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Entrepreneurial competencies and the conceptual dimension of intentions: Insights from a hybrid machine learning approach

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Abstract

PURPOSE: *This study examines the relationship between entrepreneurial competencies and intention-related characteristics among university students, addressing the need for a deeper understanding of how psychological traits shape entrepreneurial tendencies in young populations. Focusing on students at the University of Information Technology and Management (UITM) in Poland, the research explores how adaptability, problem-solving, and cognitive flexibility contribute to the conceptual configuration of entrepreneurial intention.* ***METHODOLOGY:*** *A hybrid methodological approach was adopted, combining bibliometric analysis using SciMAT with data-mining techniques. A survey of 1,520 students provided the empirical basis for the analysis. Rough set theory was used to address incomplete data, while the C5.0 decision-tree classifier and feature interdependency analysis were applied to identify informative item-level patterns in the dataset. Demographic variables were incorporated to examine group-differentiating structural patterns across student groups. The study draws on TPB and self-efficacy as theoretical lenses for interpreting the conceptual patterns identified, without modelling TPB constructs as predictive variables.* ***FINDINGS****: The analysis highlights that adaptability (A12), problem-solving ability (A19), goal orientation (A18), and cognitive flexibility (A13) recur in the most informative branches of the decision-tree structures, indicating their central role within the broader configuration of entrepreneurial competencies. The results reflect how these attributes cluster within intention-related patterns rather than forming predictive relationships. The study also reveals distinct competency profiles across gender, age, nationality, and field of study, underscoring the heterogeneous nature of entrepreneurial characteristics in the student population.* ***IMPLICATIONS:*** *The findings contribute to the entrepreneurship literature by demonstrating conceptual coherence between intention-related attributes observed at the item level and dominant thematic patterns identified in recent research. Rather than testing or extending formal intention theories, the study offers an interpretative perspective on how adaptability, resilience, and problem-solving attributes cluster within student populations. From a practical standpoint, the results highlight the importance of entrepreneurship education initiatives that foster adaptive learning, coping with difficulty, and problem-solving skills. The use of data-driven decision-support tools may further assist educators in designing personalized learning environments that respond to heterogeneous student profiles.* ***ORIGINALITY/VALUE:*** *This study offers a novel contribution by integrating bibliometric validation with machine-learning-based pattern discovery. By mapping the conceptual landscape of intention-related attributes rather than predicting entrepreneurial intention, it provides a distinctive analytical perspective and actionable insights for educators and policymakers seeking to cultivate entrepreneurial competencies among university students.*

Keywords: *entrepreneurial intentions, entrepreneurial competencies, rough set theory, decision tree classifier, attribute dependency analysis, cognitive flexibility, problem-solving, resilience, entrepreneurship education, self-efficacy, machine learning, bibliometric analysis.*

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INTRODUCTION

The globalization of the business world has made the establishment of new ventures both more important and worth investigating (Mueller, 2001). Entrepreneurship is considered as one of the main determinants of the growth and innovation capacity of modern economies in the context of the process of transforming individuals' innovative ideas (Braunerhjelm & Henrekson, 2024) into economic and social products (Sendra-Pons, Comeig, & Mas-Tur, 2022). The stronger the entrepreneurship ecosystem, the more efficient the technology becomes, thereby increasing its impact on economic growth (Zahra, Liu, & Si, 2023). In this context, entrepreneurs act as a bridge, transforming innovative ideas into economic growth by bringing them to market (Acs, Estrin, Mickiewicz, et al., 2018). When literature is examined, it is evident that entrepreneurship research largely focuses on adults, and studies of young individuals are insufficient (Anwar & Saleem, 2019). In particular, the entrepreneurial tendencies of young individuals are of strategic importance for combating unemployment, fostering innovation, and advancing local development policies (Mutarubukwa, 2015). In this context, it is believed that this study will provide valuable information for examining the entrepreneurship competencies and tendencies of university students, for developing education policies and support mechanisms, and for filling the gap in this field. Entrepreneurial competencies are influenced by multidimensional variables such as individuals' intrinsic characteristics, psychological tendencies, environmental factors, and demographic structures (Maheshwari et al., 2023). Accurate analysis of this complex structure is possible not only with traditional statistical methods but also with more powerful analytical approaches, such as data mining techniques (Shu & Ye, 2023). In this study, a hybrid analysis method was adopted using rough set theory to handle incomplete data, the pattern discovery method for pattern inference, and the C5.0 algorithm for classification (Bujlow et al., 2012). The aim of this study is to reveal the relationships between entrepreneurial competencies and entrepreneurial intention among the students at the University of Information Technology and Management (UITM) in Poland. The research was carried out using data from 1,520 students, and the main variables affecting students' entrepreneurial tendencies were identified. Although this study was theoretically inspired by TPB, rather than an empirical design aimed at testing a TPB-oriented structural model, this study examines entrepreneurial intent and related characteristics using the entrepreneurial potential tool, which does not include standard TPB components as separate constructs. Accordingly, the present study aims to (i) examine the conceptual structure of entrepreneurial competencies among university students using pattern-mining and science-mapping techniques, (ii) explore how adaptability, resilience, problem-solving, and related attributes cluster within this structure, and (iii) identify how these attributes conceptually align with the thematic evolution of the entrepreneurship literature revealed through SciMAT analysis. The study ultimately seeks to provide an integrated understanding of intention-related characteristics by linking survey-based item patterns with bibliometric thematic development.

