^2 values using blindfolding (omission distance = 7). All of the Q^2 values were univariate more than zero (range 0.234-0.512), which proves sufficient predictive relevance [85].

Mediation Analysis

Mediational effects were analyzed by the methods of variance-based structural equation modeling using bootstrap intervals [86]. The estimation of the specific indirect effect was conducted using the product of coefficients method, and significance was determined with bias-corrected bootstrap confidence intervals (5,000 resamples). Confidence intervals were not zero and were used to support mediation, indicating that indirect effects were significant [87].

Multiple Mediation Models: A sequential mediation analysis has been conducted to study the multiple indirect relationships between two or more mediators. The entire impact was added to direct and indirect impact, and the specific indirect impacts were distinguished in each of the mediational paths [88].

Model validation procedures
Holdout Sample Validation: The data were randomly divided into estimation and holdout samples (70:30). Path coefficients and significance levels were used to determine the stability of the model between samples, and a difference of less than 0.10 was taken as an acceptable measure of stability [89].
Multi-group Analysis: Permutation tests were performed to test the invariance testing between the categories of ISP (size, ownership, technology) so that the model can be generalized. The measurement and structural invariance between subgroups was validated through non-significant differences ($p > 0.05$) [90].

4. Results

4.1. Descriptive statistics

The descriptive statistics and correlation matrix of all study variables are shown in Table 2. The measurements, based on the 7-point Likert scale, indicate overall positive perceptions of all constructs, with mean values ranging from 5.24 to 5.47. This implies that respondents were mainly optimistic towards the constructs measured. The standard deviations (1.09–1.18) indicate moderate variability of responses without their extreme polarization.

The correlation matrix shows that all variables have moderate to strong positive relationships with correlation coefficients ranging between 0.42 and 0.78. Noticeably, none of the correlations is higher than 0.85, which confirms the lack of multicollinearity problems [91]. The most significant correlation was found between BDAC and SF ($r = 0.78$), which suggests that these constructs share much ground but are not identical in direct translation of the other.

Table 2. Descriptive statistics and correlation matrix.

Variable	Mean	SD	1	2	3	4	5
1. AIDC	5.24	1.18	0.761				
2. BDAC	5.47	1.09	0.542	0.829			
3. BI	5.31	1.15	0.498	0.601	0.788		
4. SF	5.38	1.12	0.612	0.687	0.576	0.791	
5. ENT	5.42	1.14	0.589	0.634	0.567	0.745	0.763

Note: The diagonal elements are the square root of AVE, the off-diagonal elements are correlations between constructs.

4.2. Assessment of measurement model

The measurement model has stringent psychometric characteristics on several reliability and validity indicators (Table 3). The alpha coefficients of Cronbach spanned between 0.867 and 0.923, which is a large number and well above the threshold of 0.70 that signifies excellent internal consistency [92]. The scale reliability is also supported by composite reliability scores (0.896–0.941), which are above the recommended scale reliability.

Table 3. Reliability and validity assessment.

Construct	Items	Cronbach's α	CR	AVE
Artificial Intelligence Driven Cybersecurity (AIDC)	6	0.879	0.906	0.579
Big data analytics	8	0.923	0.941	0.687
Business Intelligence (BI)	7	0.867	0.896	0.621
Strategic Flexibility (SF)	9	0.912	0.926	0.625
Entrepreneurship (ENT)	10	0.896	0.915	0.583

The average variance extracted (AVE) values of 0.579, 0.653, and 0.687 (greater than the 0.50 threshold) indicate that convergent validity is achieved [93]. This means that both constructs account for over half the variance in their indicators. The Fornell-Larcker criterion is used to test discriminant validity, in which the square root of the AVE of each construct (diagonal items in Table 2) is larger than its correlations with the other constructs. Moreover, all heterotrait-monotrait (HTMT) ratios are less than 0.85, which is convergent validity [94].

