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Aina Nindiani, Machfud, Ono Suparno, Elisa Anggraeni

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## **Linking business ecosystem structure to risk perception: a network analysis of Indonesia's bamboo craft industry**

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Aina Nindiani\*, Machfud, Ono Suparno and Elisa Anggraeni

Agroindustrial Engineering Study Program,  
Faculty of Engineering and Technology,  
IPB University,  
Bogor, Indonesia

Email: [ainanindiani@apps.ipb.ac.id](mailto:ainanindiani@apps.ipb.ac.id)

Email: [aina.nindiani@ubpkarawang.ac.id](mailto:aina.nindiani@ubpkarawang.ac.id)

Email: [machfud@apps.ipb.ac.id](mailto:machfud@apps.ipb.ac.id)

Email: [ono.suparno@apps.ipb.ac.id](mailto:ono.suparno@apps.ipb.ac.id)

Email: [elisa.anggraeni@apps.ipb.ac.id](mailto:elisa.anggraeni@apps.ipb.ac.id)

\*Corresponding author

**Abstract:** The bamboo craft industry, part of the weaving sector, once experienced the highest negative growth among rural industries (-9.48%). This study analyses the business ecosystem structure and risk profile of bamboo craft MSMEs using network analysis and an IFS-based HOR approach. The findings show that area 1 exhibits a broad but loosely connected ecosystem dominated by marketing ties, whereas area 2 demonstrates a more cohesive and consultative structure. Distinct risk profiles emerge across areas: external market risks are more salient in area 1, while operational and technical risks are more prominent in area 2. These empirical insights suggest an interpretative association between ecosystem configuration and dominant risk perception. The study contributes by integrating network structure and risk analysis to support mitigation and business model innovation strategies.

**Keywords:** business ecosystem; network analysis; IFS-based HOR; MSME risk potential; business model innovation; Indonesia.

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**Biographical notes:** Aina Nindiani is a Lecturer in the Industrial Engineering Study Program, Faculty of Engineering, Universitas Buana Perjuangan Karawang, Indonesia. She has more than 14 years of experience in industrial and educational fields. Her previous job at a leading multinational company has brought her expertise in the MSME sector. She is currently pursuing her Doctorate in Industrial and Systems Engineering, Agroindustrial Engineering Study Program, Faculty of Engineering and Technology, IPB University, Indonesia.

Machfud is a Professor of Agroindustrial Technology at Agroindustrial Engineering Study Program, Faculty of Engineering and Technology, IPB University, Indonesia. He earned his Doctor degree from IPB University. His

current field of research interest relates to system management and engineering of agroindustrial development and design, production system and supply chain system of agroindustry.

Ono Suparno is a Professor of Agroindustrial Process Technology at Agroindustrial Engineering Study Program, Faculty of Engineering and Technology, IPB University, Indonesia. He earned his PhD from The University of Leicester, UK. His current field of research interest relates to collagen science and technology, phenolic reactions for leather tanning and dyeing, and technology and management for leather, fibre, and polymer environmentally friendly processing.

Elisa Anggraeni is a Senior Lecturer of Agroindustrial Technology at Agroindustrial Engineering Study Program, Faculty of Engineering and Technology, IPB University, Indonesia. She earned her PhD from Delft University of Technology, Netherlands. She has more than 25 years of experience in higher education. Her current field of research interest relates to technology, strategy and entrepreneurship with recent focus on network and open innovation.

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## 1 Introduction

All organisations face risks, and small enterprises are often more vulnerable because they have fewer resources and are less resilient (Sadgrove, 2016). An increasing number of organisations worldwide are confronted with growing complexity in customer demand and market expectations within an increasingly turbulent global business environment (Hong et al., 2016). According to Ciocoiu et al. (2024), MSMEs are a source of elements that ground the economy but keep it weak due to their constrained financial resources, making them prone to risks and, hence, affecting their long-term business sustainability initiatives.

The rural bamboo craft sector has been chosen as the study area for this research, which falls under the MSME category. The production of bamboo crafts in rural areas is essential in many developing countries, including Indonesia. Many rural communities run businesses in this sector by processing bamboo into multiple products, most of which are produced to meet domestic demand. Its presence in rural areas creates structural constraints. The industry is mainly operated by artisans from lower-middle economic backgrounds. These conditions impose various limitations in many aspects of running their businesses.

Several previous studies regarding the bamboo industry include research by Wang et al. (2021) on China's bamboo industry, which found that the natural and socio-economic circumstances of poor rural communities created various challenges, such as transportation issues, insufficient understanding of the bamboo industry, unhealthy competition among bamboo farmers, and insufficient training for workers in the bamboo industry. A separate study by Binfield et al. (2024) examined the global industrialisation of bamboo through expert interviews in Ecuador, Ethiopia, Nepal, China, and Nigeria, among others, by analysing the strengths, weaknesses, challenges, and barriers. The study concluded that the global bamboo industry remains at a relatively

low level of commercialisation. It has not yet fully utilised the available technological advancements.

Nindiani et al. (2022) reported that the bamboo craft industry, categorised under the weaving industry, once experienced the largest negative growth among eight types of rural industries, at -9.48%. Furthermore, this sector has achieved an international market share of no more than 3%, even though the supply of bamboo raw materials in Indonesia is abundant compared to other countries. Ekawati et al. (2023) stated that bamboo resources owned by communities in Ngada Regency, East Nusa Tenggara (Indonesia) have not been properly managed or utilised. This is due to the absence of an integrated program linking the on-farm and off-farm sectors. In addition, the roles and responsibilities of the involved stakeholders remain unclear.

As MSME organisations operating with various limitations, bamboo craft industries are highly dependent on various other parties within the business environment. Hopkin (2018) noted that organisations today operate in increasingly complex and challenging environments, and in such uncertain conditions, they are expected to meet higher stakeholder expectations. Chen et al. (2022) argued that MSMEs face various uncertainties and challenges arising from a rapidly changing environment when entering a business ecosystem. Therefore, studies on MSME risks in relation to changes in the business environment are important to sustain their operations.

Prior studies on business ecosystems have emphasised the importance of collaboration/cooperation (Georgescu et al., 2022; Chen et al., 2022; Riquelme-Medina et al., 2022), innovation (Liu et al., 2023; Snihur and Bocken, 2022; He and Sun, 2023), value creation (Agarwal and Kapoor, 2023; Awano and Tsujimoto, 2022, Rong et al., 2021), governance (Li et al., 2022; Liu et al., 2025), and performance (Micheli and Muctor, 2021; Lee and Roh, 2023).

Meanwhile, previous studies on networks showed that employing network approaches can provide an empirical depiction of the relational structure among actors (Iyer et al., 2006; Anggraeni et al., 2007). A longitudinal ethnographic study conceptualises entrepreneurial ecosystems as inter-organisational networks and emphasises how relational configurations and governance mechanisms evolve at critical junctures (Scott et al., 2021). Adner's typology differentiates the ecosystem as a structure perspective from more simplified network or value chain views by explicitly linking actors' positions within an ecosystem to network metrics such as degree centrality and density. It further conceptualises multi-actor interdependence as the fundamental basis for value creation and value capture within the ecosystem (Ribeiro et al., 2024).

On the other hand, risk management studies typically assess operational and strategic risks at the firm level (Kleindorfer and Saad, 2005). Another study by Siegrist and Árvai (2020) argues that some research highlights the significant role of risk perception in shaping individual behaviour. Wilson et al. (2019) mentioned that risk perception is best understood as a multidimensional construct that is predominantly affective in nature, showing that common surveys often conflate affect, probability, and consequences.

The business ecosystem literature underscores the importance of interactions among actors. The network literature provides analytical tools to map relational structures. The risk management literature explains firm-level risk dynamics. However, limited research has integrated these perspectives. Hallikas et al. (2002) provided a framework for identifying and assessing risks in production networks. The primary objective of their study was to demonstrate how a firm can analyse and assess risks associated with networking. Although the study highlights interdependencies as sources of network risk,

it does not explore the structural positions of interconnected actors that may explain how such risks emerge from the existing network. The recent study from Paniello-Castillo et al. (2025) conceptualises risk perception as a networked structure in which multiple hazards are interlinked through an individual's perceived likelihood, impact, and authority knowledge, and applies network analysis to identify central hazards and interconnections over time. However, while their study mapped the relational structure among perceived risks, they did not examine how actors' positions within real-world networks shape the formation of these interconnected risk perceptions.

Addressing this gap, this study integrates business ecosystem analysis with network analysis and risk analysis to examine how variations in network structure are associated with different risk perceptions in the bamboo craft industry. Specifically, this study aims to explore the network structure of the business ecosystem, analyse potential risks, and analyse the interrelationship between the ecosystem configuration and risk characteristics. Therefore, this research contributes conceptually by positioning risk as an outcome associated with ecosystem configuration, and empirically by providing comparative evidence across two ecosystem contexts.

