Future of Work and Digital Management Journal

Article type:
Original Research

Article history:
Received 26 November 2024
Revised 12 February 2025
Accepted 26 February 2025
Published online 01 April 2025

Identification of Accounting Factors in the Development of Knowledge-Based Companies

Moein. Ilaghi Hosseini[1], Abbasali. Haghparast[2*], Alireza. Hirad[3], Habib. Piri[4]

1 Liva Healthcare, Research and Innovation, 1434 Copenhagen, Denmark
2 Research Unit for General Practice, Department of Public Health, University of Southern Denmark,5230 Odense, Denmark

Corresponding author email address:
aa.haghparastt@iau.ir

How to cite this article:
Ilaghi Hosseini, M. , Haghparast, A. , Hirad, A. & Karimi, M. (2025). Identification of Accounting Factors in the Development of Knowledge-Based Companies. *Future of Work and Digital Management Journal,* *3*(2), 1-17. https://doi.org/10.61838/fwdmj.136

ABSTRACT

This study was conducted with the aim of identifying accounting factors in the development of knowledge-based companies. The required data were collected through interviews with 15 participants, including faculty members in the field of accounting and accountants working in knowledge-based companies. Using the fuzzy Delphi method and interpretive structural modeling (ISM), the accounting factors contributing to the development of knowledge-based companies were identified. Based on the exploratory model analysis, the study determined five main factors and 25 sub-factors at four hierarchical levels. At the fourth level, financial management and planning include dimensions such as accurate budgeting for research and development, cash flow management, debt and working capital management, and optimization of financial resources. Additionally, auditing and compliance at the fourth level encompass adherence to national and international accounting standards, transparency in financial reporting, regular internal and external auditing, maintaining the company's financial credibility, and accountability and reporting to stakeholders. At the third level, technology and innovation in accounting consist of using advanced accounting software, implementing cloud technologies and data mining, automating financial and accounting processes, analyzing financial data, employing artificial intelligence in financial management, and updating accounting systems with new technologies. At the second level, the strategic and business development dimension of accounting involves financial analysis to support strategic decisions, evaluating research and development projects from a financial perspective, financial planning for market development and investment, accounting support for attracting investors, developing strategic financial capacity, creating financial capability for sustainable growth and development, and aligning financial objectives with the company's overall strategic goals. Finally, the factors and dimensions at the previous three levels collectively contribute at the first level to the development of knowledge-based companies, with dimensions such as financial analysis to support strategic decision-making, evaluation of research and development projects from a financial perspective, and financial planning for market development and investment.

Keywords: knowledge-based development, accounting, knowledge-based companies, accounting factors

Introduction

The insurance industry is undergoing a profound structural reconfiguration as digital technologies reshape risk discovery, pricing, distribution, claims, and even the institutional logic of intermediation. Under the umbrella of "InsurTech," incumbent carriers and new entrants are assembling stacks that combine cloud-native architectures, data-intensive analytics, automation, and platform partnerships to deliver outcomes that are faster, more transparent, and—critically—more personalized across the policy lifecycle [1-3]. While the rhetoric of transformation is now ubiquitous, empirical and design-oriented research has begun to map the concrete levers that translate technology into measurable performance in insurance enterprises—innovation capability, digital operating models, and governance arrangements that balance agility with risk and compliance [4]. Against this backdrop, a feasibility-oriented model for “smart insurance” must take seriously not only the component technologies but also their orchestration into coherent processes and institutions that deliver value to customers, ecosystems, and regulators simultaneously.

Artificial intelligence and machine learning (AI/ML) are central to this reconfiguration because they convert heterogeneous data exhaust into predictive and prescriptive signals for underwriting, claims triage, fraud detection, retention, and cross-sell. Recent syntheses show steep growth in AI/ML adoption across underwriting and claims, accompanied by new bibliometric clusters around explainability, fairness, and MLOps in insurance settings [5]. In parallel, practitioner research documents how big-data infrastructures and analytics pipelines extend the informational frontier, enabling carriers to ingest telematics, IoT device streams, geospatial imagery, and behavioral data for real-time decisioning [6]. The promise hinges on reliable data governance and model-risk management: models that are accurate in training but brittle in production can destroy value when claims volumes spike or when covariate shift undermines risk segmentation. Designing a smart insurance model therefore requires embedding AI/ML capabilities within resilient data platforms, model monitoring, and feedback loops—capabilities that our framework treats as separable but tightly coupled layers [1, 2].

A second pillar is distributed ledger technology and smart contracts, which reconfigure the contract layer itself. Concept and maturity assessments suggest that while blockchain is no panacea, there are well-defined use cases where shared, tamper-evident records and autonomous contract execution reduce reconciliation costs and accelerate claims—particularly in parametric products, reinsurance treaties, and multi-party processes [7]. Methodological work has specified how to implement blockchain-backed insurance for natural hazards, coupling oracles and event data with robust policy logic [8], while engineering studies show end-to-end solutions for parametric insurance in transport and logistics, where external data triggers automated indemnification under predefined conditions [9]. Architecture and governance remain decisive: aligning business process management (BPM) with on-chain logic clarifies roles, auditability, and exception handling [10], and cyber-insurance prototypes layering self-sovereign identity (SSI) on blockchain demonstrate privacy-preserving claims and credential flows [11]. More broadly, institutional analyses caution that enforceability, dispute resolution, and consumer protection must be designed around smart contracts to avoid shifting legal and operational risk to customers [12].

The sensorized world expands these opportunities and risks. IoT deployments in vehicles, homes, workplaces, and supply chains create continuous “evidence streams” that can price exposure dynamically, support loss prevention, and trigger automated claims; cloud–IoT reference models for integrated disaster management illustrate the operational patterns—ingest, detect, respond—needed when physical risk unfolds in real time [13]. At the same time, sector-specific models are emerging: for marine cargo, smart insurance concepts tie telemetry and workflow automation to coverage conditions [14]; for accidents, IoT-based detection and automated claim initiation have been prototyped with end-to-end paths from device to payout [15]. Smart home insurance has become a testbed for these ideas, with collaborative pricing schemes that require novel mechanism design to align insurer–insuree incentives while processing high-frequency device data [16]. Health insurance intensifies privacy, consent, and cybersecurity requirements; secure, technology-driven architectures and empirical validations demonstrate how confidentiality and integrity constraints can be embedded without blocking data-driven services [17]. Complementary security frameworks and reference designs for blockchain-based insurance emphasize authenticated data feeds, permissioning, and resilient contract upgrades as first-class design goals [18].