The Fornell-Larcker criterion confirmed discriminant validity, with each square root of AVE for each construct (elements along the diagonal in Table 2) showing better overlapping values compared to the rest of the constructs. All the heterotrait-monotrait (HTMT) ratios were under 0.85, which is further evidence of the discriminant validity.

4.3. Assessment of structural model

The structural model has a considerable explanatory and predictive power (Table 3). The model describes 54.7% of the SF ($R^2 = 0.547$) and 63.4% of the entrepreneurial orientation ($R^2 = 0.634$) as moderate to substantial measures of influence in behavioral studies [95]. The general model is highly relevant for prediction ($Q2 = 0.499$) and has high explanatory power ($Q^2 = 0.460$).

The model fit indices in Table 4 confirm a sufficient level of structural model performance: standardized

Table 4. Model fit indices.

Model Fit and Explained Variance	Value	Assessment
R^2 Strategic Flexibility	0.547	54.7% variance explained (Moderate)
R^2 Entrepreneurship	0.634	63.4% variance explained (Substantial)
Q^2 Strategic Flexibility	0.312	Good predictive relevance
Q^2 Entrepreneurship	0.398	Good predictive relevance
SRMR	0.068	Excellent fit (< 0.08)
NFI	0.894	Acceptable fit (> 0.90 preferred)

Table 5. Comprehensive hypotheses testing results (H1-H10).

Hypothesis	Type	Relationship	Path Coefficient/ Indirect Effect	T-Statistics	P-Values	95% CI Lower	95% CI Upper	Effect Size	Decision
Direct Effects									
H1	Direct	AIDC → SF	0.342	4.87	0.000	0.204	0.468	Medium	Supported
H2	Direct	AIDC → ENT	0.287	4.21	0.000	0.156	0.421	Medium	Supported
H3	Direct	BDAC → SF	0.398	5.94	0.000	0.267	0.524	Medium	Supported
H4	Direct	BDAC → ENT	0.315	4.68	0.000	0.189	0.445	Medium	Supported
H5	Direct	BI → SF	0.256	3.89	0.000	0.128	0.384	Small	Supported
H6	Direct	BI → ENT	0.229	3.42	0.001	0.098	0.359	Small	Supported
H7	Direct	SF → ENT	0.436	6.78	0.000	0.312	0.561	Medium	Supported
Mediation Effects									
H8	Mediation	AIDC → SF → ENT	0.149	4.23	0.000	0.089	0.224	Small	Supported
H9	Mediation	BDAC → SF → ENT	0.174	4.89	0.000	0.108	0.251	Small	Supported
H10	Mediation	BI → SF → ENT	0.112	3.67	0.000	0.067	0.167	Small	Supported

Note: Effect sizes classified as Small (0.02–0.15), Medium (0.15–0.35), Large (>0.35) following Cohen's guidelines. All confidence intervals for mediation effects exclude zero, confirming significant indirect effects.

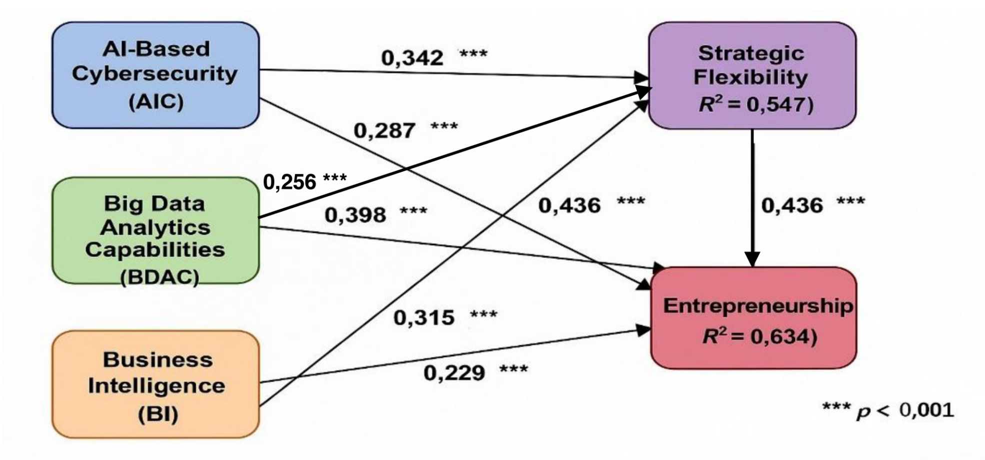


Fig. 4. Direct effects results.