## **2 Literature review**

### *2.1 Business ecosystem/network theory*

The concept of a business ecosystem was initially introduced by James Moore in 1993. Moore described it as an economic community built upon networks of relationships among organisations and individuals, which act as the 'organisms' within the business environment. This ecosystem encompasses customers, producers, competitors, and various stakeholders (Peltoniemi and Vuori, 2004).

Anggraeni et al. (2007) further emphasised that a business ecosystem, as an extended form of a business network, embodies an organisational arrangement distinguished by its unique characteristics and interrelationships. Unlike conventional networks, a business ecosystem encompasses not only firms but also a wider range of stakeholders, including owners, government institutions, associations, and standardisation bodies.

Iyer et al. (2013) observed that many complex systems can be conceptualised as networks, in which elements are represented as nodes (or vertices) and the interconnections among them are depicted by lines (or edges). Furthermore, Iyer et al. (2006) highlighted that within small, interconnected ecosystems, each element – whether an individual or an entity – is linked through multiple forms of interaction, creating an intricate network in which changes to one component can influence others. According to Iyer et al. (2006), the network measures used to analyse complex business ecosystems include density and centrality.

A study by Ribeiro et al. (2024) explicitly integrates business ecosystem theory with social network theory, distinguishing the ecosystem as a structure and SNA metrics as natural measures of ecosystem position. Ahlqvist et al. (2020) compared risk governance and SCRМ and argue that inter-organisational risk processes must be governed across multiple levels and actors in a network. Pournader et al. (2020) show how SCRМ has evolved toward themes that explicitly combine network structure with risk-taking behaviour and risk perception.

## 2.2 Risk

Risk is defined as the impact of uncertainty on the achievement of objectives (ISO 31000, 2018). According to Sadgrove (2016), all types of risk ultimately lead to financial consequences, underscoring the importance of addressing them, as uncertainties can disrupt business continuity. Kleindorfer and Saad (2005) further explained that disruption-related risks may stem from operational issues – such as equipment malfunctions, unexpected supply interruptions, or human-related incidents, including strikes and fraud, as well as from external factors such as natural disasters, terrorism, or political unrest.

A study of risk perception by Siegrist and Árvai (2020) synthesises three dominant perspectives: hazard characteristics, perceiver characteristics, and heuristics, and highlights persisting challenges in integrating these streams. Goerlandt et al. (2021) map thematic clusters and methodological frontiers in risk perception research and show its strong roots in psychology and social sciences.

Recent empirical evidence highlights the evolving understanding of resilience in MSMEs and their ecosystems, emphasising the important role of risk management in sustaining resilience. Eichholz et al. (2024) mentioned that economic crises can severely affect businesses across sectors and found that a risk management orientation, alongside effective planning, plays a crucial role in organisational resilience. Another research by Ismiyanti et al. (2025) suggested that MSME actors who endured the COVID-19 pandemic need to embrace calculated risk-taking, sustain continuous innovation, cultivate a strong entrepreneurial mindset, and remain adaptable to environmental changes. Satpathy et al. (2025) investigate critical strategies to enhance the adaptability of MSMEs, encompassing technological adoption, effective risk management, and sustainable practices. On the other hand, Pizzichini et al. (2025) conceptualised local innovation ecosystem resilience as a multidimensional mechanism that integrates entrepreneurial orientation, including risk-taking, with cognitive and emotional responses to uncertainty. These perspectives imply that resilience is closely related to how risk is perceived and interpreted within the business ecosystem. Scherer and Cho (2003) noted that an approach based on the network theory of contagion holds that relationships among individuals within networks and self-organising systems influence risk perception.

Numerous studies have explored risk mitigation using the house of risk (HOR) methodology. HOR combines failure mode and effect analysis (FMEA) with the house of quality (HoQ). According to Pujawan and Geraldine (2009), FMEA is a risk assessment model that produces a risk priority number (RPN) derived from severity, occurrence, and detection values. In HOR, severity is associated with risk events, while probability of occurrence is associated with risk agents. One risk agent can trigger multiple risk events, and numerous risk agents can trigger a single risk event; therefore, an aggregate risk potential (ARP) calculation is needed. The HOR method is conducted in two stages: HOR 1 and HOR 2. HOR 1 aims to determine the ARP so that appropriate mitigation actions can be designed and implemented in HOR 2.

Previous studies using HOR have been conducted by Pujawan and Geraldine (2009), Widiasih et al. (2015) and Dewi et al. (2015), who applied the pure HOR method. Ma and Wong (2018), Asrol et al. (2021) and Safriyana et al. (2018) used a fuzzy-HOR approach with fuzzy type-1. This study adopts an IFS-based HOR (HOR-based on intuitionistic fuzzy sets). The utilisation of intuitionistic fuzzy sets (IFS) in data modelling helps address issues of uncertainty (Milovanović et al., 2021; Tokede, 2024; Torra, 2010). The

IFS framework has demonstrated its effectiveness in managing various forms of ambiguity and vagueness in social data, offering an objective and systematic approach to handling heterogeneous, imprecise, and uncertain information (Tokede, 2024). As noted by Torra (2010), the strength of IFS lies in its capacity to represent uncertainty within the membership functions of elements in a set. Unlike conventional fuzzy sets, which assign a single membership value to each component, IFSs incorporate a degree of hesitation or indeterminacy, thereby capturing uncertainty more comprehensively.

Atanassov (2012) developed IFS as an extension of the fuzzy sets introduced by Lotfi Zadeh. An IFS  $A$  on a set  $X$  can be described as follows: for any element  $x$  in the set  $X$  – the set of all possible elements –  $\mu_A(x)$  represents the degree to which the component of  $x$  belongs to the set  $A$ , with values ranging from  $[0, 1]$ . A higher value indicates a greater degree of membership of element  $x$  in set  $A$ .

$\nu_A(x)$  represents the degree of non-membership of element  $x$  in the IFS  $A$ , while  $\pi_A(x)$  denotes the degree of hesitation or uncertainty about whether element  $x$  belongs to set  $A$  or not. The smaller the value of  $\pi_A(x)$ , the more certain the information; conversely, a larger value indicates greater uncertainty about  $x$ . In IFS, the pair  $(\mu_A(x), \nu_A(x))$  is known as an intuitionistic fuzzy number (IFN) (Liu et al., 2015)

$$A = \{(x, \mu_A(x), \nu_A(x)) : x \in X, \mu_A(x) + \nu_A(x) \leq 1\}$$

$$\mu_A(x) : X \rightarrow [0, 1] \text{ and } \nu_A(x) : X \rightarrow [0, 1]$$

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1, \forall x \in X$$

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$$

$$0 \leq \pi_A(x) \leq 1, \forall x \in X$$

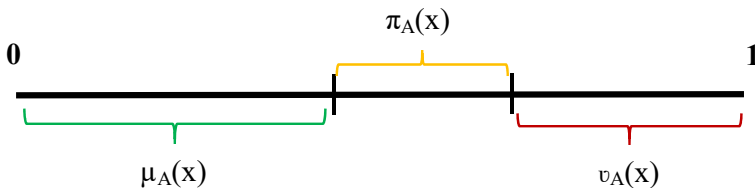
$\mu_A(x)$  membership degree

$\nu_A(x)$  non-membership degree

$\pi_A(x)$  hesitance degree of  $x \in A$ .

IFS can manage uncertainty much more effectively because it accommodates the degree of hesitation (Song et al., 2014). IFS incorporates three values: membership ( $\mu$ ), non-membership ( $\nu$ ), and hesitation ( $\pi$ ). Figure 1 illustrates the geometric interpretation of IFS (Atanassov, 2012).

**Figure 1** Geometric interpretation of IFS (see online version for colours)



Source: Atanassov (2012)

### 2.3 *State of the art*

Recent scholarship has increasingly recognised that risk within interconnected systems is relational and structurally embedded. Ahlqvist et al. (2020) frame risk as emerging from interdependencies among connected organisations, suggesting that network configurations shape which risks become visible or salient to different actors. Ribeiro et al. (2024) further argue that network metrics capture how actors positioned at the centre or periphery of ecosystems differ in strategic exposure and information access, thereby providing a structural foundation for variation in perceived risk. Complementing this, Siegrist and Árvai (2020) clarified that risk perception is shaped by both cognitive and affective processes and by social context, while Goerlandt et al. (2021) highlight the role of social amplification and communication in constructing shared risk perceptions. Taken together, these streams suggest that risk perception in business ecosystems is not merely an individual judgement but an emergent outcome of network-embedded information flows and inter-organisational interdependencies. However, empirical research explicitly linking measurable network structures to actors' risk perceptions remains limited. This study advances the state of the art by integrating business ecosystem analysis and risk analysis to explain how business ecosystem network structures shape MSMEs' risk perception.