Digital transformation, however, is not only about components; it is an institutional process unevenly distributed across markets and lines of business. Country- and sector-level studies illustrate how policy, data infrastructure, and customer readiness shape adoption pathways. In China, post-pandemic acceleration brought remote distribution, digital claims, and ecosystem partnerships to the fore, with carriers reorganizing around platform logics and customer journeys rather than legacy product silos [19]. In rural development contexts, digital inclusive finance shows how data and mobile channels integrate primary, secondary, and tertiary industries, offering analogies for rural insurance distribution and agricultural risk pooling [20]. Conversely, research on Bangladesh documents structural bottlenecks—digital identity coverage, literacy, regulatory clarity, and distribution fragmentation—that complicate the creation of digital insurance businesses, highlighting the need for staged capability building and policy coordination [21]. These contrasts suggest that feasibility models must be sensitive to institutional baselines: the same technical pattern will have divergent costs and benefits depending on market readiness and regulatory pragmatism [1, 2].

Climate and catastrophe risk sharpen the value proposition for automation and parametrics. Theories and evidence on climate-smart insurance indicate that timely payouts and risk-reduction incentives strengthen household and firm adaptive capacity, but only when contract design and distribution are tuned to local realities [22]. Multidisciplinary implementations for natural hazards show how event detection, oracle governance, and index calibration can make parametric contracts credible and scalable [8]. Ethical scrutiny is essential: smart information systems in insurance raise questions of opacity, surveillance, and fairness in pricing and claims decisioning; case studies urge proactive ethical governance and stakeholder engagement rather than retrofit controls after deployment [23]. Even product innovation trajectories—such as "smart product insurance," where coverage is embedded into connected devices—must anticipate consent management, dark patterns in app interfaces, and distributional impacts of risk-based pricing [24]. A feasibility model that centers organizational culture, change management, and stakeholder trust is therefore not a "soft" add-on but a core mitigant against technological and reputational risk [2, 3].

Market structure and ecosystem coordination further condition outcomes. Studies of insurer–tech collaboration highlight operating models in which incumbents open APIs, curate data marketplaces, and co-innovate with startups on narrowly scoped use cases before scaling [1]. In logistics and cargo, smart contracts knit together shippers, carriers, and insurers around verifiable milestones; empirical and engineering evidence shows both feasibility and the need for standardized data schemas and dispute pathways [9, 14]. In cyber insurance, architectures that combine on-chain credentials with off-chain analytics illustrate a path to lower friction and higher assurance across underwriting and claims [11]. More generally, redefining insurance through technology requires strategy choices about "where to play" (e.g., embedded distribution vs. stand-alone channels) and "how to win" (e.g., distinctive data assets, speed of model iteration, or experience-led service design) [2]. Bibliometric and synthesis work confirms that firms that link AI/ML capability building with process redesign and talent development realize more of the theoretical gains than those that layer models on unchanged workflows [4-6].

From a governance standpoint, the feasibility of "smart" models rests on codifying rules and responsibilities at the contract, process, and organizational levels. Business-process–aware smart contract frameworks align policy wording, underwriting authorities, claims adjudication, and audit requirements with programmable logic to reduce ambiguity and operational risk [10]. InChain-style architectures and secured insurance frameworks add identity, access control, and cryptographic assurances to the mix [11, 18]. IoT-heavy configurations, particularly in property and catastrophe domains, depend on resilient cloud backbones and well-specified incident response, as demonstrated in integrated disaster management patterns [13]. Because customers experience the service layer most directly, collaborative pricing and incentive design in smart home insurance show how insurers can co-produce risk reduction with policyholders, though not without addressing equity and behavioral responses [16]. Institutional commentary suggests regulators will increasingly scrutinize smart contracts' consumer outcomes, mandating explainability, recourse mechanisms, and defaults that protect vulnerable groups [12].

Strategic alignment with sustainability adds a further axis of feasibility. Green human resource management and green supply chain practices have been empirically linked to sustainable performance, implying that smart insurance programs should not only digitize but also "green" their operations and partner networks [25]. This resonates with environmental-risk products, where index-based or usage-based coverage aligns financial incentives with mitigation behaviors [8, 22]. At the same time, industrial and regional development agendas will push insurers to support digital inclusion—rural distribution, MSME enablement, and interoperable payment rails—consistent with evidence from inclusive finance contexts [20]. Taken together, these strands suggest that the feasibility of smart insurance is path-dependent: it emerges from reinforcing loops between technology maturity, process redesign, workforce skills, ecosystem standards, and public policy [1-3].

Finally, feasibility is an empirical question about fit: which capabilities, in what sequence, for which lines and segments? Research on the technology innovation level of insurance firms indicates that leadership commitment, cross-functional data teams, and investment in reusable platforms are strong predictors of InsurTech performance, but effects vary by market and by the orientation of partners and distributors [4, 19]. Case-led contributions across domains—parametric logistics, cyber identity, marine cargo, health, home, and disaster management—accumulate into a design space where smart contracts, AI/ML, IoT, and cloud are not buzzwords but configurable building blocks [9, 11, 13, 14, 16, 17]. Early conceptualizations of smart product insurance foreshadowed this embedded, data-rich future [24], and institutional analyses now chart the guardrails required to scale without eroding trust [7, 12, 23]. Building on this literature, the present study proposes and tests a comprehensive, multi-dimensional model that integrates technological, organizational, regulatory, market, and sustainability factors to assess and guide the establishment and implementation of smart insurance in practice.

Methodology

The present study is exploratory in nature, as it addresses an issue that has not previously been examined in this way and at this level. To achieve this aim, a mixed-methods approach was employed, with the objective of integrating qualitative and quantitative research methods to develop an appropriate strategy for fulfilling the study's goals. In exploratory research designs, the researcher seeks to investigate an unclear or poorly understood situation. For this purpose, qualitative data are initially collected. Conducting this stage enables the researcher to describe numerous aspects of the phenomenon under investigation. Based on this initial identification, the components needed to design the model are determined.

Subsequently, the researcher uses the fuzzy Delphi method to refine and validate the identified components and then applies interpretive structural modeling (ISM) to design the research model. To determine the importance of the indicators and to screen and prioritize the most significant ones, the fuzzy Delphi technique was adopted. One of the key advantages of the fuzzy Delphi method compared to the traditional Delphi technique in screening indicators is the ability to condense and filter items efficiently within a single phase.

Given the research aims and questions, and because this study employs a mixed-methods design, there are no strict limitations on sampling procedures; it is possible to use one or more strategies to select participants. Furthermore, as the logic of mixed-methods design indicates, combined sampling strategies should include both probability-based quantitative sampling and non-probability-based qualitative and quantitative approaches.