In the following sections, the article first situates the study within the existing literature on entrepreneurial competencies and intention-related attributes, highlighting conceptual gaps that motivate the present analysis. The methodological section then outlines the hybrid research design, including the bibliometric validation procedure and the machine-learning techniques applied to the student dataset. The results section presents the thematic structures emerging from SciMAT and the item-level patterns identified through decision-tree modelling. This is followed by a discussion that interprets these patterns considering contemporary entrepreneurship research. The article concludes by summarizing the main contributions and outlining implications for future studies and educational practice.

LITERATURE REVIEW

Entrepreneurship research has identified key personality traits that lead individuals to engage in entrepreneurial behavior (Awwad & Al-Aseer, 2021). In this context, the two characteristics that stand out the most are internal locus of control and innovativeness (Nisula & Olander, 2025). While the internal locus of control refers to the belief that individuals can direct events in their lives through their own efforts (Tentama & Abdussalam, 2020), innovation is the ability to generate and implement new ideas, as emphasized in Schumpeter's definition of an entrepreneur. According to Fong et al. (2016), culture is one of the factors that shape the behavior of individuals. Hofstede's (1980) theory of cultural dimensions has been a guide to understanding differences between countries in values, beliefs, and ways of doing business. In this context, how entrepreneurial characteristics differ across cultures and the reasons for these differences emerge as important research questions (Mueller, 2001). According to Heredia-Carroza et al. (2024), entrepreneurship is an important tool for economic and social development in rural areas and mobilizes local potential. In this respect, it offers a promising opportunity to revitalize rural areas and ensure sustainable growth. In their study, Heredia-Carroza et al. (2024) examined the factors that increase entrepreneurial intentions among university students in Comarca Sierra Sur, Andalusia, a rural region of Spain. They also emphasized that individual values and psychological factors should be considered to promote entrepreneurship in rural areas, and suggested that entrepreneurship education, gaining a sense of personal control and supporting entrepreneurial role models in the family should be supported. While supportive tax policies encourage entrepreneurship (Tsou et al., 2023). In some cultures, rewarding risk-taking, viewing failure as a learning process, and emphasizing individual success are among the factors that strengthen entrepreneurial intention. In cultures with a high fear of failure and dominant collectivist structures, the tendency toward entrepreneurship may be relatively low (Henriquez-Daza et al., 2023). Henriquez-Daza et al. (2023) found that fear of failure negatively affects entrepreneurs' growth targets. They also noted that collectivist culture significantly mitigates this negative impact in developing countries. This situation underscores the need for culturally aware education and policy approaches to develop entrepreneurial competencies. Accordingly, entrepreneurial competencies should be considered as a multidimensional structure (Tetteh et al., 2024). Understanding this structure is critical for developing effective entrepreneurship policies, supporting entrepreneurial individuals, and achieving sustainable development goals.