## 3 **Methodology**

### 3.1 *Research design*

This research adopts an exploratory mixed-methods design, with the necessary data and information for analysis gathered through semi-structured interviews and risk-assessment questionnaires. According to Zohrabi (2013), in mixed-method research, qualitative and quantitative data are collected simultaneously, and the use of multiple data collection procedures from various sources can enhance validity and reliability.

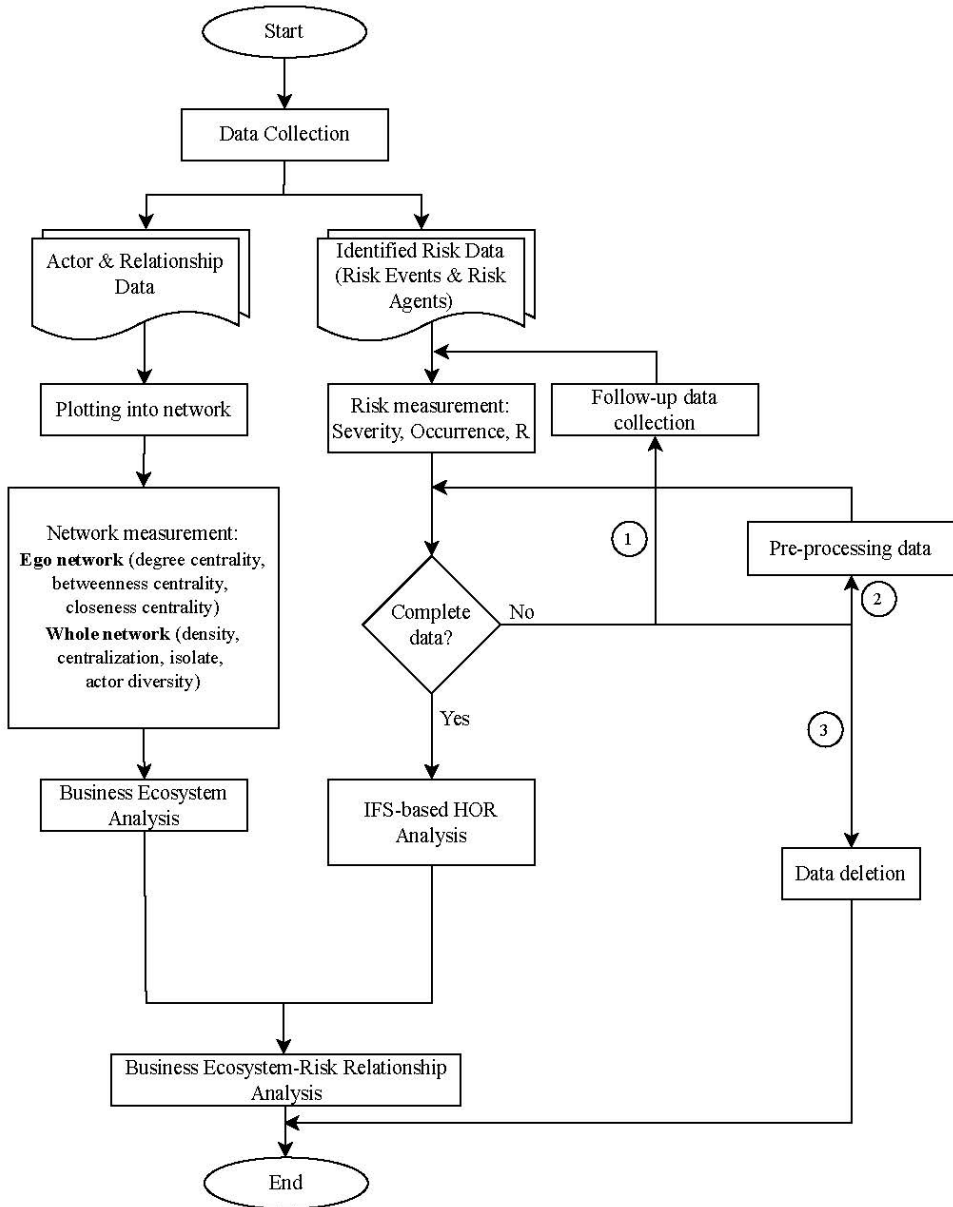
In this study, semi-structured interviews were conducted to identify key actors, map inter-organisational relationships within the business ecosystem, and explore potential risk events and risk agents. At the same time, structured questionnaires were administered to assess the perceived severity and occurrence of identified risks. The integration of qualitative and quantitative components occurred at two stages. First, qualitative insights derived from interviews informed the construction of the network and the formulation of risk variables included in the questionnaire. Second, quantitative results from the network and risk analysis were interpreted in conjunction with contextual insights obtained from the interviews, enabling a more comprehensive understanding of the relationship between ecosystem structure and risk characteristics.

To provide a clearer overview of the research process regarding the exploratory mixed-methods design and the sequential integration of network and risk analysis, the overall research flow diagram is presented in Figure 2.

The business ecosystem was described by selecting two study areas in the districts located in two different provinces in Indonesia: area 1, located in West Java province, and area 2, in the Special Region of Yogyakarta province. The justification for selecting these two areas is that they exhibit different growth patterns; therefore, the business ecosystem and its risks will be analysed to explain the observed differences. Area 1

experienced negative growth, while area 2 experienced positive growth. Both areas are compared.

Figure 2 Research flow diagram



### 3.2 Data collection

In this study, the sample was drawn from the population of bamboo craft MSMEs using a non-probability (non-random) sampling approach. The non-probability approach was

chosen because the total population of artisans was not precisely known. According to Saunders et al. (2009), non-probability sampling is practical in exploratory research. Respondents were selected using convenience sampling, considering that the research sites were located far apart and some artisan locations were difficult to reach (hilly terrain). Convenience sampling (haphazard sampling) can be used by selecting cases that are easiest to access, such as random interviews or samples from a specific location. This method is appropriate when there is low variation within the population. In this study, only MSMEs producing bamboo-based woven crafts were sampled, excluding artisans using other materials; thus, the variation was considered low, and convenience sampling was deemed suitable.

A total of 64 MSME respondents were obtained in area 1 and 43 respondents in area 2. The MSME respondents provided assessments of both the business ecosystem and risk, including evaluations of risk severity and occurrence for the identified risks. This study also involved ten expert respondents, consisting of bamboo craft MSMEs representatives and other stakeholders who frequently interact with MSMEs, such as officials from the Department of Industry and Trade, the Department of Cooperatives and MSMEs, Joint Village-Owned Enterprise (Bumdesma), and Regional National Craft Council (Dekranasda), particularly for the risk analysis.

### *3.3 Business ecosystem network analysis procedure*

In the business ecosystem network analysis, the collected data included actors, relationship types, and the quality (strength) of relationships among actors. The actors and types of relationships within the business ecosystem were identified, and the strength of these relationships was measured and plotted into a network.

Previous studies indicate several relationships, such as those of McGuinness and Johnson (2014), who argued that, under challenging circumstances, rapid access to diverse resources can be a crucial factor in enhancing organisational resilience. The notion of social capital offers considerable potential to strengthen the capacity to withstand and recover from disruptions. On the other hand, Pasman et al. (2020) emphasised that effective recovery from disruptions necessitates preparation through the availability of substitute materials and equipment, temporary labour, sufficient financial reserves, and the preservation of market share. Lazega et al. (2012) contended that advisory networks function as vital channels for the exchange of information, in which resource distribution occurs through informal interactions; accumulated expertise and experience often encourage ongoing dependence on others' advice. Furthermore, Fernández-Olmos and Ramírez-Alesón (2017) observed that technological collaboration networks can stimulate innovation and support the development of new products, as partnerships between SMEs and other stakeholders serve as an effective mechanism for improving innovation performance.

Thus, this study examined the various forms of relationships within the business ecosystem concerning access to essential resources – such as raw and supporting materials, equipment, social networks, financial capital, and human resources – as well as marketing and technological capabilities. The structural position of MSMEs within their business ecosystem networks was then analysed using ego-network analysis (Freeman's (1978) centrality measures: degree centrality, betweenness centrality, and closeness centrality) and whole-network analysis (density, centralisation, isolates, and variance). The formulas used are presented in the Appendix.

In this study, the business ecosystem network was plotted in R software, along with the computation of degree centrality, betweenness centrality, closeness centrality, centralisation, and network density.