The study population consisted of all accounting professors who are university faculty members with at least 10 years of executive experience. The sample size in the qualitative stage was determined through theoretical saturation, meaning data collection continued until no new concepts emerged from the interviews. For the semi-structured interviews, 15 accounting faculty members were selected. In the quantitative stage, the sample size was determined based on the Morgan table, covering the full statistical population. In the interview stage, 15 interviews were conducted with 15 experts until theoretical saturation was reached.

Findings and Results

In this study, data analysis was conducted using the fuzzy Delphi method and interpretive structural modeling (ISM), which are described step by step below.

Fuzzy Delphi Method

At this stage, interviews were initially conducted with experts on topics related to the subject matter. The analysis of the interview data resulted in the identification of 40 items. Because these items were extracted from the interviews, the fuzzy Delphi method was applied to achieve consensus among the experts. Accordingly, a questionnaire containing all 40 items was designed and distributed to the experts. After data collection and analysis (as discussed in Chapter Three), items with a defuzzified value higher than the threshold of 0.80 were approved (25 items), while the remaining items were rejected. Table 1 summarizes the fuzzy Delphi process.

Table 1

Results of the Fuzzy Delphi Method

No.	Item	L	M	U	Defuzzified Value	Status
1	Accurate budgeting for research and development	0.616	0.866	0.983	0.82	Approved
2	Cash flow management	0.600	0.850	0.983	0.81	Approved
3	Debt and working capital management	0.616	0.866	0.983	0.82	Approved
4	Optimization of financial resources	0.633	0.883	0.983	0.83	Approved
5	Compliance with national and international accounting standards	0.683	0.933	1.000	0.87	Approved
6	Transparency in financial reporting	0.633	0.883	1.000	0.84	Approved
7	Regular internal and external auditing	0.633	0.883	1.000	0.84	Approved
8	Prevention of financial misconduct	0.435	0.700	0.916	0.68	Rejected
9	Maintaining company financial credibility (initial)	0.550	0.800	0.966	0.77	Rejected
10	Maintaining company financial credibility (validated)	0.616	0.866	0.966	0.82	Approved
11	Accountability and reporting to stakeholders	0.666	0.916	0.983	0.86	Approved
12	Use of advanced accounting software	0.600	0.850	1.000	0.82	Approved
13	Adoption of cloud technologies and data mining	0.683	0.933	1.000	0.87	Approved
14	Automation of financial and accounting processes	0.583	0.833	1.000	0.81	Approved
15	Financial data analytics	0.616	0.866	1.000	0.83	Approved
16	Designing new accounting software	0.550	0.800	0.983	0.78	Rejected
17	Digital accounting training	0.550	0.800	0.950	0.77	Rejected
18	Cybersecurity of financial data	0.550	0.800	0.983	0.78	Rejected
19	Application of artificial intelligence in financial management	0.600	0.850	0.983	0.81	Approved
20	Big data management in finance	0.550	0.800	0.983	0.78	Rejected
21	Updating accounting systems with new technologies	0.583	0.833	0.983	0.80	Approved
22	Use of key financial performance indicators	0.533	0.783	0.983	0.77	Rejected
23	Financial analysis to support strategic decisions	0.600	0.850	0.983	0.81	Approved
24	Evaluation of R&D projects from a financial perspective	0.600	0.850	0.983	0.81	Approved

25	Financial planning for market development and investment	0.600	0.850	0.983	0.81	Approved
26	Tax management and optimization of company financial structure	0.533	0.783	0.983	0.77	Rejected
27	Accounting support in attracting investors	0.600	0.850	1.000	0.82	Approved
28	Use of specialized accounting consultancy	0.533	0.783	0.983	0.77	Rejected
29	Cost-benefit analysis of projects	0.550	0.800	0.983	0.78	Rejected
30	Development of strategic financial capacity	0.600	0.850	1.000	0.82	Approved
31	Encouragement of continuous learning and innovation	0.501	0.766	0.933	0.73	Rejected
32	Updating accounting knowledge with latest standards	0.550	0.800	0.950	0.77	Rejected
33	Motivation and financial reward systems	0.550	0.800	0.983	0.78	Rejected
34	Improving financial performance to increase productivity	0.550	0.800	0.950	0.77	Rejected
35	Creating financial capacity for sustainable growth and development	0.583	0.833	0.983	0.80	Approved
36	Alignment of financial objectives with corporate strategic goals	0.600	0.850	1.000	0.82	Approved
37	Capital structure optimization	0.600	0.850	0.983	0.81	Approved
38	Development of financial reporting systems	0.583	0.833	0.983	0.80	Approved
39	Development of optimal and targeted financial management	0.600	0.850	0.983	0.81	Approved
40	Tax management and use of exemptions	0.550	0.800	0.983	0.78	Rejected

As Table 1 shows, out of the 40 items extracted from the interviews, 15 were rejected, and 25 were approved by all experts. These items were categorized into five main variables. Table 2 presents the grouping of the approved items into their respective variables.

Table 2

Categorization of Items into Components

No.	Items	Components
1	Accurate budgeting for research and development	Financial management and planning
2	Cash flow management	
3	Debt and working capital management	
4	Optimization of financial resources	
5	Compliance with national and international accounting standards	Auditing and compliance
6	Transparency in financial reporting	
7	Regular internal and external auditing	
8	Maintaining company financial credibility	
9	Accountability and reporting to stakeholders	
10	Use of advanced accounting software	Technology and innovation in accounting
11	Adoption of cloud technologies and data mining	
12	Automation of financial and accounting processes	
13	Financial data analytics	
14	Application of artificial intelligence in financial management	
15	Updating accounting systems with new technologies	
16	Financial analysis to support strategic decisions	Strategic and business development dimension of accounting
17	Evaluation of research and development projects from a financial perspective	
18	Financial planning for market development and investment	
19	Accounting support in attracting investors	
20	Development of strategic financial capacity	
21	Creating financial capacity for sustainable growth and development	
22	Alignment of financial objectives with corporate strategic goals	
23	Capital structure optimization	Development of knowledge-based companies
24	Development of financial reporting systems	
25	Development of optimal and targeted financial management	

At this stage, the content validity ratio (CVR) was calculated for each component. For this purpose, a questionnaire was distributed among experts asking them to evaluate each component using a three-point scale: “essential,” “useful but not essential,” and “not necessary.” Because the number of experts was 15, if the CVR value for any component exceeded 0.49, the content validity of that component was confirmed. The results of applying the content validity ratio (CVR) are presented in Table 3.

