International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-0385
Article

Research on Innovation and Entrepreneurship Opportunity Identification and Risk Avoidance in Digital Transformation of Housing Industry Chain

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Abstract: Against the background of accelerated digital transformation of the housing industry chain, innovation and entrepreneurship have become an important engine to promote industrial structure upgrading and economic growth. Identifying entrepreneurial opportunities and effectively avoiding entrepreneurial risks have become the core issues of concern for policy makers and entrepreneurs. This study focuses on the identification of innovation and entrepreneurship opportunities and risk avoidance in the context of digital transformation of the housing industry chain, and adopts the fuzzy set qualitative comparative analysis (fsQCA) method and the DEMATEL-ISM model to conduct a systematic analysis. 492 valid samples were collected through questionnaires, and variable calibration was completed after reliability and validity tests. The results of the fsQCA indicate that entrepreneurial alertness, learning ability, social network and educational environment constitute a "two-factor entrepreneur-environment driven" path; Digital technology, policy and education conditions constitute the "all-factor-driven" path, and three high entrepreneurial opportunity identification groupings were identified, with an overall consistency of 0.841 and a coverage of 0.426. In terms of risk aversion, the DEMATEL-ISM model identifies the influence of financial support and government support as 0.6983 and 0.6918 respectively, which are core risk factors. The study reveals the entrepreneurial opportunity generation mechanism and entrepreneurial risk hierarchy relationship under multiple concurrent conditions, which provides a basis for entrepreneurial decision-making in the digital upgrading of the housing industry chain.

Keywords: housing industry chain; digital transformation; fsQCA; entrepreneurial opportunity identification; entrepreneurial risk; DEMATEL-ISM

1. Introduction

With the development of the Internet and digital technology, the housing industry is experiencing a shift from scale-led to value-led [1-2]. The comprehensive development of the digital industry has led the government to strengthen its support for the digital industry. For example, the new urbanization plan proposes to "deeply integrate information technology with urban development" and accelerate the construction of digital and smart cities, which provides a good policy environment and support for the digital transformation of the housing industry [3-5]. In addition, the sharing economy, smart tourism, smart building, smart home, digital marketing, intelligent management and other emerging industries are rising rapidly, from building materials, builders, construction machinery, to real estate developers, property management, home decoration, digital technology is constantly penetrating into all aspects of the housing industry, promoting the application and transformation of the housing industry [6-9]. The popularity of the sharing economy has promoted the transformation and upgrading of the industry, the development of smart tourism has given rise to the demand for the digital transformation of the living environment, and smart homes have given rise to the demand for smart buildings and smart management, thus promoting the digital transformation process of the entire housing industry [10-12].

The digital transformation of the housing industry chain, through cloud computing, IoT, BIM, blockchain, network communication and other technologies, shortens the construction cycle from architectural design and building construction for housing development, and together with smart property management and smart home, saves the development cost, which provides impetus for innovation and entrepreneurship [13-16]. In addition, in the digital transformation of the housing industry chain, it is more concentrated on the development and construction links, but the digital penetration rate is low for the preliminary land development assessment and the selection of building materials and construction machinery, etc. as well as for the later property management, which leads to the digital transformation of the housing industry chain presenting the trend of the mid-end being strong and the two ends being weak [17-19]. The reason for this is the low data interaction rate of each link in the industry chain, the serious phenomenon of data silos, and the low matching degree and scenario applicability of technology, the lack of professional talents, and the insufficient industrial contact at the talent end [20-22]. Because of this, providing targeted solutions for the trend of digital transformation of the housing industry chain has gained opportunities for innovation and entrepreneurship.

Against the dual background of the current economic restructuring and the widespread application of new technologies, the digital transformation of the industrial chain has become a key means of enhancing overall competitiveness. Especially in the housing industry, all aspects from project development, building materials supply to property services are being reconstructed by digital technology. In this process, how to identify emerging entrepreneurial opportunities has become an important topic of concern for both academia and practice. Digitalization has not only spawned new business forms but also reshaped the innovation ecosystem, but new opportunities are often accompanied by uncertainty and multidimensional risks, and there is a lack of identification and response mechanisms guided by a systematic theoretical framework.