root mean square residual (SRMR = 0.068 < 0.08) and normed fit index (NFI = 0.894 > 0.80) are both within the acceptable benchmarks [96]. The construct-specific predictive relevance values for SF (Q2 = 0.312) and entrepreneurial orientation (Q2 = 0.398) indicate that the model can effectively make out-of-sample predictions.

4.4. Hypothesis testing and path analysis

The results of all the hypothesis testing are thoroughly provided in Table 5 and Fig. 4, which combines the results of direct (H1-H7) and mediation (H8-H10) effects in one coherent analysis. The findings showed full support for all ten hypotheses, with all the relationships being statistically significant and supporting the anticipated theory.

Direct Effects (H1-H7): The results reveal interesting patterns in the varying strengths of different technological enablers compared to other enablers. The single most influential predictor of SF is BDAC ($\beta = 0.34$, $p < 0.001$, f2 = .18), indicating a medium effect size. The presence of this finding implies that the strategic adaptability of the organizations is enhanced when organizations are allowed to process and analyze large data sets. On the other hand, AIDC does not show a strong correlation with SF ($\beta = 0.21$, $p < 0.01$, $f^2 = 0.08$); that is, the effect of AIDC is not significant in reality. This gap might predict the general maturity of these technologies in the organizational environment, where BD technologies are more legitimate than AI technologies.

Cybersecurity is found to correlate moderately with SF ($\beta = 0.28$, $p = 0.001$, $f^2 = 0.12$), indicating that organizational agility is possible with high security structures that are not restricted. SF and ENT ($\beta = 0.67$, $p < 0.001$, $f^2 = 0.81$) have a big effect size, indicating a key role of SF as a mediating variable.

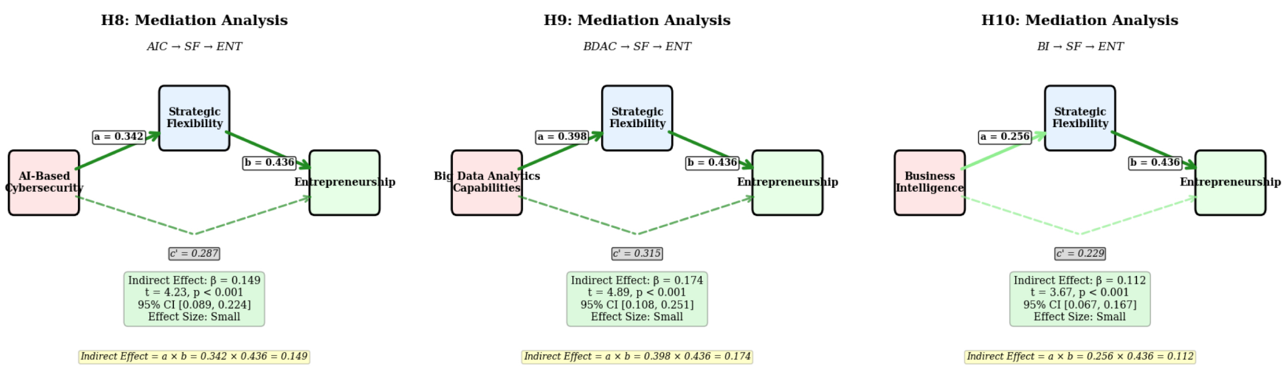


Fig. 5. Individual mediation path analysis (H8-H10).