### *3.4 Risk analysis procedure*

In conducting the risk analysis, identification was performed through direct observation, preliminary interviews, and an extensive literature review, which the risk owners, bamboo craft MSME, subsequently validated. The identified risks were then categorised into their respective causes and effects, referred to as risk agents and risk events. Measurements were undertaken to evaluate the severity of each risk event and the likelihood of occurrence for each risk agent, based on respondents' perceptions of bamboo craft MSMEs, and the R correlation.

Severity refers to the level of seriousness of the impact caused by an identified risk event, occurrence refers to the frequency level of a risk agent, and R represents the relationship strength between a risk agent and a risk event. Risks were identified through direct interviews with bamboo craft MSME practitioners – the risk owners – and through literature reviews, which were confirmed with the risk owners. Risk events and risk agents were evaluated on a 1–10 rating scale, and the correlations between them (R) were categorised as no correlation, weak, medium, or strong, shown on a scale of 0, 1, 3, and 9.

The collected data were then verified for completeness; in cases of missing information, follow-up visits were conducted to obtain the required details. Once all data had been collected, any incomplete responses were then preprocessed.

Data preprocessing was conducted using multiple imputation, as uncertainties encountered during data collection resulted in missing values classified as missing completely at random (MCAR) and missing at random (MAR). According to de Goeij et al. (2013), multiple imputation predicts missing values based on other available data, computes standard errors for each set, and then combines them into an overall estimate and standard error. Multiple imputation can still be used to predict missing data when the missingness is MCAR or MAR (de Goeij et al., 2013).

Once complete, the data were analysed using IFS-based HOR to accommodate the imprecision of human perception in risk measurement, and incomplete data were subsequently excluded from the analysis.

Regarding risk, IFS has been applied in several studies. For instance, Nguyen (2016) used IFS to estimate risks in maritime systems by integrating it with AHP; Chang and Cheng (2010) applied IFS-FMEA combined with DEMATEL for risk assessment; Liu et al. (2013) examined risk preferences by integrating IFS with MCDM; and Liu et al. (2015) integrated IFS with TOPSIS to determine FMEA risk priorities. This study integrates IFS with HOR to better assess ARP, thereby reducing uncertainty and enabling more effective risk mitigation. The methodological implication of incorporating  $\nu$  (non-membership) and  $\pi$  (hesitation) values is that it makes the HOR analysis more adaptable to the uncertainty inherent in human judgement.

In the IFS-based HOR, fuzzification was applied to the aggregate values of severity, occurrence, and R. The calculation of ARP was conducted using the de-fuzzified results for each variable (severity, occurrence, and correlation R) according to the formula from Pujawan and Geraldine (2009). This method is called IFS-based HOR because fuzzification is applied from the beginning to handle the uncertainty inherent in

respondents' perceptions when evaluating risks. This is because respondents may express uncertainty in evaluating the severity and occurrence of risks. Single-value risk assessment may not adequately capture this. The intuitionistic fuzzy framework allows the incorporation of membership, non-membership, and hesitation degrees, thereby providing a more nuanced representation of uncertain perceptions. By integrating this framework into the HOR model, the study accommodates perceptual variability while maintaining a structured mechanism for identifying risks.

IFS fuzzification was performed on both risk agents ( $\tilde{O}_j$ ) and risk event ( $\tilde{S}_i$ ) using the membership function that produced the smallest RMSE value. An example of the fuzzification process for occurrence in Area 1 is presented in the Appendix. The IFS-based fuzzification process generates  $\tilde{O}_j$  and  $\tilde{S}_i$ , which are subsequently defuzzified for utilisation in the computation of  $ARP_j$ . All steps in the IFS-based HOR were carried out using the R software.

The ARP ( $ARP_j$ ) is then calculated to help decide which risk sources to address first. The basis for calculating  $ARP_j$  in the HOR 1 matrix uses the following formula.

$$ARP_j = O_j \sum S_i R_{ij}$$

$O_j$  occurrence of risk agent j

$S_i$  severity of risk event i

$R_{ij}$  correlation of risk agent j and risk event i.

Subsequently, in the HOR 2 matrix, the  $ARP_j$  values are used to establish risk-mitigation priorities by calculating the total effectiveness ( $TE_k$ ) of each proactive action using the following formula.

$$TE_k = \sum_j ARP_j E_{jk} \quad \forall k$$

$TE_k$  total effectiveness

$E_{jk}$  correlation of preventive action k and risk agent j.

### 3.5 Integration of network and risk analysis














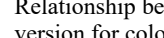
Both analyses, the business ecosystem network analysis and the risk analysis, were then revisited to interpret their relationship. This was done to examine whether the structural position of MSMEs within their business ecosystem is related to the potential risks they face. This enables a clearer understanding of how network structure influences risk perception. Furthermore, it provides a basis for developing more targeted mitigation strategies, informing business model innovation, and deriving policy-relevant insights tailored to different ecosystem configurations.

## 4 Discussion









### 4.1 Business ecosystem network analysis

In the business ecosystem analysis, several actors were identified in areas 1 and 2, as shown in Table 1. The identified actors include bamboo artisans (MSMEs), collectors located within the same city or district, resellers based outside the city, government agencies, customers (end users), universities, social organisations, material suppliers (bamboo farmers or bamboo traders and suppliers of auxiliary materials), village-owned enterprises (Bumdes), artisan associations, the private sector (companies), and shipping agents.

**Table 1** Actors identified in the business ecosystem network (see online version for colours)

<i>Node symbol</i>	<i>Node colour</i>	<i>Actors</i>	<i>Number of nodes</i>	
			<i>Area 1</i>	<i>Area 2</i>
Xn		Bamboo artisans	198	104
Pn		Collectors (the same city/district)	44	19
Rn		Resellers (outside the city)	18	26
Gn		Government agencies	7	10
Cn		Customers	10	-
Un		Universities	4	5
On		Social organisations	1	-
Sn		Material suppliers	9	36
Dn		Village-owned enterprises	2	-
An		Artisan associations	1	2
Wn		Private companies	1	-
Kn		Cooperatives	1	3
Bn		Banking institutions	2	2
Mn		Shipping agents	2	1

**Table 2** Relationship between actors within the business ecosystem network (see online version for colours)

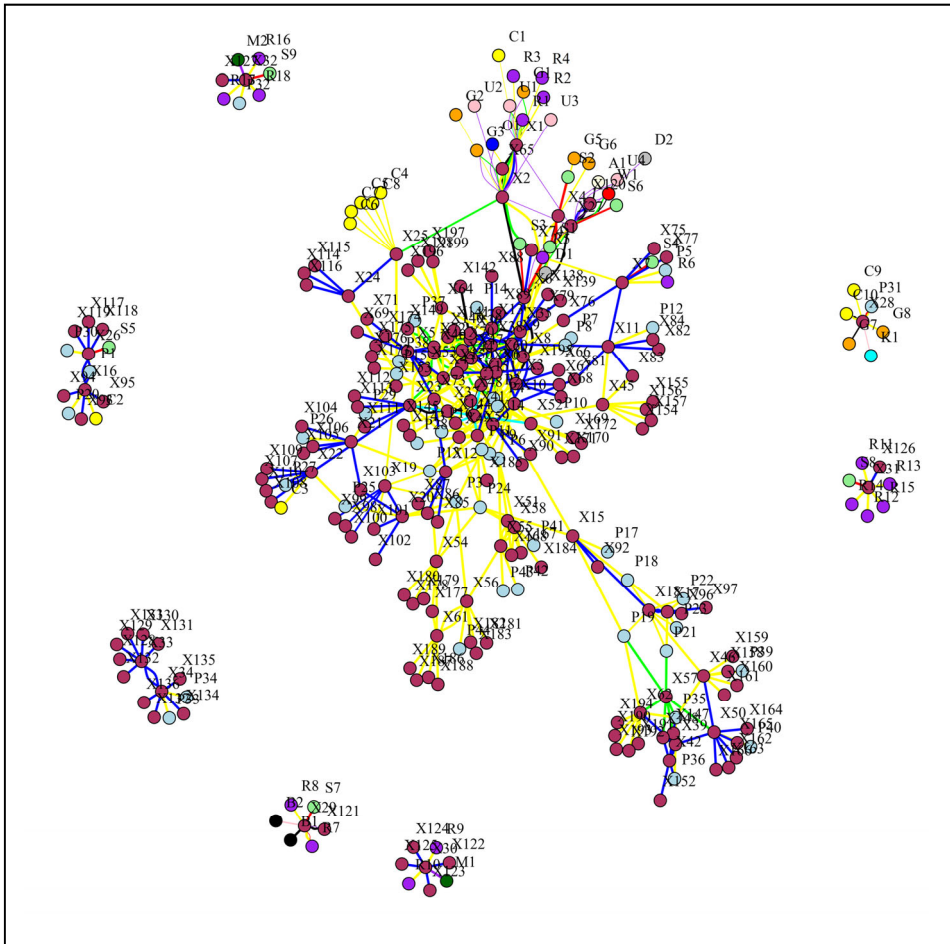
<i>Types of relationships</i>	<i>Colour of relationships</i>	<i>Average relationship weight</i>	
		<i>Area 1</i>	<i>Area 2</i>
a = business consultation		0.1816	3.9959
b = technological innovation		0.4484	0.0782
c = marketing		2.8049	1.4156
d = material supply		0.1278	0.9383
e = equipment supply		0.0605	0.0082
f = labour supply		1.4619	0.5185
g = financial provision		1.0112	0.0494
h = others		0.0628	0.1070

The actors serve as nodes (vertices) in the business ecosystem network. Seven types of relationships were measured: business consultation, technological innovation, marketing, material supply, equipment supply, labour supply, and financial provision. The average relationship weights analysed are shown in Table 2. The relationships formed constitute the edges in the business ecosystem network.