Based on the group theory, this study explores the path mechanisms affecting the identification of entrepreneurial opportunities and identifies the sources of entrepreneurial risks in the context of digitization from a multifactor concurrent perspective. First, a variable system containing factors such as entrepreneurial alertness, learning ability, social network, policy and educational environment is constructed to identify the core path of high entrepreneurial opportunity identification through the fuzzy set qualitative comparative analysis (fsQCA) method; second, the causal relationship and structural hierarchy between entrepreneurial risk factors are analyzed using the DEMATEL-ISM model to clarify the risk causes and influence chains. For data collection, 500 questionnaires were distributed in combination with the questionnaire star platform, 492 valid samples were recovered, and the scales were analyzed for reliability and validity through SPSS and AMOS. The necessity analysis, truth table generation and group path identification were completed by fsQCA software, supplemented by robustness test. In the risk analysis, the direct influence matrix was constructed through expert scores, and the coordinate distribution map of risk factors was further drawn, and finally the entrepreneurial risk influence model was constructed to provide reference for entrepreneurs to avoid key risks.

2. fsQCA-based research methodology

2.1. Fuzzy set qualitative comparative analysis (fsQCA) method

The group perspective is a global perspective for analyzing a problem, which is able to combine various conditions together into multiple concurrent causes and equivalent paths that lead to a certain outcome. This perspective is capable of grasping the essence of the problem at the macro level and avoiding simply breaking the problem into several independent parts for analysis. In the relationship between the digital transformation of the housing industry chain and the identification of innovation and entrepreneurship opportunities, the group perspective can deepen our understanding of asymmetric causality in social and economic phenomena.

The method of fuzzy set qualitative comparative analysis fsQCA adopts necessary condition analysis and histogram analysis, which can effectively analyze the effect of antecedent conditions, understand the interaction between antecedent and dependent variables, so as to configure the antecedent conditions more effectively [23]. This approach can not only help us better understand the relationship between the digital transformation of the housing industry chain and the identification of innovation and entrepreneurship opportunities, but also integrate these relationships with other factors to better explain the nature of the problem. Therefore, the group perspective and fuzzy set qualitative comparative analysis of fsQCA are used.

On the basis of group theory, qualitative comparative analysis methods are mainly categorized into two types: clear sets and fuzzy sets. Clear sets categorize cases as “0” or “1”, while fuzzy sets allow partial affiliation through set affiliation scores, which are both qualitatively differentiated and contain quantitative degrees.

The fuzzy set qualitative comparative analysis fsQCA method chosen in this paper is characterized by both qualitative analysis focusing on cases and quantitative analysis focusing on quantity. Compared with the clear set which categorizes cases binary as “0” or “1”, the fuzzy set allows partial affiliation, and the category and degree of its set affiliation can more accurately reflect the actual situation. Therefore, the fuzzy set qualitative comparative analysis fsQCA method can consider the influence of various factors more comprehensively when studying the relationship between executive team characteristics and company performance.

The fuzzy set qualitative comparative analysis method under the group theory can do:

(1) Through necessity analysis we can find whether there is a variable that can constitute a necessary condition for the identification of highly innovative entrepreneurial opportunities.

(2) Through the configuration of the solution we can find the paths of grouping that form different antecedent variables.

(3) Through the relationship between simple and intermediate solutions we can find the marginal and core variables, with the marginal variables having a weaker correlation with the results. Therefore, according to the characteristics of the research problem and the characteristics of the research method, the method of qualitative comparative analysis of fuzzy sets is chosen for further research.

2.2. Steps of the study

(1) Selection and calibration of variables

First of all, based on the theoretical research and literature research to determine and construct the antecedent variables, and then use the fsQCA software calibrate calibration function to calibrate the collected variable data, which is converted to the concept of set.

In order to determine the degree of affiliation of the fuzzy set during the calibration process, we need to set three anchor points, which are “fully affiliated” (1), “fully unaffiliated” (0), and the intersection point (0.5), which are very important. The intersection point is also known as the point of maximum ambiguity and can be determined by choosing either the median or the mean. It is at the intersection point that it is most ambiguous to determine whether a particular case belongs to the set or not.

By using a calibration function, we can obtain a set affiliation score between [0,1] that describes the degree to which a case belongs to a set. Where [0] and [1] denote completely unaffiliated and completely affiliated, and the score between [0,1] denotes the degree of affiliation. For the research object of this paper, we generally set three qualitative anchor values of complete affiliation (0.95), complete non-affiliation (0.05), and intersection (0.5). In addition, for the distribution characteristics of different variables, we can also set the upper and lower quartiles as anchor point values to better describe the differences between different variables.