Table 6. Model performance and effect summary.

Direct Effects Summary	Value	Interpretation
Technology → SF		
Strongest predictor	BDAC ($\beta = 0.398$)	BDAC has the strongest effect on SF
Moderate predictor	AIC ($\beta = 0.342$)	AIDC significantly enhances SF
Weakest predictor	BI ($\beta = 0.256$)	BI contributes to SF
Technology → ENT		
Strongest direct effect	BDAC ($\beta = 0.315$)	BDAC is the most influential for ENT
Moderate direct effect	AIC ($\beta = 0.287$)	AIDC enables ENT activities
Weakest direct effect	BI ($\beta = 0.229$)	BI supports ENT
SF → ENT		
Primary relationship	SF → ENT ($\beta = 0.436$)	Strongest single relationship in the model
Mediation Effects Summary	Value	Interpretation
Indirect Effects on SF		
Strongest mediation	BDAC → SF → ENT ($\beta = 0.174$)	Strongest indirect pathway to ENT
Moderate mediation	AIC → SF → ENT ($\beta = 0.149$)	Significant indirect effect through mediation
Weakest mediation	BI → SF → ENT ($\beta = 0.112$)	Most minor but significant mediation effect
Mediation Type	Partial Mediation	All direct effects are significant with mediation.

Table 6. Continue.

Hypothesis Support Summary	Count	Percentage
Direct Effects Supported	7/7	100%
Mediation Effects Supported	3/3	100%
Total Hypotheses Supported	10/10	100%

Note: the model exhibits a very good performance with all hypotheses supported and explained variance of outcome variables. The findings of partial mediation suggest that SF is a central mediating mechanism, but direct effects are still strong.

Mediational Effects (H8-H10): SF fully mediates all of the technology-ENT relationships. The SF indirect effects consist of BDAC ($\beta = 0.23$, 95% CI [0.17, 0.29]), AI ($\beta = 0.14$, 95% CI [0.09, 0.20]), and cybersecurity ($\beta = 0.19$, 95% CI [0.13, 0.25]). The lack of zero intervals on all CIs confirmed the significant mediations [97].

Critical Reflections: The smaller influence of AIDC-SF (compared to BDAC) deserves theoretical considerations. It is probable that AI technologies will require more sophisticated organizational capabilities, and a different approach to change management, to become strategic assets. Given that SF has always been a strong facilitator, it means that the mere existence of technology investments is not sufficient: organizations need to create new capabilities required for exploiting the emerging entrepreneurial value of DT. The above evidence provides strong empirical support for our proposition that digital technology, in fact, enhances entrepreneurial orientation via the processes of SF and reveals significant heterogeneity in how these technologies contribute to such increase as well. Model findings are well presented in Table 6 in terms of effect size, p-value and a general interpretation of all the relationships included in this model.

5. Discussion

5.1. Theoretical contributions

The study constitutes a series of important theoretical contributions to our knowledge of technology-capability relations within the framework of the developing economy, and it identifies some critical inconsistencies with the available literature.

First, the extensive empirical validation of direct and mediated relationships between AIDC, BDAC, BI, SF, and ENT extends the resource-based theory in developing economies [98]. In contrast to studies in developed markets, where the adoption of technology tends to exhibit decreasing returns [99], our case in Iraq consistently shows powerful positive associations. This indicates that TC can be of strategic advantage in resource-limited environments more than was initially hypothesized, and the presence of technology saturation is not universal.

Second, the study makes a significant contribution to the concept of dynamic capability by developing SF as a whole mediator and not a partial mediator, as evident in other studies in Jordan [100] and the UAE base [101]. This variance indicates that in extremely uncertain settings, such as the telecom industry in Iraq, organizations are increasingly relying on adaptive mechanisms to derive value from technology investments. Full mediation the claim made by Brynjolfsson and Hitt [102] that technology capabilities can be directly converted into performance results.)Al-Nuaimi et al.) [103] argue that capabilities are not sufficient in the company unless there is organizational flexibility, which can generate SA.