Based on average weights, marketing relationships appear particularly prominent in area 1, suggesting a stronger external market orientation. In contrast, business consultation is more prominent in area 2, suggesting a comparatively stronger emphasis on coordination and knowledge exchange.

Figures 3 and 4 illustrate the business ecosystem network models for areas 1 and 2.

**Figure 3** Business ecosystem network structure of the bamboo craft industry in area 1 (see online version for colours)



In the business ecosystem network, the relationship weights shown in Table 2 were derived from the average values of each relationship identified across all bamboo craft MSME respondents. In area 1, the strongest inter-actor relationships were those related to marketing activities, followed by labour supply and financial provision. This pattern may



central actors dominate the network’s connections, while density indicates the proportion of connections distributed at random across the network (Balsa-Barreiro et al., 2020). In the context of this study, the relatively lower centralisation and density observed in area 1 suggest a more dispersed and loosely connected structure, with limited concentration of coordination. In contrast, the slightly higher centralisation and density in area 2 indicate comparatively stronger coordination and a more cohesive distribution of ties. These differences in structural configuration provide an empirical basis for interpreting variations in interaction patterns and potential risk exposure across the two ecosystem contexts.

The results show that the centralisation values are relatively low in both areas (0.050 in area 1 and 0.072 in area 2), suggesting that both network structures are decentralised, with no single actor dominating information flow or other resources. However, area 2 shows a slightly higher centralisation value, suggesting a stronger tendency toward the formation of a coordination hub than area 1.

**Table 3** Business ecosystem network measures in Area 1 and Area 2

<i>Measures</i>	<i>Area 1</i>	<i>Area 2</i>	<i>Remarks</i>
Number of respondents	64	43	
Number of nodes	300	205	
Number of edges	446	243	
Centralisation	0.050	0.072	More MSMEs in area 2 serve as hubs in the network system compared to those in area 1
Density	0.010	0.012	Area 2 has slightly denser node connectivity compared to area 1
Isolate	7	4	Area 1 has more MSMEs that are isolated from the central network system compared to area 2
Variance	14	11	Area 1 has a more diverse set of actors compared to area 2
Average degree centrality	8.344	6.279	More MSMEs in area 1 have a greater number of direct connections compared to those in area 2
Average betweenness centrality	1,246.729	1,277.009	More MSMEs in area 2 serve as important connectors or intermediaries within the network compared to those in area 1
Average closeness centrality	0.016	0.021	MSMEs in area 2 have greater closeness within the network compared to those in area 1

Based on the density value and isolates, neither area has reached optimal cross-sector collaboration. Area 1, with seven isolates, and area 2, with four isolates, limit connectivity. These isolates can increase their operational risks because they are outside the ecosystem’s collaborative system. A wider range of actors in Area 1 will enable them to place more value due to various relationship possibilities and connections. Such diversity expands the opportunity structure within the ecosystem, enabling actors to access alternative partners, diversify market channels, and reduce dependence on single

relationship pathways. In this sense, increased actor diversity does not automatically generate value but provides greater relational options that can support value creation and risk dispersion when effectively coordinated within the network.

The average degree centrality in area 1 (8.344) is higher than in area 2 (6.279). This indicates that business actors in area 1 have more direct connections or greater access and support across different actors. As a result, they can get resources, share information, and work together more easily, which helps them respond quickly to disruptions. The MSME with a high degree of centrality can also make new connections during disturbances, which supports short-term adaptation. On the other hand, area 2 has a higher closeness centrality value compared to area 1. This indicates that the average distance between actors is smaller in area 2. Such a condition allows resources and information to move more quickly, even though area 2 has fewer connections.

The higher closeness centrality value in area 2 shows that actors can reach the entire network more rapidly. This is especially important for detecting disruptions early and enabling timely adaptation. On the other hand, the betweenness centrality values are similar in both areas, meaning that the business ecosystems have almost the same level of connectivity through brokers. These brokers connect groups and manage the flow of information, helping in risk management, resource coordination, and network problem-solving. The results of these three centrality measures are consistent with the findings of Zhang and Luo (2017). Their study indicates that degree centrality relates to transfer and communication, betweenness centrality to mediation and control, and closeness centrality to network efficiency and accessibility.

In area 1, the strongest links are found in marketing, labour provision, and financial support, which means the focus is on economic transactions and daily operations to maintain production continuity. Meanwhile, in area 2, business consultation is the most important connection, forming the core of interactions. This shows that MSMEs in area 2 value information and knowledge sharing, as well as collective learning, more than economic transactions. Although connections related to marketing and material supply in area 2 also display notable significance, they function as secondary linkages that follow consultation processes. These results imply that capacity building within the business ecosystem of area 2 often originates in knowledge transfer, thereby strengthening market and supply chain relationships.

## 4.2 *Risk analysis*

Risk identification in this study was carried out through a combination of literature review and interviews. The risks identified from the literature were listed, confirmed with bamboo craft MSMEs, and later categorised into risk events and risk agents (see Table 4). In this study, risk events are defined as observable adverse outcomes or disruptions experienced by MSMEs. In contrast, risk agents refer to the underlying sources or causes that trigger these events. The differentiation was made to ensure analytical clarity in the HOR framework, in which risk agents are evaluated based on their contributions to multiple risk events.

The bamboo craft MSMEs identified ten risk events and twelve risk agents. Risk assessments were carried out in both areas, covering the identified risk events and risk agents. The findings reveal diverse perceptions among respondents.

The bamboo craft MSMEs identified ten risk events and twelve risk agents. Risk assessments were conducted in both areas, yielding 1,408 expected responses in area 1

and 946 in area 2. A small proportion of missing data was observed (3.48% in area 1 and 9.20% in area 2). After field revisits, the remaining missing values were addressed using multiple imputation. The use of multiple imputation for addressing missing data is based on the assumption that the missing data mechanism can be modelled based on the available observed information, the relationships among variables can be represented through an iterative chained process, and the final estimates reflect variation across imputations rather than a single deterministic value.

**Table 4** Risk events and risk agents

<i>Code</i>	<i>Risk events (E<sub>i</sub>)</i>	<i>Code</i>	<i>Risk agents (A<sub>j</sub>)</i>
E <sub>1</sub>	Flawed product	A <sub>1</sub>	Human error in production
E <sub>2</sub>	Unclear raw material standards	A <sub>2</sub>	Product quality decreases due to storage
E <sub>3</sub>	Lack of skilled labour	A <sub>3</sub>	Product quality decreases due to delivery
E <sub>4</sub>	Raw material shortage during production	A <sub>4</sub>	Variation in raw material quality
E <sub>5</sub>	Increase in raw/auxiliary material prices	A <sub>5</sub>	The raw/auxiliary materials are difficult to obtain
E <sub>6</sub>	Delay in delivery/order fulfilment	A <sub>6</sub>	Disease outbreak
E <sub>7</sub>	Digital technology change	A <sub>7</sub>	Natural disaster
E <sub>8</sub>	Market uncertainty	A <sub>8</sub>	Electricity/water outage (utility downtime)
E <sub>9</sub>	Involvement of external collaboration in producing products with complex designs	A <sub>9</sub>	Equipment failures
E <sub>10</sub>	Unclear product standards	A <sub>10</sub>	Changes in customer orders
		A <sub>11</sub>	Inaccurate production planning
		A <sub>12</sub>	Threat/competition from other products, including imports/substitutes