Table 3

CVR Values for Each Component

No.	Components	Items	CVR Value	Result
1	Financial management and planning	1–4	1	Approved
2	Auditing and compliance	5–9	1	Approved
3	Technology and innovation in accounting	10–15	1	Approved
4	Strategic and business development dimension of accounting	16–22	1	Approved
5	Development of knowledge-based companies	23–25	1	Approved

The results showed that all five variables were accepted and that the experts fully agreed on their inclusion in the model design.

Interpretive Structural Modeling (ISM)

Step 1: Identification of Components Related to the Problem

As described in the previous section, 25 approved items extracted from expert interviews were grouped into five components. The content validity ratio (CVR) confirmed these components. All five components were approved by the experts and were therefore used to develop the model.

Table 4

Identified Components for Model Design

No.	Components
1	Financial management and planning
2	Auditing and compliance
3	Technology and innovation in accounting
4	Strategic and business development dimension of accounting
5	Development of knowledge-based companies

Step 2: Formation of the Structural Self-Interaction Matrix (SSIM)

After defining the components, another matrix-based questionnaire was designed. Experts were asked to examine the components in pairs and, using the scale provided in Chapter Three, determine the relationships among them. According to Bolanos et al. (2005), to integrate expert opinions, the aggregated responses for each cell of the matrix should be used. The results obtained from the expert questionnaires regarding the components under study are presented in Table 5.

Table 5

Results Obtained from Expert Questionnaires

No.	Components	1	2	3	4	5
1	Financial management and planning	0	25	36	39	28
2	Auditing and compliance	24	0	37	40	27
3	Technology and innovation in accounting	10	10	0	36	29
4	Strategic and business development dimension of accounting	8	12	20	0	42
5	Development of knowledge-based companies	10	10	14	20	0

Step Three: Formation of the Initial Reachability Matrix

The initial reachability matrix is created by determining the relationships in binary form (0 and 1) based on the structural self-interaction matrix and is obtained in two stages:

In the first stage, a unified numerical scale is considered, and the numbers in the previous table are compared to this threshold. If the number in the table is greater than the threshold value, it is replaced by 1 in the new table; otherwise, it is replaced by 0.

Accordingly, following the logic proposed by Bolanos et al. (2005), all numbers in Table 5 that are less than 30 are converted to zero (0), and numbers equal to or greater than 30 are converted to one (1). Table 6 shows the structural self-interaction matrix after this transformation.

Table 6

Structural Self-Interaction Matrix

No.	Components	1	2	3	4	5
1	Financial management and planning	0	0	1	1	0
2	Auditing and compliance	0	0	1	1	0
3	Technology and innovation in accounting	0	0	0	1	0
4	Strategic and business development dimension of accounting	0	0	0	0	1
5	Development of knowledge-based companies	0	0	0	0	0

In the second stage, the matrix obtained in the first step (Table 6) is added to the identity matrix to produce the initial reachability matrix. This step converts all diagonal elements from 0 to 1. Table 7 shows the initial reachability matrix.

Table 7

Initial Reachability Matrix

No.	Components	1	2	3	4	5
1	Financial management and planning	1	0	1	1	0
2	Auditing and compliance	0	1	1	1	0
3	Technology and innovation in accounting	0	0	1	1	0
4	Strategic and business development dimension of accounting	0	0	0	1	1
5	Development of knowledge-based companies	0	0	0	0	1

Step Four: Creation of the Final Reachability Matrix

After the initial reachability matrix was obtained, the secondary relationships among the components were checked. A secondary relationship exists when component *i* leads to component *j*, and component *j* leads to component *k*; consequently, component *i* also leads to component *k*. If this condition is not met in the initial reachability matrix, the matrix must be adjusted and the missing relationships added. This process is called “stabilizing the initial reachability matrix.”

In this step, all secondary relationships among the components were examined, and three secondary relationships were identified. These are marked with an asterisk (*1) in Table 8. Additionally, the driving power and the dependence of each component are shown. The driving power of a component is calculated by summing the number of components it influences plus itself. The dependence of a component is calculated by summing the number of components it is influenced by plus itself.

Table 8

Final Reachability Matrix

No.	Components	1	2	3	4	5	Driving Power
1	Financial management and planning	1	0	1	1	*1	4
2	Auditing and compliance	0	1	1	1	*1	4
3	Technology and innovation in accounting	0	0	1	1	*1	3
4	Strategic and business development dimension of accounting	0	0	0	1	1	2
5	Development of knowledge-based companies	0	0	0	0	1	1
Dependence		1	1	3	4	5	

Step Five: Determination of Relationships and Hierarchical Leveling of Factors

In this step, using the reachability matrix, the input and output sets for each component are determined.

- The **output set** of a component includes the component itself and all other components it influences, identified by the “1”s in its row.
- The **input set** of a component includes the component itself and all other components that influence it, identified by the “1”s in its column.

After determining the input and output sets, their intersections are identified for each component. Components whose output and intersection sets are identical are placed at the highest level of the interpretive structural model. To identify the next level, the highest-level components are removed from the matrix, and the process is repeated until the full hierarchy of the system is established.

Table 9.

First Iteration of Leveling

No.	Components	Output Set	Input Set	Intersection	Level
1	Financial management and planning	5, 4, 3, 1	1	1	
2	Auditing and compliance	5, 4, 3, 2	2	2	
3	Technology and innovation in accounting	5, 4, 3	3, 2, 1	3	
4	Strategic and business development dimension of accounting	5, 4	4, 3, 2, 1	4	
5	Development of knowledge-based companies	5	5, 4, 3, 2, 1	5	1

As shown in Table 9, the output and intersection sets of component 5 (Development of knowledge-based companies) are identical; therefore, this component is placed at Level 1 and removed from further calculations. The next iterations of the leveling process are summarized in Table 10.