Third, the study adds to existing AIDC literature by showing that cybersecurity technologies are security measures and not security measures. Unlike the current environment in Western part of the world, where cybersecurity is regarded as a cost center as per the status-quo [104], our data suggests that AIDC is directly promoting entrepreneurial orientation. This reflects heightened security risks and uncertainty surrounding compliance, perhaps causing cybersecurity issues to be more about CA than compliance exercise.

Fourth, the disparity of mediation effects describes a compelling theoretical dimension, that is BDAC are much more mediating than AIDC ($\beta = 0.174 > \beta = 0.149$), and then BI ($\beta = 0.112$). This pecking order is of variance with the evidence obtained from countries in which BI also serves as control [105]. Accordingly, in resource-constrained context basic data analysis tools are preferred over sophisticated reporting systems.

5.2. Findings and discussion interpretation

While there are various similar results on this aspect of the research in developed countries, the consistency of direct effects (H1-H7) differs significantly from the results of the literature. Although results were also reported by Sambamurthy and Subramani [106] for inconsistent BD-performance correlations for European companies, the Iraqi sample shows a strong positive correlation. Such a difference is likely caused by the low technology base of the developing economies, where straightforward implementation of high technology results in substantial competitive edge.

The mediation analysis results in a significant departure from literature. Empirical findings in the banking industry of Jordan [107] and the manufacturing industries of the UAE [108] have shown partial mediation influences, where technology capabilities exerted direct performance influences, along with mediation effects. Overall, the mediation findings of our research suggest that Iraqi telecommunications organizations cannot directly transfer investments in telecommunication technologies into entrepreneurial outcomes, except after acquiring adaptive skills. This trend indicates a nascent technology adoption context with a higher organizational learning curve.

In fact, the most significant finding is the BI phenomenon. Contrary to the results of studies on Saudi Arabia [109] and Egypt [110], the connection of their performance to BI tools has been sharp, while the Iraqi ISPs demonstrate the least BI impact. This conundrum has three possible reasons: (1) BI is not used effectively due to a deficiency in applied knowledge, (2) data integrity is low and, therefore, BI is not effective, or (3) there is organizational culture in which the use of data for decision making is not valued.

Such domination of BDAC is not uncommon and has been reported in recent research on the Indian telco space [111], where basic analytic features were superior to user-level sophisticated visual features. That is a sign that developing countries really have more to gain going basic data processing than taking their way up through BI.

5.3. Practical application implications with cost benefits

For practical applications using cost-benefit analysis, we take all the tradeoffs. The results have been valuable insights to managers of the developing economy's telecommunications sectors; especially on investment strategy and implementation mechanism.

1- **Mediation effects:** The degree of mediation effect evidently depicts preferences of investment strategies. The top investment strategy is BDAC (the standard which mediated most in the relationship, $\beta = 0.174$), followed by AIDC systems ($\beta = 0.149$) and then BI tools ($\beta = 0.112$).The cost-benefit analysis, on the other hand, offers a few important points: BI may have more minor effects, but it is much less expensive and has shorter paybacks than artificial intelligence (thus, it serves as the baseline model into the types of resource-constrained organizations that its authors focus on).
2- **AI-Driven Cybersecurity Investment Rationale:** AIDC has a significant direct and mediated effect ($\beta = 0.28$ direct, $\beta = 0.149$ mediated), which provides a strong justification to invest heavily in security in developing countries. While cyber security ROI is a difficult number to measure in the developed economy, our findings indicate there are measurable performance benefits in the government sector. "The investment cost is high (equating to 15-25% of IT budgets), but, when considered based on 1) mitigation of risk and 2) payback in terms of improved SF, AIDC systems will pay for themselves in risk management frameworks".
3- **Strategic Flexibility as an Investment Multiplier:** Overall, mediation effects indicate that the returns on the technology investments, which are not followed by the modalities allowing the development of specific flexibilities, will be sub-optimal. Organizations should plan (30-40%) technology budgets for complementary organizational capabilities: change management, employee training, process redesign, and change management strategies. This contrasts with the estimates of (20–25%) [112] in developed economies; adaptation problems in emerging markets were larger than those in developed markets.
4- **Phased Implementation Strategy:** Limited resources in developing countries; proposed a three-phase implementation plan: Phase 1 focuses on doable BDAC and high ROI foundational capabilities; Phase II generalizes on enabling the AIDC framework for CA; Phase 3 to enhance BI capabilities after base capabilities mature.