After the calibration is completed, we will get the fuzzy affiliation scores of each variable, which provides a strong support for practical applications.

(2) Analysis of necessary conditions

After completing the calibration of the data, we can carry out the necessary conditions analysis to determine whether there are necessary conditions in the antecedent variables that lead to the results. A necessary condition is a condition that must be met in order for a result to occur under certain circumstances. When performing a necessary condition analysis, we need to look at the affiliation scores of the antecedent variables and determine whether there is a necessary condition in the antecedent variables that causes the outcome to occur based on the distribution of the antecedent variables and our domain knowledge.

In general, for the necessity analysis results of the calibrated antecedent variables, if the consistency level of the antecedent conditions is lower than 0.9, we can assume that the necessary conditions that lead to the emergence of the results do not exist in the antecedent variables. This is because the lower the consistency level, the less influence the antecedent variable has on the outcome and cannot be a necessary condition for the outcome to appear. Therefore, the necessary condition analysis can help us to identify the factors in the antecedent variable that have the greatest impact on the outcome, so that we can better understand and interpret the data.

(3) Generate truth table

After completing the data calibration, each antecedent variable has two possible scenarios: presence and absence, which corresponds to an affiliation score of 1 and 0. If there are k antecedent variables, then there are 2k combinations of antecedent variables, which can be presented in the form of a truth table. The truth table has 2k rows, and each row represents a case of one combination of the antecedent variables, so the number of rows in the truth table is related to the number of antecedent variables. In addition, each antecedent variable combination also corresponds to a vector space corner in the fuzzy set, and the number of this corner is also 2k.

(4) Conditional grouping analysis

When using fsQCA software for Standard analysis, we can obtain three different solutions: simple, intermediate and complex [24]. The simple solution refers to the result obtained without the inclusion of logical residuals. The intermediate solution, on the other hand, selectively includes logical remainder terms under certain circumstances, while the complex solution completely includes logical remainder terms. By combining the simple and intermediate solutions, we can obtain different combinations of conditions that make up the outcome variable, as well as distinguish between core and marginal conditions. The core conditions are more strongly correlated with the outcome, while the edge conditions explain the outcome relatively weakly. The core condition exists in both the simple and intermediate solutions, and the condition that appears only in the intermediate solution is the edge condition.

This method of analysis allows us to better understand the relationship between the outcome variable and the antecedent variable. Once we understand the core and edge conditions, we can more accurately predict the changes in the outcome variable and thus make better decisions. Thus, the use of fsQCA software provides us with an effective tool to help us better analyze and interpret data.

Finally, we can plot the results of the conditional grouping based on the resulting solution, where we use "●" to indicate the presence of a condition and "ⓧ" to indicate the absence of a condition.

3. Study of entrepreneurial opportunity recognition drivers and their pathways

3.1. Study design

3.1.1. Questionnaire design, distribution and data collection

(1) Questionnaire design

The variables of the study refer to the widely recognized mature scales, and the variable items are appropriately modified in accordance with the topic and object of the study, and the variables are measured using the Likert 5-point scale method, and the measurement items and the reliability are shown in Table 1.

Table 1. Measure the validity of the item and the letter

Variable	CR value	AVE value	*Cronbach'α*
Digital support	0.839	0.561	0.845
Entrepreneurship alertness	0.827	0.563	0.841
Entrepreneurial learning ability	0.838	0.507	0.844
Social network scale	0.885	0.578	0.882
Entrepreneurial policy environment	0.914	0.639	0.903
Entrepreneurship education environment	0.851	0.594	0.837
Entrepreneurship opportunity recognition	0.888	0.591	0.893

(2) Questionnaire Distribution and Retrieval

The research object of this study is mainly entrepreneurial start-ups. A total of 500 questionnaires were distributed through the Questionnaire Star platform, and after excluding invalid questionnaires such as inconsistent responses to questions and short response time, 492 valid questionnaires were screened out, with a validity rate of 98.4%.

3.1.2. Reliability tests

In this study, SPSS and AMOS were used to analyze the reliability and validity of each variable. According to the results of reliability analysis, the Cronbach' α coefficients of each variable are greater than 0.8, and the CR values are greater than 0.8, indicating that the measurement items of each variable have consistency and correlation, and that the reliability of the scale is good. According to the results of validity analysis, the KMO value is 0.892, close to 0.900. The Bartlett's test of sphericity is significant (p<0.001), which meets the requirements of factor analysis. The factor loading values of each variable were all greater than 0.600, and the AVE values were all greater than 0.5, which indicated that the measurement question items of each variable had good consistency, and the convergent validity of the scale was good.