Table 10

Subsequent Leveling Iterations

Iteration	Components	Output Set	Input Set	Intersection	Level
Second	Strategic and business development dimension of accounting	4	4, 3, 2, 1	4	2
Third	Technology and innovation in accounting	3	3, 2, 1	3	3
Fourth	Financial management and planning	1	1	1	4
	Auditing and compliance	2	2	2	4

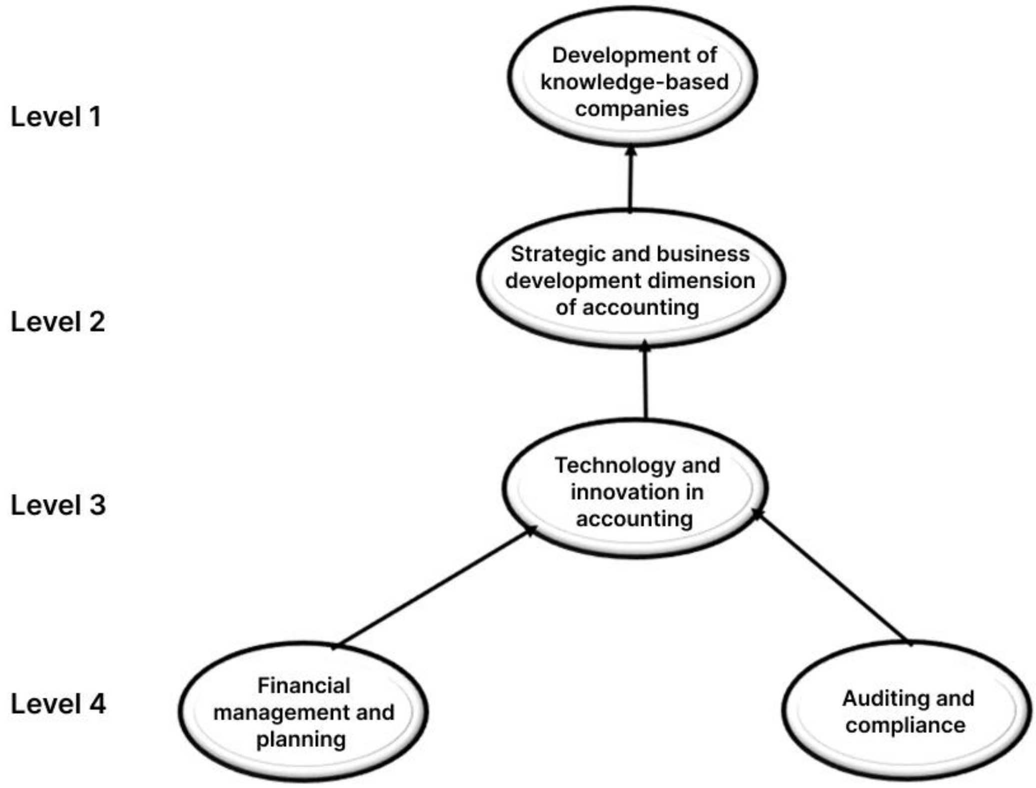
Ultimately, components 1 (Financial management and planning) and 2 (Auditing and compliance) occupy the fourth (top) level of the model, completing the hierarchical structuring.

Step Six: Drawing the Final Model

At this stage, using the determined levels and the final reachability matrix, an initial model was drawn and then simplified by removing transitive links. The final interpretive structural model (ISM) derived from the components influencing the development of knowledge-based companies is presented in Figure 1.

Figure 1

Final ISM Model



As illustrated in Figure 1, the five components of the model are structured across four hierarchical levels. Component 5 (Development of knowledge-based companies) is at the first (lowest) level and is the most dependent and influenced element of the model. At the top (fourth) level are components 1 (Financial management and planning) and 2 (Auditing and compliance), which are the most influential and driving elements. At the second level is component 4 (Strategic and business development dimension of accounting), which influences component 5 and is itself affected by lower-level elements. At the third level is component 3 (Technology and innovation in accounting), which impacts higher-level elements while being influenced by the top-level drivers. No direct relationships were found between the two components at the fourth level.

Step Seven: Analysis of Driving Power and Dependence (MICMAC Diagram)

In this step, the components are categorized into four groups:

1. **Autonomous components (Quadrant 1):** Low driving power and low dependence; relatively isolated with minimal relationships.
2. **Dependent components (Quadrant 2):** Low driving power but high dependence on other components.
3. **Linkage components (Quadrant 3):** High driving power and high dependence; highly interactive and sensitive to change.
4. **Independent (driving) components (Quadrant 4):** High driving power with low dependence; considered key drivers.

Driving power and dependence values are obtained by summing the “1” entries in each row (for driving power) and each column (for dependence) of the final reachability matrix.

Table 11

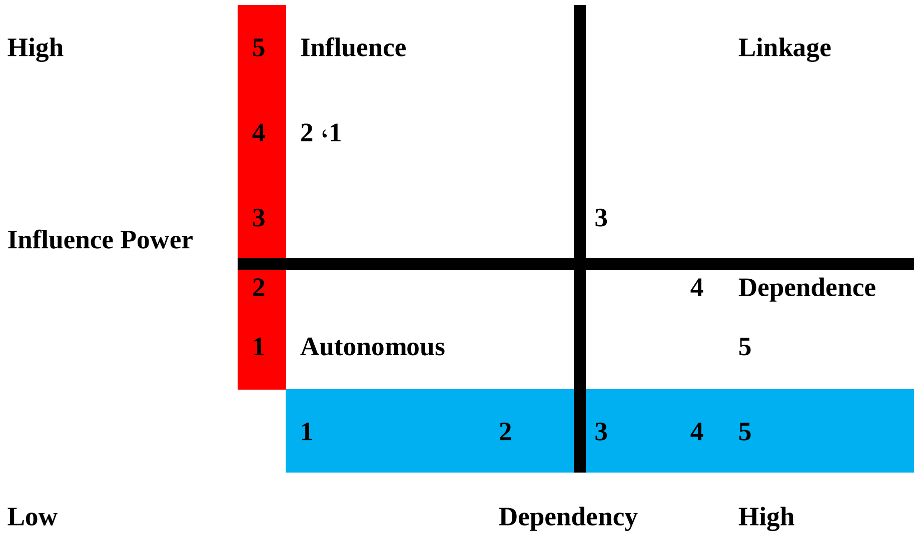
Driving Power and Dependence of Components

No.	Components	Dependence	Driving Power
1	Financial management and planning	1	4
2	Auditing and compliance	1	4
3	Technology and innovation in accounting	3	3
4	Strategic and business development dimension of accounting	4	2
5	Development of knowledge-based companies	5	1

Using these values, the MICMAC diagram was constructed as shown in Figure 2.

Figure

MICMAC Matrix



As the MICMAC diagram shows, components 4 (Strategic and business development dimension of accounting) and 5 (Development of knowledge-based companies) are located in the dependent quadrant, meaning they have low driving power but high dependence. Components 1 (Financial management and planning) and 2 (Auditing and compliance) are positioned in the driving quadrant, having strong influence with minimal dependence. Component 3 (Technology and innovation in accounting) falls within the linkage quadrant, indicating moderate driving power and dependence.

At this point, the interpretive structural modeling (ISM) process for developing the conceptual model of accounting's role in the growth and advancement of knowledge-based companies is complete.