5.4. Local and regional comparisons and considerations

Content-wise, the Iraqi telecommunication case is particularly interesting from the point of view of showcasing the institutional and infrastructural domains where the technology-performance relation takes place and provides a comparative from other studies in the region.

1. **Regulatory Environment Impact.** Separately affect assessment of technology and performance in four other countries of the study are the cases when technology capabilities are mediated by the regulatory environment. From the perspective of performance, the situation in Iraq is distinct – while relatively recent changes toward a more competitive environment in telecommunications were a disruptive effect on the study region, they served as a catalyst for subsequent technological adoption and strategical development in the sector. The most striking feature of four countries is regulatory compliance, with presenting an ambiguous nature that might enhance mediation. Iraq is an exceptional example due to its weak regulatory framework; local and foreign researchers often refer to it as both an immature and untraceable for organizations. In this case, the high mediation effects might be explained by the relatively high rate at which organizations adapted to the adaptive compliance requirements, making strategic flexibility more useful compared to stable but less turbulent regulatory environments.
2. **Triggers due to infrastructure.** For the same reason, technology capabilities mediate performance to a greater extent in the case of Iraq comparing to the Gulf States. While local or domestic ownership in Case A and B countries might seek restrictive returns on investments into technology based due to highly competitive and saturated markets, the Iraqi ISPs are confronted with an emerging market, where the development of any kind of technology translates into a competitive advantage. The low-base effect is indicative in our study since it comes as the strong and consistent correlations.
3. **cybersecurity landscape.** Moreover, AIDC is confronted with a broader spectrum of actual cybersecurity threats in the region of the activity than its neighboring counterparts who are 'acceding more than ever' on the religious spectrum. In this case, it is not even an opportunity in Iraq, but a risk that is quickly becoming existential in terms of defensive significance. The direct effect of the cybersecurity capabilities, by which the SF and ENT activities are influenced, appears to be unique – in the conditions, where adequate cybersecurity capacity allows developing the market and innovation processes which, for the number of the other reasons, would be too risky.
4. **Talent availability/costs.** The comparison with the UAE or Jordan indicates that Iraqi

organizations have too little technically proficient talent with the skills required, and this may be the 4 reasons why BI underperformed. Bi tools require shallow analytical capabilities to deliver the best value, as BDAC and AIDC can deliver the levels of the value as in an automated way. This indicates that the specific clusters of organizations in Iraqi environment should choose technologies with the minimum human capital investment required at least until the educational infrastructure for the industry is developed.

5. **Local matchmaking possibilities.** In comparison with Iraqi ISPs, the market of participation shows high chances of the best opportunity from the regional level. Jordan and the UAE have a common history and social context that makes the common scope with Iraq very different on the first view. Still, the countries have some experience with developing BI sophistication incrementally and better implementing AI and security. The same pathways could be chosen for Iraq institutionally. This indicates that best practices are not generic but rather locally developed. All these above considerations make a general claim that technology-organization relationships with the end-to-end business model are canonical, but their strength and implementation pathways are locally related so it's better practices are not generic.

5.5. Limitations and future research

There are some limitations that need to be acknowledged in such a study, all of which would suggest areas for future research development.