Despite the increasing number of studies on entrepreneurial intention among students, literature lacks an integrated perspective that connects item-level behavioral patterns with the evolving thematic structure of entrepreneurship research. No existing study simultaneously examines (i) how intention-related traits cluster together within student populations and (ii) how these clusters align with thematic trajectories identified in recent bibliometric analyses. Therefore, a clear gap exists in bridging individual-level response patterns with the macro-level evolution of entrepreneurship knowledge, which the present study aims to address.

Entrepreneurial competencies, intention, and tendency

Entrepreneurship is not just the process of starting a business. It is also the capacity to create value through innovation and is one of the key drivers of economic development (Sedeh, Pezeshkan, & Caiazza, 2022). Schumpeter (1934) defines entrepreneurs as „people who try to change the production model by using untested technical possibilities to produce an invention or a new product, or to produce an old product in a new way." This definition emphasizes that entrepreneurship is not a static activity but a dynamic, creative process. Especially in today's digital age, qualities such as technological literacy, innovation capacity, and rapid adaptation skills have become important determinants of entrepreneurship (Baron & Shane, 2008). It can be considered as a reflection of individuals' entrepreneurial intentions, potential, and competencies. When considered within the framework of Ajzen's planned behavior theory (1991), entrepreneurial intention is a combination of factors such as attitudes, perceived behavioral control, and social norms that shape an individual's desire to be an entrepreneur, and it is a phenomenon that has micro-level effects (Morales-Pérez et al., 2022). Studies conducted especially among university students associate entrepreneurial intentions with factors such as risk-taking, innovation, and autonomy of individuals in this group (Liñán et al., 2011).

Entrepreneurial intention is defined as an individual's desire and determination to become an entrepreneur in the future. It is considered the starting point of the entrepreneurial process and a psychological factor that strongly affects the probability of entrepreneurship (Krueger et al., 2000). The most widely used theoretical framework in entrepreneurial intention research is Ajzen's theory of planned behavior (Ajzen, 1991). TPB was developed to describe the intention of individuals to perform a certain behavior. In this model, in the context of entrepreneurship, attitude indicates that entrepreneurship is seen as beneficial and meaningful for the individual (Baba et al., 2025), while perceived behavioral control reflects an individual's self-confidence in entrepreneurial skills and access to resources (Liñán & Chen, 2009). Liñán and Fayolle (2015) examined a large number of studies on entrepreneurial intention and found that TPB components have high explanatory power in understanding entrepreneurial intention. In a study by Liñán and Chen (2009), the scales developed within the TPB framework were found to be reliable and valid for measuring entrepreneurial intention. Studies conducted especially on university students have shown that attitude and perceived behavioral control are the most determining factors in entrepreneurial intention (Fayolle & Liñán, 2014).

Entrepreneurship tendency is considered as a basic determinant that affects the entrepreneurial intention of individuals and the processes of transforming this intention into behavior. Research conducted especially on university students reveals that this trend plays an important role in shaping future entrepreneur profiles (Zhao et al., 2005; Lüthje & Franke, 2003). In this regard, various studies conducted among students show that individual characteristics and demographic factors influence entrepreneurship tendencies and yield meaningful findings on their effects (Anwar & Saleem, 2019).

Numerous studies among university students show that this group exhibits a high level of entrepreneurship. In comparative analyses, especially among students studying in different academic fields such as business, economics, engineering and social sciences, significant differences in entrepreneurship tendency have been observed (Wilson et al., 2007). In addition, it is emphasized that entrepreneurship courses, seminars, and practical training significantly increase students' entrepreneurial orientation (Fayolle & Gailly, 2008). Gender is one of the main demographic factors influencing the propensity for entrepreneurship. The literature generally indicates that male students exhibit higher entrepreneurial tendencies than female students (Zhao et al., 2005; Wilson et al., 2007). Zhao et al. (2005) found that self-efficacy perceptions among American college students have a strong effect on entrepreneurial intention. Business management students had higher entrepreneurial tendencies. In addition, applied entrepreneurship programs (incubators, competitions, mentoring, etc.) have been shown to significantly increase students' motivation to become entrepreneurs at many universities in the USA. Lüthje and Franke (2003) demonstrated, in studies conducted at German technical universities, that engineering students are highly entrepreneurial but that environmental factors limit the transformation of this potential into an intention to start a business. Among these factors, risk perception, uncertainty, avoidance and financing difficulties stood out. In studies conducted among university students in Spain, it has been found that entrepreneurship tendency is closely related to cultural values. Entrepreneurial intention was observed to be stronger, especially in students with a high level of individualism (Liñán et al., 2011). For this reason, it is thought that entrepreneurship training carried out with interdisciplinary approaches can increase the entrepreneurship tendencies of students in different fields.