3.1.3. Data calibration

In this study, direct calibration was used by setting the upper quartile (75%), median (50%), and lower quartile (25%) of the sample data as three calibration points for complete non-affiliation, intersection, and complete affiliation of the variable and the outcome variable, respectively, and non-high-entrepreneurial opportunity identification was taken as a non-set of high-entrepreneurial opportunity identification, and fsQCA 3.0 was utilized to perform the calibration, and the data were calibrated as shown in Table 2.

Table 2. Data calibration

Study variable		Calibration anchor		
		Full membership	**Crossing point**	**Completely unaffiliated**
Conditional variable	Digital support	4.241	3.763	2.975
	Entrepreneurship alertness	3.777	3.272	2.743
	Entrepreneurial learning ability	3.786	3.333	2.759
	Social network scale	3.345	2.677	2.158
	Entrepreneurial policy environment	4.03	3.62	3.041
	Entrepreneurship education environment	4.207	3.592	2.965
Result variable	Entrepreneurship opportunity recognition	4.207	3.592	2.965

3.2. Data analysis

3.2.1. Analysis of necessary conditions

Based on the asymmetric character of the fsQCA method, fsQCA was used to test whether individual condition variables were necessary for high or non-high entrepreneurial opportunity identification. If the consistency of a condition is higher than 0.900, it constitutes a necessary condition for the outcome variable. Conversely, it does not constitute a necessary condition. The results of the necessity analysis are shown in Table 3 ("~" indicates non-set). The consistency level of each condition is lower than 0.900, which does not constitute a single or multiple necessary conditions, indicating that the drivers of entrepreneurial opportunity identification are multiple and concurrent, and that the effect of condition grouping on entrepreneurial opportunity identification must be further explored.

Table 3. Necessity analysis results

Predue condition	High entrepreneurship opportunity recognition		Non-high entrepreneurship opportunity recognition	
	Consistency	**Coverage**	**Consistency**	**Coverage**
Digital support	0.516	0.628	0.475	0.542
~Digital support	0.523	0.541	0.599	0.57
Entrepreneurship alertness	0.714	0.708	0.372	0.377
~Entrepreneurship alertness	0.422	0.407	0.683	0.622
Entrepreneurial learning ability	0.608	0.667	0.384	0.457
~Entrepreneurial learning ability	0.487	0.478	0.713	0.643
Social network scale	0.612	0.619	0.464	0.443
~Social network scale	0.425	0.461	0.605	0.647
Entrepreneurial policy environment	0.617	0.607	0.468	0.441
~Entrepreneurial policy environment	0.438	0.431	0.63	0.634
Entrepreneurship education	0.691	0.7	0.429	0.399

environment ~Entrepreneurship education environment	0.451	0.407	0.69	0.633

3.2.2. Configuration analysis

The logical combinations in the truth table were filtered by setting the case frequency threshold to 1, the raw consistency threshold to 0.800, and the PRI consistency threshold to 0.700. Conditions that are both in the intermediate and parsimonious solutions are core conditions of the solution, and conditions that only appear in the intermediate solution are edge conditions of the solution. The groupings of high and non-high entrepreneurial opportunities identified are shown in Table 4 (: "●" indicates the presence of core conditions. "•" indicates the presence of edge conditions. "⊗ " indicates that the core condition is missing. "⊗ " indicates that the edge condition is missing). By comparing the results of the intermediate solution with the parsimonious solution, the final result is 3 groupings of high entrepreneurial opportunity identification paths (H1, H2, and H3) and 5 groupings of non-high entrepreneurial opportunity identification paths (NH1, NH2a, NH2b, NH3, and NH4), with overall consistency of the solutions being 0.841, 0.849, and explanatory strength of 42.6% and 44.2%, respectively.