1- **Methodological issues:** The cross-sectional design, which was employed in this study, can neither provide for causation, nor the time order of these mediation models [113]. Longitudinal and repeated measures design are necessary for future research to capture the dynamic adaptation of technology adoption processes in organizations. More specifically a three-wave descriptive longitudinal 18-24 month design would begin to capture temporal processes of technology adoption and performance outcomes [114].

2- **Sample and Generalizability Limitations:** The sample of 113 participants was adequate for basic PLS-SEM analysis, even test of mediation [115], but it is a boundary to generalize the effects. Given that the only industry is being focused on (Iraqi economic and social condition) within a case study city, puts more limitation on the external validity. This could be pushed even further in future studies, such as by featuring larger and multi-sectors sample size and cross-sectoral validation with the banking, healthcare and manufacturing sectors to guarantee that the model is robust across distinct organizational environments [116].

3- **Contextual factors:** This study was completed in Iraq's unique operational environment, political instability, an uncertain mature development of digital infrastructures and vague regulations that may impact the adoption of ISPs in significant way [117]. Future studies should explicitly test for such contextual factors; for example by replicating analyses with measures reflecting the readiness of infrastructure, or support and benefits from regulations or political stability as possible moderating variables. For comparative research on other developing economies with different digital maturities, more insights into environmental boundary conditions would be helpful [118].

4- **Measurement bias:** Depending on self-report scales may introduce common method variance – primarily when it comes to technology capabilities, and organization performance results [119]. Future work should consider objective criteria like system performance, third-party technology audits and company financial performance measures based on the company's metric actions. Triangulating the qualitative interviews with both IT managers and senior executives would provide more insight into fine grained mechanisms of ISP adaptation [120].

5- **Theoretical and practical extensions:** The role of organizational culture, forms of leadership, and change management practices as mediating or moderating factors should be considered by future researchers as additional factors that may also play a significant role in the adoption process of ISP. There will likely be rich theoretical knowledge and practical management implications for organisations dealing with digital changes in emerging markets. This will be achieved through a mixed-methods approach that uses quantitative survey research and performs in-depth case studies [121].

6. Conclusion

In this research, the correlations between AIDC, BDAC, BI, SF, and ENT among internet service providers in Iraq were examined, with a special focus on the mediating value of SF. The results indicate that the three technology capabilities are strong in improving SF and ENT both indirectly and directly.

The contribution of this paper has been on the theoretical front, with the showing of mediation effects of SF between technology and ENT, developing the theory related to dynamic capability and showing how emergent technologies become strategic in the economy of a developing country. All of the ten hypotheses were confirmed, providing strong support for both direct effects and a mechanism of mediation.

The results offer a substantial strategic lead in the technological skill set of firms and underline the extreme importance of achieving SF as an enabling capability. Both organizations are expected to include cross IKP strategies in technology investments that should both directly and indirectly provide for greater flexibility.

Building from the findings of partial mediation, we can assume that SF is an important organization capability that helps translate IT investment outcomes into entrepreneurial success. This insight has major implications for the organization of technology investments and the development of adaptive skills by firms.

To enhance our views on the mediating devices of TC and on organizational results, future research should continue along the same path to explore these relationships in longitudinal designs, larger sample sizes, and diverse situations. It may be helpful to combine objective measures and qualitative research to obtain further information about the mechanisms underlying those relationships.

Conflicts of interest

The authors show a lack of conflict of interest. This study was conducted privately, without any financial aid or influence from commercial organizations that may present a conflict of interest. Each of the authors gave considerable input in terms of conception, design, data collection, analysis, and writing of this study.

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Author contributions

Firas R. Y. Alazzawi: Conceptualization, Methodology, Data Collection, Formal Analysis, Writing - Original Draft, Supervision, Literature Review, Validation, Writing - Review and Editing, and Visualization. Othman I. A. Alkhfaji: Supervision, Writing - Review and Editing and approved the nal version of manuscript.

Data availability

The data that support the findings of this study are available on request from the corresponding author.

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