Use of data mining methods in social sciences

In the social sciences, data mining offers a variety of technologies that allow previously undetected patterns (Shu & Ye, 2023) and autonomous decision-making (Kusiak, 2001). In this way, it becomes possible to generate innovative ideas and develop new theoretical approaches in different disciplines (Shu & Ye, 2023). According to Shu and Ye (2023), to increase predictive power and manage causal diversity, data mining methods evaluate many variables – whether cooperating or independent – systematically and often automatically. Data mining is an emerging field of computational intelligence that is often used to go beyond traditional analysis and reveal complex relationships among multiple variables (Kusiak, 2001).

The rough set theory developed by Pawlak (1982) is an effective method for handling incomplete data. Rough clusters provide a solid foundation for decision support systems in data sets where uncertainty and incompleteness are intense. Rough set theory is a tool for data mining and knowledge discovery (Mroczek, 2023). Missing data can be estimated effectively using the maximum consistent blocks (MCB) method (Sun et al., 2021; Kryszkiewicz, 1998; Leung & Li, 2003). The C5.0 algorithm is a decision tree-based classification technique that provides high accuracy, especially when working with categorical data (Quinlan, 1993).

METHODOLOGY

Research sample and data collection process

The aim of the study is not to generalize to all university students, but to identify conceptual and behavioral patterns within a well-defined student population.

The data source for the research was an original survey questionnaire developed in collaboration with experts in economics, sociology, and psychology (see Appendix 1). The research was conducted between 17.01.2023 and 21.03.2023 and covered students of all fields of study offered at the University of Information Technology and Management in Rzeszów, UITM (Poland), i.e. Computer graphics and multimedia production, Programming, Computer science, Cybersecurity, Data science, Game design and development, Dietetics, Cosmetology, English Philology, English Philology with Chinese, Finance and accounting in management, Aviation Management, Global aviation management, Graphic design, Management, International business management, Journalism and social communication, Logistics, Nursing, Physiotherapy and Psychology in management), both modes of study (full-time and part-time studies), as well as both study paths (Polish and English) and both levels of education (first and second cycle studies).

In the research process, it was assumed that each field of study must be represented by at least 20% of students. As a result, a sample of 1,520 respondents (i.e., research participants) was obtained (i.e., 29.8% of all UITM students), which was representative of all fields of study and the population of students studying at UITM (see Appendix 2).

The first part of the survey (A), consisting of 28 questions, examined the characteristics of respondents' entrepreneurship. The second part of the survey (B) included a set of questions on gender, age, professional situation, mode and path of study, country of origin, level, and field of study. Cronbach's alpha was used solely as a basic reliability indicator; the study does not aim to validate latent constructs or test measurement invariance across language versions (see Appendix 3).

Since this study does not include Ajzen's TPB scales, attitude, subjective norm, and perceived behavioral control structures are not measured separately. The empirical analysis is based on a trait- and attitude-based survey instrument designed to capture entrepreneurial competencies and intention-related characteristics. In this context, the term "pattern-level analysis" refers to identifying recurring configurations of responses within the Likert-type items, rather than to product-level or market-related patterns. The analytical focus is therefore on conceptual and behavioral structures emerging from students' psychological attributes.

To ensure easy access to the survey and the largest possible study scale, data was collected using the LimeSurvey online platform. The platform allowed all students to access the survey in both language versions (Polish and English). This was important due to the dual nature of the courses of study offered at the university. The solution used eliminated language barriers and thus removed limitations in the study.

Although the sample size is large and covers all programmes at UITM, the data come from a single university in Poland. Therefore, the findings should not be generalised to "university students" globally. Rather, they reflect patterns observed among students in this specific institutional and cultural context. Future studies should incorporate multi-institutional or cross-country samples to enhance generalizability and test the robustness of the patterns identified in this research.