Table 4. High, non-high entrepreneurship opportunity recognition configuration

Predue condition	**High entrepreneurship opportunity identification group state**			**Non-high entrepreneurship opportunity identification configuration**				
	H1	**H2**	**H3**	**NH1**	**NH2a**	**NH2b**	**NH3**	**NH4**
Digital support(DTS)		●	•		⊗	⊗	⊗	⊗
Entrepreneurship alertness(EA)	●	●	●	⊗	⊗	⊗	⊗	●
Entrepreneurial learning ability(ELA)	●	●	⊗			⊗	⊗	⊗
Social network scale(SNS)	●		⊗	⊗	⊗		⊗	⊗
Entrepreneurial policy environment(EPE)		•	●	⊗		●	⊗	●
Entrepreneurship education environment(EEE)	●	●	⊗	⊗	⊗	⊗		•
consistency	0.827	0.884	0.874	0.846	0.862	0.851	0.86	0.892
Original coverage	0.284	0.237	0.061	0.309	0.279	0.141	0.211	0.078
Unique coverage	0.088	0.023	0.035	0.079	0.004	0.01	-0.001	0.035
Consistency of solutions		0.841				0.849		
The coverage of the solution		0.426				0.442		

1) Antecedent grouping patterns for high entrepreneurial opportunity identification

(1) Entrepreneur and Environment Dual Factor Driven (EA*ELA*SNS*EEE). In group H1, entrepreneurial alertness, entrepreneurial learning ability and social network size at the entrepreneurial level, and entrepreneurial education at the environmental level are the core conditions for high entrepreneurial opportunity identification. It is named as "entrepreneur-environment dual-factor driven".

(2) Digital technology-driven total factor-driven (DTS*EA*ELA*EEE). In configuration H2, digital technology support at the technology level, entrepreneurial alertness and entrepreneurial learning ability at the entrepreneurial level, and entrepreneurial education at the environmental level exist as the core conditions, and complement the entrepreneurial policy and environmental support that exists as the peripheral conditions, which can generate high entrepreneurial opportunity recognition. It is named "digital technology-led total factor-driven".

(3) Entrepreneurship policy-driven all-factor-driven (EA*EPE). In configuration H3, entrepreneurial alertness at the entrepreneurial level and entrepreneurial policy at the environmental level exist as core conditions, while entrepreneurial learning ability and social network size at the entrepreneurial level and entrepreneurial education at the environmental level are missing as core

conditions, and digital technology support, which exists as a peripheral condition, is complementary and can generate a high level of entrepreneurial opportunity identification. It is named "Entrepreneurship Policy-led Total Factor Driven".

2) Antecedents of non-high entrepreneurial opportunity identification

The five antecedent groupings that generate non-high entrepreneurial opportunity recognition are asymmetrically related to high entrepreneurial opportunity recognition. Based on the absence of core conditions, the antecedent patterns of non-high entrepreneurial opportunity recognition are further classified into digital technology support absence and entrepreneurial alertness absence, which confirms the core dominance of digital technology in the digital transformation of the housing industry chain.

3.2.3. Robustness Tests

In this study, we adjusted the PRI consistency threshold, the calibration thresholds for non-intersections and intersections, respectively, to test the robustness of the antecedent groupings of high entrepreneurial opportunity identification. First, the PRI consistency was increased from 0.700 to 0.750, producing three groupings that were largely consistent with the original groupings. Second, the anchor point of the intersection point was kept unchanged, and the fully affiliated and fully unaffiliated calibration anchors were adjusted from 73% and 25% to 82% and 18%, respectively, producing three group states that were consistent with the original group states. Finally, the calibration threshold of the intersection point was adjusted from 50% to 58%, and the essential interpretation remained unchanged after the adjustment. In summary, the results of the study are robust.

4. Research methodology based on the DEMATEL-ISM model

4.1. Modeling

According to the design idea of DEMATEL-ISM model, the specific modeling steps are as follows:

Step 1: Set the entrepreneurial risk factor indicators as $f_1, f_2, \cdots, f_n (n=14)$.

Step 2: Determine the direct impact matrix. According to the degree of direct influence of risk factor f_i on f_j , the judgment scale is divided into five levels from "0 to 4", which means no influence, weak, general, strong, and strong, respectively. The data on the degree of direct influence between risk factors are obtained by expert scoring method, and the direct influence matrix $F=[f_{ij}]_{n\times n}$ is obtained.

$$F=\begin{bmatrix} 0 & f_{12} & \cdots & f_{1n} \\ f_{21} & 0 & \cdots & f_{2n} \\ \vdots & \vdots & \vdots & \\ f_{n1} & f_{n2} & \cdots & 0 \end{bmatrix} \tag{1}$$

where $f_{ij}(i=1,2,\cdots,n; j=1,2,\cdots,n; i\neq j)$ denotes the degree of direct influence of the influencing factor f_i on f_j, and $f_{ij}=0$ when $i=j$.