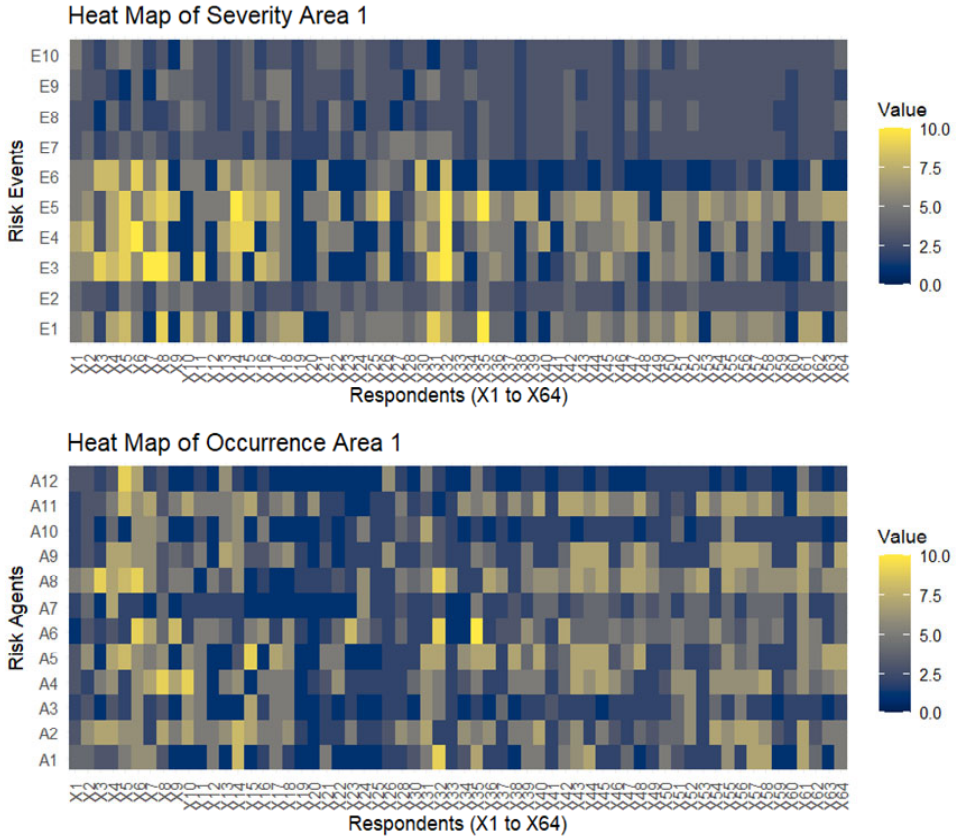
Figure 5 presents the heat map of perceived severity and occurrence after data preprocessing. The colour gradients illustrate the concentration and dispersion of perceived risk intensity. The dark blue colour indicates risk events with insignificant impact, while the bright yellow colour represents those with severe impact. For risk agents, the dark blue colour indicates infrequent occurrences, and the bright yellow colour indicates frequent ones. The observed intensity patterns in the heat map subsequently inform the calculation of ARP values using IFS-based HOR, thereby linking respondent perceptions with the structured quantification and ranking of risk agents.

The variation in perceptions is consistent with the argument of Streicher et al. (2023), who suggested that individual characteristics, social context, prevailing risk conditions, and organisational values, norms, and traditions influence risk perception. Accordingly, within the bamboo craft MSME business ecosystem, the degree of information exposure and the accumulation of shared experiences collectively shape how risks are perceived.

The measured severity and occurrence values were then applied to the HOR 1 matrix to calculate the ARP, which reflects the overall risk faced by MSMEs. Figure 6 presents the Pareto chart illustrating the derived ARP values. The Pareto cut-off was around 80%

cumulative ARP threshold to ensure that mitigation efforts address the majority of total risk exposure.

**Figure 5** Heat map of respondents’ perception of severity and occurrence in area 1 (see online version for colours)



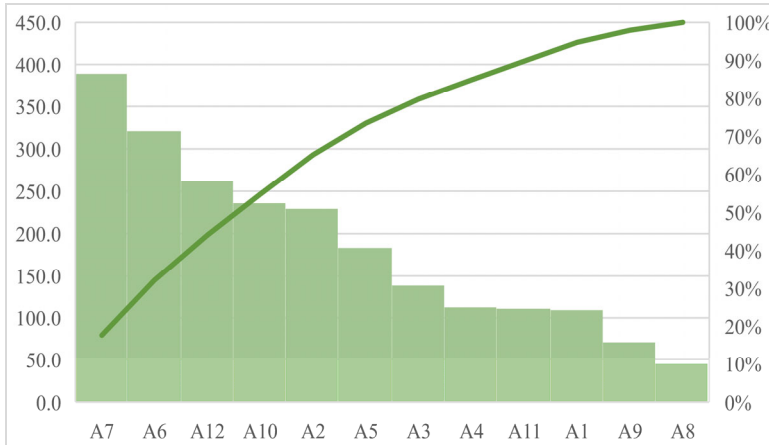
Based on Pareto analysis, the risk with the highest ARP values in area 1, in order: A7 (natural disaster), A6 (disease outbreak), A12 (threats/competition from other products, including imports/substitutes), A10 (changes in customer orders), A2 (product quality decreases due to storage), A5 (the raw/auxiliary materials are challenging to obtain), A3 (product quality decreases due to delivery), and A4 (variation in raw material quality).

Meanwhile, in area 2, the highest ARP values are A6 (disease outbreak) and A7 (natural disaster), followed by A5 (the raw/auxiliary materials are challenging to obtain), A4 (variation in raw material quality), A8 (electricity/water outage), A11 (inaccurate production planning), A2 (product quality decreases due to storage), A9 (equipment failure), and A1 (human error in production).

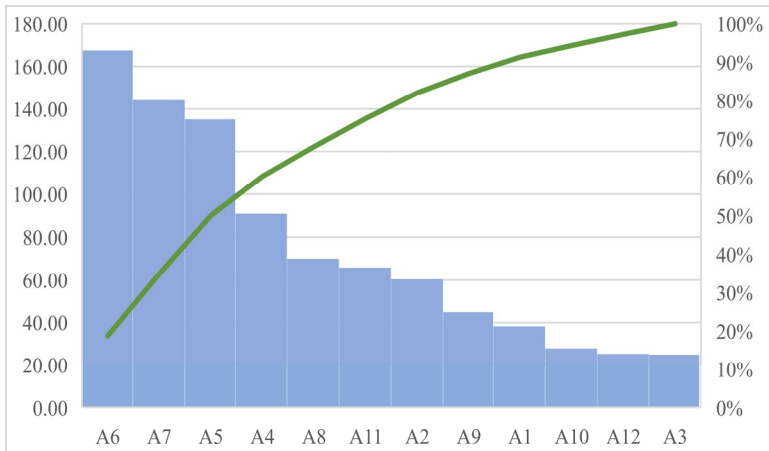
These findings indicate a similarity in risk perception for the two highest ARP values in both areas – namely, that both areas view external risks, such as natural disasters and disease outbreaks, as the most threatening. The subsequent rankings, however, indicate perceptual variations between the two areas. The HOR 2 matrix outlines the total effectiveness ( $TE_k$ ) values of proactive measures, prioritising the risk mitigation actions

to be implemented. In HOR 2, the risk mitigation process is based on the ARP results from HOR 1. In area 1, the recommended mitigation strategies, in order of priority, include: coordination/collaboration with other parties, formation of artisans association for price stability and other purposes, preparing/adding stock, conducting online sales, and maintaining raw material stock that is not excessive.

**Figure 6** Pareto diagram of ARP in (a) area 1 and (b) area 2 (see online version for colours)



(a)



(b)

In area 2, based on the highest  $TE_k$  values, the suggested risk-mitigation approaches include: preparing/adding stock, switching to manual tools during an electricity outage, ensuring precise material analysis, avoiding dependence on a single supplier, and clearly specifying product standards. The HOR matrix with the ARP calculations is presented in the Appendix, as an example for area 1.

### *4.3 Relationship between the business ecosystem network and risk analysis*

Based on the analysis of MSMEs' structural positions within the business ecosystem, as represented by the calculated measures, a further analysis examined their relationship with risk analysis. The structural configuration observed in both study areas reflects a varying degree of interconnectedness among actors within their respective business ecosystems. The findings suggest an interpretative association between the pattern of interconnectedness and dominant risk perceptions. In this sense, differences in network structure correspond with variations in how risks are perceived and prioritised across the two areas.

In area 1, the network structure appears transactional and market-oriented rather than knowledge-based or designed for long-term coordination. The high weight of marketing relationships indicates that MSMEs primarily interact in trade or product sales contexts. This reflects openness to markets but also a strong dependence on external demand. Reliance on market interactions or external labour resources increases exposure to demand-related risks, such as competition from other products or changes in customer orders.