The survey was distributed among the student population through three channels. First, use a link sent directly to students' email accounts with an invitation to the survey. Second, by providing students with QR codes connecting to the LimeSurvey platform. Finally, a direct approach was also used, inviting students to take part in the survey during breaks in subject classes. The research design was discussed with the Research Ethics Committee at UITM and subsequently approved for implementation. In line with the adopted approach, the privacy and confidentiality of participants were strictly maintained, and the collected data was used only for research purposes.

Bibliometric analysis–based validation of the research questionnaire

This bibliometric procedure serves as a conceptual validation of thematic relevance, not as a psychometric validation of the survey instrument (Cobo et al., 2012; as cited in Vila-Lopez & Küster-Boluda, 2021). Based on this approach, a bibliometric analysis was conducted using the SciMAT software (Cobo et al., 2012), incorporating a systematic literature review focused on factors influencing students' entrepreneurial intentions. As a result of the search based on competency-related keywords and entrepreneurship-related terms, a total of 7,424 studies published in English and available in open access through the Web of Science (WOS) database were identified.

The Web of Science search was conducted using the following Boolean structure applied to titles, abstracts, and author keywords (TS): ("entrepreneur*" OR "entrepreneurial intention*") AND ("adaptability" OR "resilience" OR "cognitive flexibility" OR "self-efficacy" OR "problem solving" OR "grit" OR "initiative" OR "goal orientation" OR "open-mindedness").

The restriction to open-access publications was applied to ensure full-text accessibility required for reliable keyword standardization and thesaurus construction in SciMAT. While this introduces a systematic selection mechanism that may affect topic distributions, the bibliometric analysis in this study is used for conceptual validation and thematic alignment rather than for estimating population-level research prevalence.

The bibliometric analysis identified 22,421 keyword groups related to entrepreneurship. Keyword standardization was performed using a manually curated thesaurus, following SciMAT guidelines. Singular–plural forms, spelling variants (e.g., British/American English), acronyms, and semantically equivalent expressions were merged into unified word groups. As a result of this preprocessing, the number of keyword groups was reduced to 1,139, enabling more accurate thematic analysis and strategic mapping in SciMAT. Because these standardization decisions directly affect cluster density and centrality values, the bibliometric results are interpreted at a conceptual rather than a strictly quantitative level.

RESULTS

In the first step of the SciMAT analysis, keywords are aggregated into "word groups," which represent conceptually similar terms and act as the basic units for subsequent analysis (Table 1). In the second step, SciMAT uses these word groups to generate thematic clusters based on co-occurrence networks and the strategic diagram (Tables 3–5). Thus, "word groups" are the building blocks of the analysis, while "clusters" represent higher-level thematic structures formed from these groups.

In SciMAT, "word groups" represent standardized keyword units created during preprocessing, while "clusters" refer to higher-level thematic structures formed from co-occurrence networks of these word groups. This two-stage process is consistently applied throughout the analysis.

Table 1. Groups of words

Group name	Number of docs	Group name	Number of docs	Group name	Number of docs
Innovation	1305	Technology	375	Opportunities	261
Impact	1149	Perspective	374	Intentions	253
Model	677	Capabilities	351	Orientation	247
Business	671	Organizations	336	Enterprise	236
Firms	584	Behavior	336	Resources	231
Strategy	578	Networks	336	Social-Entrepreneurship	215
Knowledge	503	Dynamic-Capabilities	336	Market	210
SMEs	389	Framework	283	Identity	199

The clusters in Table 1 represent key concepts identified in the literature, along with the number of articles associated with each. *"Innovation"* and *"impact"* are the most frequently discussed topics, confirming their central importance in the research landscape. Other significant concepts include *"model," "business," "strategy,"* and *"knowledge,"* encompassing both theoretical and practical dimensions (e.g., SMEs, social-entrepreneurship). The analysis reveals a balanced research structure grounded in a multidisciplinary approach. Topics with fewer associated documents, such as *"market"* or *"identity,"* point to potential gaps and emerging directions for future research.