Discussion and Conclusion

The findings of this study highlight a coherent and multi-level structure of accounting factors that drive the development of knowledge-based companies. Using interpretive structural modeling (ISM), five major components—financial management and planning, auditing and compliance, technology and innovation in accounting, the strategic and business development dimension of accounting, and development of knowledge-based companies—were hierarchically organized. At the top of the model, financial management and planning and auditing and compliance emerged as the most influential drivers. This aligns with research showing that robust financial planning and adherence to accounting standards are foundational for innovation-driven firms to achieve sustainable growth [26, 27]. Strong cash flow management, precise R&D

budgeting, and optimization of financial resources create the financial agility needed for knowledge-based companies to invest in technology and talent while maintaining operational stability [28, 29]. Moreover, effective auditing and compliance reduce information asymmetry, increase stakeholder trust, and provide a reliable platform for attracting external investment [30, 31].

The pivotal role of technology and innovation in accounting as an intermediate enabler in the model resonates with the ongoing digital transformation of the profession. Our results confirm that implementing advanced accounting software, cloud technologies, data analytics, and artificial intelligence supports both strategic and operational decision-making in dynamic knowledge-intensive contexts [32, 33]. Prior studies have emphasized that digital accounting tools not only automate routine processes but also enhance strategic insight by generating timely, comparable, and data-driven reports [34, 35]. By situating technology and innovation below strategic business development in the hierarchy, the model underscores that digital enablement acts as a bridge, linking core financial controls to higher-level entrepreneurial and market expansion objectives [36, 37]. This sequencing reinforces the argument that digital transformation is not an end in itself but a facilitator of strategic agility and competitiveness [31, 38].

The presence of a distinct strategic and business development dimension within the structure is significant because it reflects the growing recognition that accounting must evolve beyond compliance to inform competitive strategy. Our findings show that capabilities such as financial analysis to support strategic decisions, evaluating R&D projects, and aligning financial objectives with corporate goals are critical to scaling knowledge-based enterprises. This aligns with prior evidence that entrepreneurial orientation and network capabilities enhance performance when supported by adaptive management accounting systems [39, 40]. In particular, Iranian and other emerging-market firms operating under the Fourth Industrial Revolution need models that integrate innovation with financial discipline to remain competitive in fast-changing technological landscapes [28, 41]. Our findings support these perspectives by structurally linking strategic development to both foundational accounting controls and technology adoption.

Another contribution of this study is clarifying how sustainability and resilience thinking can be embedded into accounting for knowledge-based companies. While not an explicit standalone factor in the model, sustainability considerations permeate the influential drivers identified. For example, prudent financial management and compliance with both national and international standards create the transparency necessary for sustainable business practices and long-term stakeholder engagement [42, 43]. The digitalization of accounting further supports sustainability reporting and resource efficiency monitoring [32, 33]. This is consistent with emerging studies that integrate sustainability metrics into strategic management accounting to balance profitability with environmental and social goals [36, 44]. Thus, our results reinforce the idea that advancing toward sustainable, innovation-driven growth requires accounting frameworks capable of capturing non-financial and future-oriented indicators.

Our findings also confirm the significance of comparability and informativeness of accounting information for investor confidence and market stability. The model shows that auditing and compliance, when combined with digital innovation, strengthen transparency and reduce volatility—echoing findings that comparable accounting data mitigates risks such as stock price crashes [26, 31]. For knowledge-based companies seeking to scale globally, adherence to recognized standards while adopting contextually relevant reporting enhances legitimacy and access to capital [30, 45]. This is particularly important in innovation-led markets where intangible assets dominate and traditional balance sheets often fail to convey real value creation [38]. Our hierarchical structure thus provides an actionable roadmap to improve both internal decision-making and external stakeholder communication.

Importantly, the position of “development of knowledge-based companies” at the base of the model highlights its dependent nature—it is the outcome of well-structured financial controls, technology adoption, and strategic orientation. This finding is in line with research stressing that knowledge-based entrepreneurship is an ecosystem result, requiring enabling accounting practices rather than emerging spontaneously [40, 45]. Our model shows that by strengthening the top drivers—financial and compliance capabilities—companies create the conditions for sustainable innovation and competitive advantage [35, 36]. This systemic perspective is especially useful for policy and ecosystem development in emerging economies where knowledge-based entrepreneurship is promoted but lacks financial and governance infrastructure [28, 29].

Moreover, the MICMAC analysis confirms the practical value of distinguishing components by their driving power and dependence. Financial management and auditing, as high-driving-power elements, should be prioritized when building capacity in new or scaling knowledge-based firms. Technology and innovation, being highly interactive (linkage quadrant), require dynamic management and investment because any instability here can cascade through the system [33, 34]. Conversely, the dependent nature of strategic expansion and ultimate development means that interventions at the foundational level can shape the entire growth trajectory. These findings reinforce contemporary calls to reframe accounting as a strategic infrastructure rather than merely a reporting obligation [37, 38].

In summary, the discussion shows that the study contributes theoretically by offering a validated, context-sensitive model that integrates digital innovation, strategic management accounting, and rigorous compliance to support knowledge-based growth. It aligns with global debates on the future of accounting in knowledge economies while providing actionable insights for emerging markets.

Despite its contributions, this research has several limitations. First, the study was based on expert judgment and interviews, which, while valuable for exploratory modeling, may reflect biases or subjective interpretations of accounting priorities. The reliance on a limited number of experts may not fully capture the diversity of perspectives within knowledge-based industries, especially across different technological domains and firm sizes. Additionally, the structural interpretive modeling (ISM) approach, while powerful for clarifying hierarchical relationships, assumes linear and relatively stable interactions between components. In dynamic markets, where feedback loops and non-linear influences are common, these relationships might shift over time. The study also focused primarily on the Iranian knowledge-based ecosystem; contextual and regulatory differences may limit the direct transferability of findings to other economies with distinct financial infrastructures or digital maturity levels.

Future research could address these limitations by employing larger and more diverse samples of experts, including practitioners from multiple industries and international contexts to test the universality of the proposed model. Longitudinal studies would be valuable to track how the relationships among components evolve over time under conditions of technological disruption or regulatory change. Integrating quantitative validation techniques, such as structural equation modeling (SEM), with the ISM approach could strengthen the predictive and explanatory power of the model. Future studies might also explore how emerging technologies such as blockchain, advanced AI, and integrated sustainability dashboards influence the structure and importance of accounting factors for knowledge-based companies. Comparative studies across developed and developing economies could further clarify how institutional quality and market maturity shape the effectiveness of these accounting frameworks.