Step 3: Normalize the direct influence matrix F according to equation (2) to obtain $G=[g_{ij}]_{n\times n}$:

$$G=\frac{1}{\max\limits_{1\le i\le n}\sum_{j=1}^{n} f_{ij}}F \tag{2}$$

In Eq. (2), $0\le g_{ij}\le 1$ and $\max\limits_{1\le i\le n}\sum_{j=1}^{n} g_{ij}=1$.

Step 4: Calculate the integrated impact matrix $X=[x_{ij}]_{n\times n}$ according to equation (3):

$$X=G(I-G)^{-1} \tag{3}$$

where the matrix I is denoted as a unit matrix.

Step 5: Calculate the degree of influence and the degree of being influenced among the analyzed risk factors according to the comprehensive influence matrix $X=[x_{ij}]_{n\times n}$, and the calculation process is shown in Equation (4) and Equation (5):

$$a_i = \sum_{j=1}^{n} x_{ij}, (i = 1, \cdots, n) \tag{4}$$

$$b_i = \sum_{j=1}^{n} x_{ji}, (i = 1, \cdots, n) \tag{5}$$

where the risk factor $f_n, (i = 1, \cdots, n)$ has an influence degree of a_i and an affected degree of b_i.

Step 6: Calculate the centrality degree m_i and the cause degree n_i of the risk factor. The sum of the influence degree and the influenced degree of the risk factor is the centrality degree of the factor. The difference between the two is the cause degree of the factor. The calculation is shown in equation (6) and (7):

$$m_i = a_i + b_i, (i = 1, \cdots, n) \tag{6}$$

$$n_i = a_i - b_i, (i = 1, \cdots, n) \tag{7}$$

Step 7: Plot the Cartesian coordinate system with the centrality m_i of the risk factor f_n as the horizontal axis and the causality n_i as the vertical axis, and judge the importance of each factor by combining its position in the coordinate system.

Step 8: Calculate the overall impact matrix $H = [h_{ij}]_{n \times n}$ of the set of risk factors, and hierarchically classify the risk factors:

$$H = X + I \tag{8}$$

where the matrix I is the unit matrix.

Step 9: According to the ISM method, determine the reachable matrix $K = [k_{ij}]_{n \times n}$, which is calculated as shown in equations (9) and (10):

$$k_{ij} = \{1 \mid h_{ij} \geq \lambda\}, (i = 1, \cdots, n; j = 1, \cdots, n) \tag{9}$$

$$k_{ij} = \{1 \mid h_{ij} < \lambda\}, (i = 1, \cdots, n; j = 1, \cdots, n) \tag{10}$$

In Eqs. (9) and (10), the λ threshold is set in combination with the real problem, and the influence relationship with a small degree of influence among the risk factors is eliminated, which makes the hierarchical division clearer [25].

Step 10: Determine the reachable set R_i and the set of antecedent factors S_i, and the calculation process is shown in Eq. (11) and Eq. (12):

$$R_i = \{a_j \mid a_j \in A, k_{ij} \neq 0\}, (i = 1, \cdots, n) \tag{11}$$

$$R_i = \{a_j \mid a_j \in A, k_{ji} \neq 0\}, (i = 1, \cdots, n) \tag{12}$$

Step 11: Verify whether Eq. (13) is valid, if Eq. (13) is valid then delete i rows and i columns in the reachable matrix K. Continue to repeat the step until all risk factors are removed and classify the hierarchy of all risk factors according to the order of removal.

$$R_i = R_i \cap S_i, (i = 1, \cdots, n) \tag{13}$$

4.2. Data acquisition and application

According to the modeling steps of the DEMATEL-ISM model and the risk factors of entrepreneurs' entrepreneurship, a questionnaire survey was conducted in October 2024 using video calls and e-mails with five entrepreneurs, five academic experts engaged in entrepreneurship research, and five local principals to score the intensity of the direct impact between different risk factors. The questionnaire data were processed using the integration rule of the mean value method, and the mean value was also rounded based on the principle of rounding to the nearest integer to cope with the problem of invalid algorithm caused by the destruction of the scale, to determine the intensity of the direct impact between two or two risk factors, and to obtain the direct impact matrix F.