Table 2. Word groups statistics

Period	Documents	Units	Mean	Standard Dev.	Variance
2020-2021	2227	900	3.57	2.28	5.18
2022-2023	2870	977	3.96	2.24	5.03
2024-2025 (May)	2290	895	3.76	2.19	4.79

Statistical information on the periodic keyword groups is presented in Table 2. The "Mean" values in Table 2 do not represent the ratio of documents to units. Instead, they reflect the average normalized frequency of keyword occurrences within each period, as calculated by SciMAT. Because SciMAT applies frequency weighting and normalization during preprocessing, the resulting means (3.57, 3.96, 3.76) are higher than the simple documents/units ratios (2.47, 2.94, 2.56). The explanation in the text has been revised to clarify this distinction. Table 2 presents the number of documents, units, and descriptive statistics for three periods. In 2020–2021, 2,227 documents were published; in 2022–2023, the number increased to 2,870 (a 29% rise); and in 2024–2025 (up to May), it decreased to 2,290 (a 20% drop). Despite the decline in the number of units, the count remains comparable, indicating sustained thematic richness. The mean normalized frequency of keyword occurrences increased to 3.96 in 2022–2023, indicating a higher concentration of research activity around core thematic units. The standard deviation (2.28 → 2.19) and variance (5.18 → 4.79) have steadily decreased, indicating a more even thematic distribution.

Figure 1 presents the temporal overlap of thematic units across periods. The continuity between periods is evaluated using a continuity ratio, calculated by dividing the number of units that persist into the subsequent period by the size of the earlier period. Between 2020–2021 and 2022–2023, 778 of 900 units continued, yielding a continuity ratio of 0.86. In the following transition, 766 of 977 units persisted, corresponding to a continuity ratio of 0.78. These values indicate a high degree of thematic stability across periods, while also reflecting the emergence of new thematic units over time.

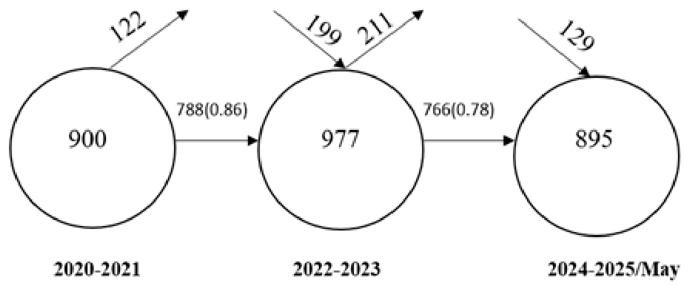

Figure 1. Overlapping map

Tables 3–5 present clusters of keywords by time interval. Each cluster includes four indicators: centrality (strength of the cluster's connections to the network), centrality range (normalized value between 0 and 1), density (internal cohesion of the cluster), and density range (normalized cohesion value).

Table 3. Cluster information (2020-2021)

Name	Centrality	Centrality range	Density	Density range
Knowledge	204.60	1.00	7.96	0.25
Business	168.96	0.99	8.37	0.29
Framework	150.62	0.95	13.47	0.52
Opportunities	146.83	0.93	17.09	0.69
Market	159.32	0.96	7.17	0.21
Perceptions	145.14	0.92	8.52	0.31
Competitive-Advantage	160.68	0.97	7.38	0.24
Uncertainty	134.94	0.91	3.74	0.07
Entrepreneurs	133.48	0.89	7.10	0.20
Culture	76.90	0.87	11.92	0.39

According to Table 3, "*knowledge*" is the most central concept in the network (centrality 204.60), indicating its strong connections with other concepts in 2020–2021. "*Opportunities*" is characterized by high density (17.09), while "*framework*" – despite a lower centrality (150.62) – exhibits substantial cohesion (density 13.47), reflecting a well-integrated literature. "*Knowledge*" and "*business*" form the foundation of the network structure, whereas less developed areas, such as "uncertainty," justify further research.