The business ecosystem in Area 1 has a fairly high level of connectivity, shown by its degree centrality. Several isolated members and low network density create gaps that slow information sharing between groups, making it harder for the ecosystem to react quickly to disruptions. Area 1's business ecosystem seems open but fragile. This characterisation does not derive from a single network metric but represents a conceptual synthesis of multiple structural indicators. The relatively high degree centrality suggests that actors maintain several connections, indicating openness in terms of relational reach. However, this openness is accompanied by low network density and several isolated actors, suggesting limited cohesion and fragmented coordination. Area 1 maintains strong market-focused relationships, but weak internal cohesion makes it more vulnerable to external risks.

According to Granovetter (1985), coordinating actions becomes difficult when social ties are weak or absent. Therefore, based on Granovetter's statement, mitigation efforts in Area 1 should focus on compensating for a weak network through collaborative actions, such as coordinating or cooperating with other parties, forming artisan associations, preparing inventory, and engaging in online sales. All these initiatives demonstrate a collective awareness aimed at strengthening institutional relationships in area 1.

The network structure in area 2 is primarily knowledge-oriented, supporting mutual learning that could help MSMEs for long-term adaptation to disruptions. Because its main relationships are consultative, the identified risks are mostly operational and technical. These include limited access to raw materials, power or water outages, and inaccuracies in production planning that are linked to internal organisational capacity.

The marketing relationship weight (1.4156) indicates that interactions among actors in area 2 for market expansion are ongoing but still limited, relatively lower than in area 1. The strong consultative interactions in area 2 increase MSMEs' awareness of the importance of technical capacity to support production. The material supply relationship value (0.9383) shows that the supply chain is pretty active but not yet stable. Dependence on one or a few suppliers explains the high raw material availability risk reflected in the ARP values.

Area 2 demonstrates a high intensity of consultative relationships and better cohesion (as indicated by a slightly higher closeness centrality value than area 1), but the risks are

more internal and technical. With information about disruptions spreading more quickly, MSMEs can respond adaptively. However, because average degree centrality is lower, each actor's connections are narrower, leading to local, small-scale solutions.

Risk mitigation strategies in area 2 include preparing or adding stock, switching to manual tools during an electricity outage, ensuring precise material analysis, avoiding dependence on a single supplier, and clearly specifying product standards – reflecting a knowledge-based, process-efficiency-oriented mitigation pattern. Internal strengthening becomes a priority to address emerging risks through information-based problem-solving and technical innovation.

Thus, the results suggest that the loose, market-oriented network structure in area 1 is associated with greater exposure to external demand shocks and patterns of negative growth. In contrast, the tighter and knowledge-based network in area 2 appears to be linked to stronger collective learning dynamics and patterns of positive growth.

The analysis results indicate that the relationship between business ecosystem structure and risk profile has direct implications for the direction of business model innovation that can enhance MSME performance. In area 1, the relatively loose network structure, characterised by low density and a higher number of isolates, shows a dominance of marketing-related ties, yet collective coordination remains limited. This condition is associated with exposure to more external risks. The business model innovation involves developing order aggregation, joint marketing initiatives, product differentiation based on regional identity, and strengthening the role of intermediary institutions or creative centres as market orchestrators. Such innovation aims to reduce demand volatility, increase collective bargaining power, and create value propositions that are more difficult to substitute. In other words, performance improvement in area 1 is more effectively achieved through business model innovation that reduces external uncertainty and reinforces collective market positioning.

In contrast, area 2 exhibits a more cohesive network structure, reflected in higher closeness centrality and the dominance of business consultation and material supply relationships, indicating relatively stronger internal coordination. However, the dominant risks are operational in nature. This suggests that the primary vulnerability lies in the stability of input and production processes. Accordingly, the required business model innovation focuses on strengthening supply chain management and operational flexibility, such as adopting multi-supplier strategies, standardising material specifications, implementing measured inventory systems, and redesigning the production process to be adaptive to disruptions. Given that consultative relationships within the ecosystem are already strong, innovation can also be knowledge-based, emphasising technical knowledge sharing and the development of shared standards. Performance improvement in area 2 is thus achieved through enhanced operational reliability and consistent product quality.

The findings of this study enrich the business ecosystem and MSME risk management literature by showing that network structure not only influences performance but also shapes the dominant risk perception within an ecosystem. Previous studies on networks and business ecosystems have generally emphasised that inter-actor connectivity enhances access to resources, innovation, and firm performance. However, most of these studies have not empirically shown how variations in network structure can generate different risk profiles (Luo et al., 2022; Nyuur et al., 2018; Yang and Tong, 2025; Zhao and Zhao, 2020). Overall, in contrast to prior research that primarily discusses networks as drivers of performance or innovation, this study shows that

network configurations shape distinct risk profiles and, in turn, influence the direction of required business model innovation. The study therefore reinforces the implication that strategies for improving MSME performance should be aligned with the structure of the business ecosystem in which they operate.

## 5 Conclusions

The actors involved in the MSME business ecosystem network include bamboo artisans, collectors, resellers, government agencies, customers, universities, social organisations, material suppliers, village-owned enterprises, artisan associations, private companies, cooperatives, banking institutions, and shipping agents. The relationships among these actors differ between area 1 and area 2. In area 1, the highest relationship weights are found in marketing, followed by labour provision and financial support. In area 2, the strongest relationships are in business consultation, followed by marketing and raw material supply.

The conditions and characteristics of the bamboo craft MSME business ecosystem, as indicated by measures such as centralisation, density, isolates, betweenness centrality, and closeness centrality, are associated with variations in MSMEs' risk perceptions. The network analysis results reveal fundamental structural differences between the two areas. Area 1 has a broad but loosely connected structure, with dominant relationships in marketing and labour provision. In contrast, area 2 has a more cohesive and coordinated ecosystem structure, with dominant relationships in business consultation and marketing.

The differing conditions and characteristics of the business ecosystems in both areas also correspond to different aggregate levels of potential risk faced by MSMEs. In area 1, the five primary sources of possible risk based on ARP values are, respectively: natural disaster, disease outbreak, threat/competition from other products, including imports/substitutes, and changes in customer orders. While in area 2, the order is: disease outbreak, natural disaster, the raw/auxiliary materials, variation in raw material quality, and electricity/water outages.

The risk analysis shows that Area 1 perceives higher external risks, and area 2 perceives higher internal and technical risks. Risk mitigation strategies in area 1 are social and collective, including coordination/cooperation with other parties, formation of artisan association for price stability and other purposes, preparing/adding stock, conducting online sales, and maintaining raw material stock that is not excessive. In area 2, risk mitigation strategies are primarily technical and knowledge-oriented, involving measures such as increasing stock levels, switching to manual tools during power outages, ensuring thorough material analysis, reducing dependence on a single supplier, and also clearly defining product standards.

The empirical findings of this study indicate that the differences in business ecosystem structures between area 1 and area 2 lead to distinct risk profiles. These results can be interpreted as suggesting context-specific policy directions. In area 1, the relatively loose and weakly coordinated network structure is associated with dominant external risks, such as competition and demand fluctuations. Therefore, relevant policy measures should focus on strengthening institutional roles as market orchestration platforms to stabilise demand and enhance collective bargaining power. In area 2, a more cohesive network structure is characterised by dominant operational risks, particularly related to raw materials and the production process. The corresponding policy

implications involve strengthening supply chain management, standardising quality, and enhancing technical production capacity. These empirical findings highlight that MSME development policies need to be aligned with the configuration of the ecosystem structure and the dominant risk profile to achieve more effective and sustainable performance improvements.

This study extends the ecosystem as a structural perspective (Ribeiro et al., 2024) and complements risk perception theory (Siegrist and Árvai, 2020; Goerlandt et al., 2021) by demonstrating that risk perception is not merely an individual cognitive outcome, but embedded in network configurations and organisational interdependencies.

The exploratory study limits the generalisability of its findings, but it offers valuable insights for the business ecosystem development in the study areas. Future research should include empirical studies across various sectors to establish a broader typology of MSME business ecosystems, especially regarding network structures and risk profiles.

## Declarations

All participants in this study were informed of the purpose, procedures, and data use in this research. Participants' identities were kept confidential, and all collected data were used solely for academic purposes.

This work has been proofread and linguistically refined using Grammarly to enhance clarity and fluency.

All authors declare that they have no conflict of interest.