$$F=\begin{bmatrix}0&3&1&0&0&0&0&0&2&0&0&0&0&0\\1&0&0&0&1&0&2&0&0&0&0&0&0&0\\0&3&0&2&1&0&1&4&2&0&0&0&0&0\\4&1&1&0&0&0&0&0&0&1&0&0&0&0\\0&0&0&0&0&3&4&0&0&0&0&0&0&0\\0&0&0&0&3&0&4&0&0&0&0&0&0&0\\0&0&0&0&3&4&0&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&0&2&2&0&0&0&0\\0&0&0&0&0&0&0&0&0&1&0&0&0&0\\0&0&0&0&0&0&0&0&4&0&0&0&0&0\\2&0&0&0&0&0&0&0&1&0&0&2&0&0\\3&1&1&0&2&0&0&0&0&0&0&0&2&0\\2&0&2&1&1&1&2&0&0&0&0&1&0&0\end{bmatrix} \tag{14}$$

5. Entrepreneurial risk assessment

5.1. Structural framework of entrepreneurial risk factors

In this paper, on the results of the research of experts and scholars, combined with the unique characteristics of the entrepreneurs themselves in the digital transformation of the housing industry chain, we analyze and investigate the entrepreneurial risk evaluation factors of the entrepreneurs, and establish a structure framework of the indicators of the entrepreneurial risk factors of the initial entrepreneurs, which includes three dimensions: entrepreneurial environment, core team, and entrepreneurs, i.e., the framework of the evaluation indicators of the entrepreneurial risk of the initial entrepreneurs contains 3 level 1 indicators and 24 level 2 indicators. The entrepreneurial risk evaluation index framework is shown in Table 5.

Table 5. The framework of the risk evaluation index for entrepreneurship

Primary indicator	Secondary indicator	Serial number
Entrepreneurial environment	Government support	A1
	Industrial development	A2
	Talent environment	A3
	R&d environment	A4
	Financial support	A5
	Intermediary service	A6
	Market environment	A7
	Innovation awareness	A8
	Policy regulation	A9
Core team	Conformance	A10
	Values	A11
	Trust	A12
	Distribution mechanism	A13
	Whether it can be complementary	A14
	Innovative ability	A15
	Team experience	A16
Entrepreneur	Entrepreneurial motivation	A17
	Entrepreneurial consciousness	A18
	Psychological quality of entrepreneurship	A19
	Entrepreneurial knowledge	A20
	Personality traits	A21
	Entrepreneurial ability	A22
	Risk resistance	A23
	Personal experience	A24

5.2. Analysis of factors influencing entrepreneurial risk

The combined relationship of entrepreneurial risk factors is shown in Table 6. From the table, it can be seen that A5 (financial support) has the highest influence of 0.6983, which indicates that financial support has a more important influence on entrepreneurial risk of entrepreneurs.

Table 6. The relationship between venture risk factors

Risk factor	Influence degree	Be affected degree	Center degree	Reason degree
A1	0.6918	0	0.6936	0.6898
A2	0.303	0.1751	0.4798	0.129
A3	0.2127	0.1817	0.3938	0.0299
A4	0.0304	0.3076	0.3396	-0.2776
A5	0.6983	0.1636	0.8591	0.5401
A6	0.0737	0.262	0.333	-0.1892
A7	0.1486	0.2734	0.4263	-0.1309
A8	0	0.3537	0.3569	-0.3546
A9	0.4219	0.1212	0.5389	0.3004
A10	0.0717	0.1283	0.2044	-0.0539
A11	0.0731	0.1595	0.2342	-0.0889
A12	0.0726	0.4525	0.525	-0.3797
A13	0.1093	0.2155	0.3231	-0.1074
A14	0.2013	0.0689	0.2655	0.1323
A15	0.1591	0.2364	0.3944	-0.0766
A16	0.3199	0.2547	0.5752	0.0672
A17	0.0975	0.3527	0.446	-0.2569
A18	0.1746	0.2699	0.4447	-0.0996
A19	0.1516	0.2208	0.3744	-0.0702
A20	0.17	0.3409	0.5128	-0.1764
A21	0.2507	0	0.2522	0.2496
A22	0.1009	0.1514	0.257	-0.0493
A23	0	0.5357	0.536	-0.5381
A24	0.2058	0.1871	0.3976	0.0194

5.3. Analysis of results of factors influencing entrepreneurial risk

Based on the application of DEMATEL-ISM method to analyze the entrepreneurial risk of entrepreneurship, the centrality and influence degree of each influencing factor obtained by DEMATEL and the multilevel recursive order structure between the factors described by the ISM method are combined to determine the degree of importance of the risk factors to the success or failure of entrepreneurial ventures.