For practitioners, the study underscores the need to invest first in strengthening core financial management and compliance infrastructures, ensuring that cash flow, budgeting, and auditing systems are robust and transparent. Companies should strategically adopt digital accounting technologies to improve real-time financial insights and agility in decision-making. Management teams are encouraged to integrate strategic management accounting practices, such as scenario planning and innovation-focused financial analysis, into their growth strategies. Policymakers and ecosystem developers can use the hierarchical model to design targeted interventions that reinforce foundational accounting capabilities before promoting large-scale innovation initiatives. Finally, managers of knowledge-based companies should view accounting not as a static reporting function but as a dynamic capability that connects financial discipline with technological adaptation and strategic competitiveness.

Acknowledgments

We would like to express our appreciation and gratitude to all those who cooperated in carrying out this study.

Authors’ Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

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.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

References

[1] S. Ahmad, R. Karim, N. Sultana, and R. P. Lima, "InsurTech: Digital Transformation of the Insurance Industry," in *Financial Landscape Transformation: Technological Disruptions*: Emerald Publishing Limited, 2025, pp. 287-299.

[2] S. Cosma and G. Rimo, "Redefining insurance through technology: Achievements and perspectives in InsurTech," *Research in International Business and Finance*, 2024, doi: 10.1016/j.ribaf.2024.102301.

[3] K. Balaji and E. Ariwa, "Insurtech disruption: Reshaping the future of insurance in the fintech era," in *The Adoption of FintechPB - Productivity Press*, 2024, pp. 247-266.

[4] J. Liu, Ye, Shujun, Zhang, Yujin, Zhang, Lulu, "Research on InsurTech and the technology innovation level of insurance enterprises," *Sustainability,* vol. 15, no. 11, p. 8617, 2023. [Online]. Available: https://www.mdpi.com/2071-1050/15/11/8617.

[5] P. Kumar, S. Taneja, E. Özen, and S. Singh, "Artificial Intelligence and Machine Learning in Insurance: A Bibliometric Analysis," pp. 191-202, 2023, doi: 10.1108/S1569-37592023000110A010.

[6] K. I. Jones and S. Sah, "The Implementation of Machine Learning In The Insurance Industry With Big Data Analytics," *International Journal of Data Informatics and Intelligent Computing,* vol. 2, no. 2, pp. 21-38, 2023, doi: 10.59461/ijdiic.v2i2.47.

[7] V. Gatteschi, F. Lamberti, C. Demartini, C. Pranteda, and V. Santamaría, "Blockchain and smart contracts for insurance: Is the technology mature enough?," *Future Internet,* vol. 10, no. 2, p. 20, 2018, doi: 10.3390/fi10020020.

[8] A. J. Pagano, F. Romagnoli, and E. Vannucci, "Implementation of blockchain technology in insurance contracts against natural hazards: a methodological multi-disciplinary approach," *Environmental and Climate Technologies,* vol. 23, no. 3, pp. 211-229, 2019, doi: 10.2478/rtuect-2019-0091.

[9] H. Dutta, S. Nagesh, J. Talluri, and P. Bhaumik, "A solution to blockchain smart contract based parametric transport and logistics insurance," *IEEE Transactions on Services Computing,* vol. 16, no. 5, pp. 3155-3167, 2023, doi: 10.1109/TSC.2023.3281516.

[10] A. Rachad, L. Gaiz, K. Bouragba, and M. Ouzzif, "A Smart Contract Architecture Framework for Insurance Industry Using Blockchain and Business Process Management Technology," *IEEE Engineering Management Review,* 2024, doi: 10.1109/EMR.2023.3348431.

[11] A. Farao, G. Paparis, S. Panda, E. Panaousis, A. Zarras, and C. Xenakis, "INCHAIN: a cyber insurance architecture with smart contracts and self-sovereign identity on top of blockchain," *International Journal of Information Security,* vol. 23, no. 1, pp. 347-371, 2024, doi: 10.1007/s10207-023-00741-8.

[12] L. D. Sotiropoulos, "Addressing Smart Contracts in the Insurance Sector: Institutional Framework and Practical Aspects," *ENTHA,* vol. 20, p. 22, 2023. [Online]. Available: https://heinonline.org/hol-cgi-bin/get_pdf.cgi?handle=hein.journals/entha20&section=9.

[13] S. Koduru, P. Reddy, and P. Padala, "Integrated disaster management and smart insurance using cloud and internet of things," *International Journal of Engineering & Technology,* vol. 7, no. 2.6, pp. 241-246, 2018, doi: 10.14419/ijet.v7i2.6.10777.

[14] C. B. Santoso, H. Prabowo, H. L. H. S. Warnars, and A. N. Fajar, "Smart Insurance System Model Concept for Marine Cargo Business," in *2021 International Conference on Data Science and Its Applications (ICoDSA)*, 2021, pp. 281-286, doi: 10.1109/ICoDSA53588.2021.9617499.

[15] K. L. Narayanan, C. R. S. Ram, M. Subramanian, R. S. Krishnan, and Y. H. Robinson, "IoT based smart accident detection & insurance claiming system," in *2021 Third international conference on intelligent communication technologies and virtual mobile networks (ICICV)*, 2021, pp. 306-311, doi: 10.1109/ICICV50876.2021.9388430.

[16] D. Biswas and S. R. Vessal, "Smart home insurance: Collaboration and pricing," *European Journal of Operational Research,* vol. 314, no. 1, pp. 176-205, 2024, doi: 10.1016/j.ejor.2023.09.004.

[17] F. Al-Quayed, M. Humayun, and S. Tahir, "Towards a Secure Technology-Driven Architecture for Smart Health Insurance Systems: An Empirical Study," *Healthcare,* vol. 11, no. 16, p. 2257, 2023, doi: 10.3390/healthcare11162257.

[18] A. Hassan, M. I. Ali, R. Ahammed, M. M. Khan, N. Alsufyani, and A. Alsufyani, "Secured insurance framework using blockchain and smart contract," *Scientific Programming,* vol. 2021, pp. 1-11, 2021, doi: 10.1155/2021/6787406.

[19] X. Xie, "Digital transformation trends of China's insurance industry after the COVID-19 pandemic," *Вестник Томского государственного университета. Экономика,* no. 54, pp. 228-238, 2021, doi: 10.17223/19988648/54/13.

[20] H. Ge, B. Li, D. Tang, H. Xu, and V. Boamah, "Research on digital inclusive finance promoting the integration of rural three-industry," *International Journal of Environmental Research and Public Health,* vol. 19, no. 6, p. 3363, 2022, doi: 10.3390/ijerph19063363.