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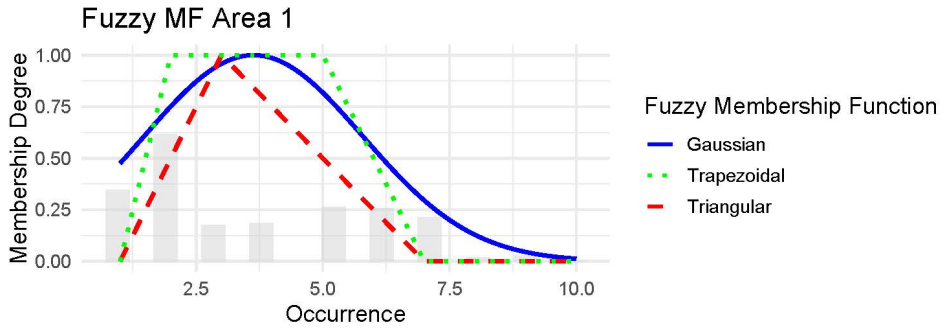
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**Appendix**

**Table A1** Measurement, definition, and formula in the business ecosystem

<i>Measurement</i>	<i>Definition</i>	<i>Formula</i>
<i>Ego network</i>		
Degree centrality	The count of nodes directly linked to a given node	$cD(x_i) = \frac{\text{deg}(x_i)}{n - 1}$ <p> <math>c_D</math> = degree centrality  <math>x_i \in V</math>, <math>V</math> is a set of nodes  <math>n =  V </math>  <math>\text{deg}(x_i)</math> = degree node <math>x_i</math> (Rochat, 2009)                 </p>
Betweenness centrality	The number of times a node appears as the shortest path (geodesic) in the graph. The more frequently it seems to occur, the more critical its role as a connector.	$C_B(i) = \frac{2 \sum \sum \frac{g_{jk}(i)}{g_{jk}}}{(n - 1)(n - 2)}$ <p> <math>C_B</math> = betweenness centrality  <math>g_{jk}</math> = sum of geodesics from node <math>x_j</math> to node <math>x_k</math>  <math>g_{jk}(i)</math> = sum of geodesics from <math>x_j</math> to <math>x_k</math> mengandung <math>x_i</math>                      Double sum is calculated over all pairs <math>(j, k)</math> where <math>j \neq i \neq k</math> and <math>j &lt; k</math> (Rochat, 2009)                 </p>
Closeness centrality	The sum of the distances from one node to all other nodes in the network	$C_c(x_i) = \frac{n - 1}{\sum_{j \neq i} \text{dist}(x_i, x_j)}$ <p> <math>C_c</math> = closeness centrality  <math>x_i \in V</math>  <math>n =  V </math>  <math>\text{dist}(x_i, x_j)</math> = distance from node <math>x_i</math> to node <math>x_j</math> (Rochat, 2009)                 </p>
<i>Whole network</i>		
Centralisation index	The degree to which a network is structured or centred around one node	$C_d = \frac{\sum_{i=1}^N C_{\max} - C_i}{\max \left[ \sum_{i=1}^N (C_{\max} - C_i) \right]}$ <p> <math>C_{\max}</math> = centrality of the focal node  <math>C_i</math> = centrality of the rest of the nodes (Farré-Perdiguer et al., 2016)                 </p>
Density	The relationship exists in relation to the possible relationships	$D = \frac{\sum_{i=1}^N \sum_{i=1}^N X_{ij}}{n(n - 1)}$ <p> <math>X_{ij}</math> = adjacency matrix  <math>N</math> = number of nodes (Farré-Perdiguer et al., 2016)                 </p>

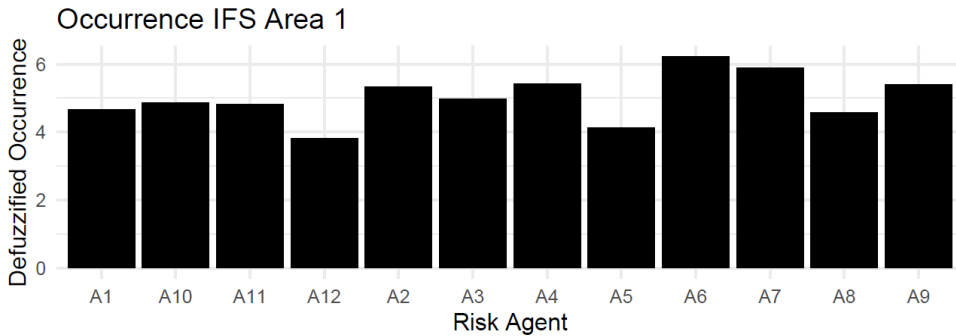
**Figure A1** MF fitting for occurrence in area 1 (see online version for colours)



**Table A2** IFS fuzzification of occurrence in area 1

<i>A type</i>	<i>Avg. membership</i>	<i>Avg. non-membership</i>	<i>Avg. hesitance</i>	<i>Count</i>	<i>Defuzzified occurrence</i>
A1	0.363	0.530	0.107	62	4.66
A2	0.411	0.443	0.146	62	5.33
A3	0.383	0.485	0.132	62	4.97
A4	0.411	0.425	0.163	62	5.42
A5	0.310	0.585	0.105	62	4.12
A6	0.504	0.366	0.130	62	6.22
A7	0.480	0.404	0.116	62	5.89
A8	0.339	0.517	0.145	62	4.56
A9	0.423	0.444	0.133	62	5.39
A10	0.375	0.496	0.129	62	4.87
A11	0.371	0.506	0.123	62	4.81
A12	0.282	0.623	0.095	62	3.81

**Figure A2** Graphical representation of IFS occurrence in area 1 (see online version for colours)



**Table A3** HOR 1 matrix of area 1

Risk events (Ei)	Risk agents (Aj)												IFS severity of event i (Si)	
	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12		
E1 Flawed product	8.69	4.69	6.81	5.98	0.00	0.00	5.03	0.00	5.49	0.00	0.00	0.00	0.00	4.24
E2 Unclear raw material standards	0.00	0.00	0.00	5.68	7.95	0.00	7.30	0.00	0.00	0.00	0.00	0.00	0.00	9.01
E3 Lack of skilled labour	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	7.95	5.98	0.00	0.00	3.42
E4 Raw material shortage during production	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.69	0.00	0.00	3.96
E5 Increase in raw/auxiliary material prices	0.00	0.00	0.00	0.00	4.69	6.86	8.41	0.00	0.00	0.00	0.00	0.00	0.00	3.42
E6 Delay in delivery/order fulfillment	0.00	0.00	0.00	0.00	5.98	4.69	8.69	5.98	6.81	5.98	8.69	0.00	0.00	3.51
E7 Digital technology change	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.69	8.9
E8 Market uncertainty	0.00	0.00	0.00	0.00	0.00	8.82	8.86	0.00	0.00	7.74	0.00	0.00	8.69	8.61
E9 Involvement of external collaboration in producing products with complex designs	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	5.98	8.73
E10 Unclear product standards	5.68	8.69	6.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.91
IFS occurrence of agent j (Oj)	4.66	5.33	4.97	5.42	4.12	6.22	5.89	4.56	5.39	4.87	4.81	3.81	643.0034	
Aggregate risk potential (ARP) j	407.5375	518.681	447.2851	414.8034	447.6755	720.6697	1311.402	95.71349	254.304	559.1744	410.61	643.0034		
Priority rank of agent j	10	5	7	8	6	2	1	12	11	4	9	3		

**Table A4** HOR 2 matrix of area 1

Risk agents (A <sub>i</sub> )	Preventive actions (PA <sub>k</sub> )													ARP <sub>j</sub>		
	PA12	PA13	PA14	PA15	PA16	PA17	PA18	PA19	PA10	PA13	PA16	PA17	PA19		PA20	PA23
A7 Natural disaster	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	0.00	0.00	0.00	0.96	0.72	0.00	1,311.40
A6 Disease outbreak	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.72	0.72	0.00	720.67
A12 Threats/competition from other products including imports/substitutes	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.77	0.77	0.72	0.00	0.18	643.00
A10 Changes in customers order	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.47	0.00	0.00	0.00	0.00	0.00	559.17
A2 Product quality decreases due to storage	0.98	0.47	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	518.68
A5 The raw/auxiliary materials are difficult to obtain	0.00	0.00	0.00	0.00	0.00	0.00	0.47	0.00	0.41	0.00	0.00	0.00	0.00	0.00	0.00	447.68
A3 Product quality decreases due to delivery	0.00	0.00	0.47	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	447.29
A4 Variation in raw material quality	0.00	0.00	0.00	0.00	0.87	0.66	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	414.80
Total effectiveness of action k	508.3073	243.78	210.224	438.3394	360.879	273.7703	210.4075	720.6697	1,442.493	262.812	495.1126	495.1126	2,240.791	1,463.092	115.7406	