According to the table, we can get the degree of influence and the degree of being influenced, the degree of cause and the degree of centrality of entrepreneurial venture risk factors, in which the centrality of entrepreneurial venture risk indicator factors indicates the size of the proportion of the risk factor that plays a role in all risk factors. Cause degree indicates the degree of influence of the risk factor on other factors, cause degree has positive and negative points, the cause degree is greater than 0 on behalf of the risk indicator on other risk indicators, is the cause of the factor, when the cause degree is less than 0 on behalf of the risk indicator is not very important, by the influence of other risk indicators. At the same time with the curve image depicts the cause degree and center degree of the factor, the cause degree and center degree of the risk factor is shown in Figure 1.

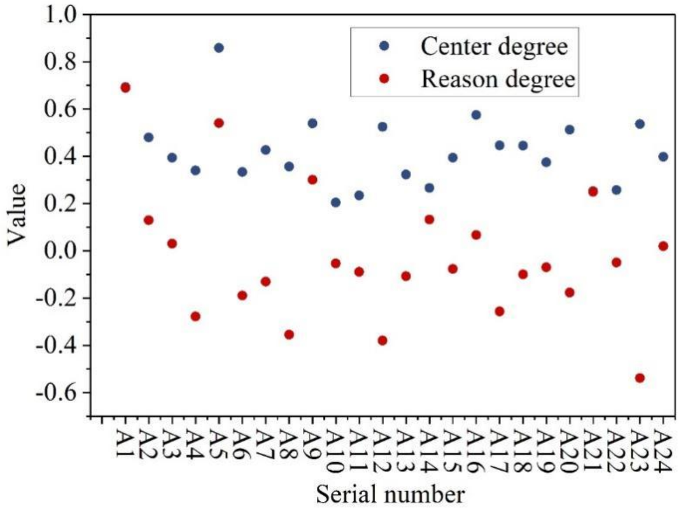

Figure 1. Degree of cause and centrality of risk factors

As can be seen from the chart, the cause degree of 9 risk factors, including government support, industrial development, talent environment, financial support, policies and regulations, whether they can complement each other's strengths, team experience, character traits, and personal experience, is greater than 0. It can be seen that the government support and financial support play the biggest role in the cause factors.

6. Conclusion

The generation of high entrepreneurial opportunities is characterized by a typical multiconditional pattern, where the core driving factor is not a single variable, but an organic combination of entrepreneurial ability, resource support and external environment. Among them, the “entrepreneur-environment dual-factor driven” path emphasizes the synergistic effect of individual traits and educational support; in the “digital technology-led all-factor driven” path, digital support, alertness, learning ability and educational environment form a highly consistent path of high entrepreneurial opportunity generation, with a group consistency of 0.884, which is the same as that in the “entrepreneur-environment dual-factor driven” path. In the “digital technology-led, all-factor-driven” path, digital support, alertness, learning ability and educational environment constitute a highly consistent high identification path, with a group consistency of 0.884 and a coverage rate of 0.237; and the “policy-led” path highlights the key guiding role of policy in opportunity identification. On the other hand, the results of the risk analysis show that financial support has the highest influence of 0.6983, followed by government support (0.6918) and policies and regulations (0.4219), which indicates that in the process of entrepreneurship, financial security and institutional environment have a decisive influence on the success or failure of entrepreneurship. In addition, financial and policy support also dominate the DEMATEL model with a cause degree of 0.5401 and 0.3004, respectively. It can be seen that in the context of digitization of the housing industry chain, the systematic identification of opportunities and risk avoidance need to be synergistically promoted from multiple dimensions such as entrepreneurs, resource support and institutional security to build an entrepreneurial support system with internal and external coupling characteristics.

Funding

This research was supported by the Major Projects on Philosophy and Social Sciences of The Ministry of Education “Research on Comprehensively Improving the Quality of Domestic Talent Development under New Circumstances” (NO. 23JZD045);

Major Projects on Philosophy and Social Sciences of The Ministry of Education “Research on the Construction of University Innovation System under the background of self-reliance in science and technology (NO. 21JZD057).

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