[21] S. Rajput and S. Ahmad, "Challenges and Opportunities in Creating Digital Insurance Business in Bangladesh," *International Journal of Early Childhood Special Education,* vol. 14, no. 5, 2022. [Online]. Available: https://www.researchgate.net/profile/Suraiya-Rajput/publication/375282535_Challenges_and_Opportunities_in_Creating_Digital_Insurance_Business_in_Bangladesh/links/6545a690ce88b87031c2161b/Challenges-and-Opportunities-in-Creating-Digital-Insurance-Business-in-Bangladesh.pdf.

[22] B. Kramer and F. Ceballos, "Enhancing adaptive capacity through climate-smart insurance: Theory and evidence from India," 2018. [Online]. Available: https://ageconsearch.umn.edu/record/275926/.

[23] K. Natalija, "Insurance, smart information systems and ethics: A case study," *The ORBIT Journal,* vol. 2, no. 2, pp. 1-27, 2019, doi: 10.29297/orbit.v2i2.105.

[24] S. Ashraf and A. Zakaria, "Smart Product Insurance," 2020.

[25] A. A. Zaid, A. A. Jaaron, and A. T. Bon, "The impact of green human resource management and green supply chain management practices on sustainable performance: An empirical study," *Journal of Cleaner Production,* vol. 204, pp. 965-979, 2018, doi: 10.1016/j.jclepro.2018.09.062.

[26] H. J. Turtle and K. Wang, "The Value in Fundamental Accounting Information," *Journal of Financial Research,* vol. 40, no. 1, pp. 113-140, 2017, doi: 10.1111/jfir.12119.

[27] A. Tudor, "Income Smoothing and Earnings informativeness," ed, 2010.

[28] Z. Karimi, S. M. Zanjirchi, S. H. Mirfakhrodini, and S. H. Mirghafoori, "Presenting a model for the competitiveness of selected Iranian knowledge-based companies in the Fourth Industrial Revolution," *International Journal of Nonlinear Analysis and Applications,* vol. 15, no. 11, pp. 309-318, 2024.

[29] A. Rezaei, "The Role of Accounting Information on the Financial and Economic Transformation of Knowledge-Based Companies," in *Second National Conference on New Applied Research in Accounting*, Damghan, 2023.

[30] R. Telberg. "Industry perspectives: How can deep accounting knowledge make you a bigger asset to your company?" (accessed.

[31] K. Yang, X. Huo, Z. Sun, P. Li, S. Sindakis, and S. Showkat, "Investigating The Role of Accounting Information Comparability in Mitigating Stock Price Crash Risk: Evidence from China's Knowledge-Based Economy," ed, 2024.

[32] L. Zhu, R. Mayer, and W. Chien, "Strategies to improve digital skills for accountants," *Journal of Finance and Accountancy,* vol. 32, pp. 1-10, 2022.

[33] E. Saadati, Z. Ansari, A. Farahmandnia, and K. Asadi Mehr, "A strategy-oriented approach to the application of artificial intelligence technology in accounting: With reference to auditing and management accounting trends," *Strategic Management Accounting Quarterly,* vol. 2, no. 2, pp. 1-20, 2025.

[34] M. Kholdarov and Z. Khatamova, "Digital Transformation Of Accounting And Financial Management," *Международный журнал научных исследователей,* vol. 10, no. 1, pp. 588-592, 2025.

[35] M. Khalilpour, J. Ramezani, J. Ebrahimian, A. Fallah, and H. Kordani, "Developing Strategic Management Accounting by Applying Accounting Information Systems in Facing Environmental Drivers," *Journal of Accounting and Management Auditing Knowledge,* vol. 14, no. 55, pp. 193-207, 2025.

[36] H. Pasaribu, Z. Ghozali, M. Susilawati, and M. Masnoni, "Transformation of Strategic Management Accounting to Support Innovation and Competitive Advantage in the Digitalization Era," *Jurnal Nawala,* vol. 2, no. 1, pp. 213-225, 2025, doi: 10.62872/y9x0ck85.

[37] B. Odorkor, S. Kaggwa, P. U. Uwaoma, H. A. Olanipekun, and O. A. Farayola, "A review of U.S. management accounting evolution: Investigating shifts in tools and methodologies in light of national business dynamics," *World Journal of Advanced Research and Reviews,* vol. 25, no. 1, 2025, doi: 10.30574/wjarr.2024.21.1.2722.

[38] E. Berlinski and J. Morales, "Digital technologies and accounting quantification: The emergence of two divergent knowledge templates," *Critical Perspectives on Accounting,* vol. 98, p. 102697, 2024.

[39] H. Ince, S. Zeki Imamoglu, and M. A. Karakose, "Entrepreneurial orientation, social capital, and firm performance: The mediating role of innovation performance," *The International Journal of Entrepreneurship and Innovation,* vol. 24, no. 1, pp. 32-43, 2023.

[40] V. Parida, O. Pesamaa, and J. Wincent, "Network capability, innovativeness, and performance: A multidimensional extension for entrepreneurship," *Entrepreneurship and Regional Development,* vol. 29, no. 1-2, pp. 94-115, 2017.

[41] G. A. Shahmoradi, T. Torabi, R. Radfar, and M. H. Cheraghali, "Designing a model for determining the level of technological complexity of research and development activities in knowledge-based companies," *International Journal of Nonlinear Analysis and Applications,* vol. 15, no. 8, pp. 247-258, 2024.

[42] H. Ren, "Sustainable Development and Accounting Conservatism," *Journal of Corporate Accounting & Finance*, 2025, doi: 10.1002/jcaf.22804.

[43] R. Sotoudeh, A. Haghpourast, and A. Hirad, "A Management Accounting and Resistance Economy Model for Sustainable Development of Manufacturing Companies," *Strategic Management Accounting Quarterly,* vol. 1, no. 1, pp. 40-64, 2025. [Online]. Available: https://www.smajournal.ir/article_217784.html.

[44] M. Radfarnia, B. Gilani Nia-ye Someh Saraei, M. Samadi Lorgani, and M. R. Pourali, "Presenting a Strategic Management Accounting Model to Improve Company Productivity: A Structural Interpretive Approach," *Dynamic Management and Business Analysis,* vol. 4, no. 4, pp. 1-19, 2025.

[45] T. Kanellos and K. Nikos, "Economic and accounting performance of Greek innovative firms through knowledge-based entrepreneurship," *Journal of Accounting and Taxation,* vol. 14, no. 2, pp. 150-160, 2022.