Table 4. Cluster information (2022-2023)

Name	Centrality	Centrality range	Density	Density range
Innovation	209.37	1.00	7.42	0.32
Intentions	109.94	0.92	9.69	0.45
Market	128.38	0.93	8.41	0.39
Context	137.15	0.96	6.45	0.24
Risk	141.90	0.99	5.17	0.18
Experience	140.70	0.98	6.67	0.26
Ownership	134.70	0.95	3.76	0.14
Start-Ups	134.25	0.94	6.90	0.27
Field	100.08	0.91	2.76	0.05
Small-Business	84.37	0.89	9.47	0.44

Table 4 shows that in 2022–2023 the thematic structure centers around "*innovation*," which has the highest centrality (209.37), indicating its key role within the network. Other important clusters include "*market*" and "*intentions*," both characterized by high centrality and density, particularly "*intentions*," reflecting the maturity of this research area. Although "s*mall-business*" has a lower centrality (84.37), it demonstrates substantial cohesion (density 9.47), suggesting strong internal connections despite its marginal position. The clusters "*field*" and "*ownership*" are less connected to the network and less developed, indicating potential for further research.

Table 5. Cluster information (2024-2025 up to May)

Name	Centrality	Centrality range	Density	Density range
Firms	185.20	0.99	11.17	0.45
Behavior	141.50	0.92	6.87	0.26
Policy	140.67	0.91	11.33	0.46
Opportunities	183.65	0.97	11.40	0.47
Industry	147.35	0.95	7.60	0.28
Technology	186.56	1.00	3.84	0.11
Identity	165.11	0.96	4.01	0.12
Orientation	145.76	0.93	5.03	0.19
Risk	100.56	0.89	3.70	0.08
Social-Enterprise	82.23	0.86	3.77	0.09

Table 5 shows that in the period 2024–2025 (up to May), research focuses on "*technology*" and "*firms*." "*Technology*" has the highest centrality (186.56) but a low density (3.84), indicating a central role but weaker internal cohesion. "*Firms*" stand out with high centrality (185.2) and density (11.17), forming a strong conceptual foundation. Similarly, "*opportunities*" and "*policy*" exhibit high density and a well-established structure in the literature. In contrast, "*social enterprise*" and "*risk*" have low centrality and density, suggesting their limited and less mature treatment in research.

SciMAT processes raw keywords by grouping semantically related terms into standardized "word groups." This word groups serve as the analytical units used to construct co-occurrence networks. In the subsequent clustering phase, SciMAT identifies thematic structures by grouping word groups into clusters. Therefore, Table 1 presents the foundational word groups, while Tables 3–5 present the higher-level thematic clusters derived from them. This two-stage process enhances interpretability and reduces noise in the keyword dataset.

The thematic clusters identified in the SciMAT analysis, such as "*knowledge*" (dominant in 2020–2021), "*innovation*" (characteristic of 2022–2023), and "*firms/technology*" (typical for 2024–2025), not only demonstrate the evolution within the scientific literature on entrepreneurial intentions but also show a clear connection with the empirical content examined in the survey study. Figure 2 presents the distribution of these elements across thematic periods, indicating conceptual continuity and alignment of the topics studied with specific characteristics and behaviors of students.

The assignment of Part-A items to the three thematic periods identified in the SciMAT analysis - 'knowledge' (2020–2021), 'innovation' (2022–2023), and 'technology/firms' (2024–2025) - reflects conceptual alignment rather than statistical linkage. The mapping expresses face-valid correspondence between item content and the dominant themes emerging in the bibliometric structure; however, it is not based on empirical associations between item responses and the thematic clusters. Accordingly, this step is intended as a conceptual coherence check that situates the questionnaire within the evolving literature, rather than as a form of psychometric validation. Item A6 ("The setbacks I experience provide me with lessons for the future") reflects a resilience- and learning-oriented mindset, emphasizing the interpretation of setbacks as opportunities for growth rather than as perceived limitations in performing tasks. The item captures students' tendency to learn from difficulties and to reinterpret negative experiences in an adaptive manner. Accordingly, A6 is treated as an indicator of resilience- and learning-oriented attributes rather than as a measure of perceived capability or task-related efficacy.

In the first period (2020–2021), the dominant theme was "*knowledge*," reflecting the literature's focus on building the theoretical foundations of entrepreneurship. The survey questions assigned to this period (i.e., A1, A2, A9, A14, A21) relate to execution-oriented engagement, reflecting perseverance and the ability to implement planned actions rather than analytical or causal reasoning. A14 ("overcoming difficulties to acquire knowledge") reflects learning-oriented engagement, while A21 ("I implement developed plans from start to finish") represents execution-oriented behavior and perseverance.

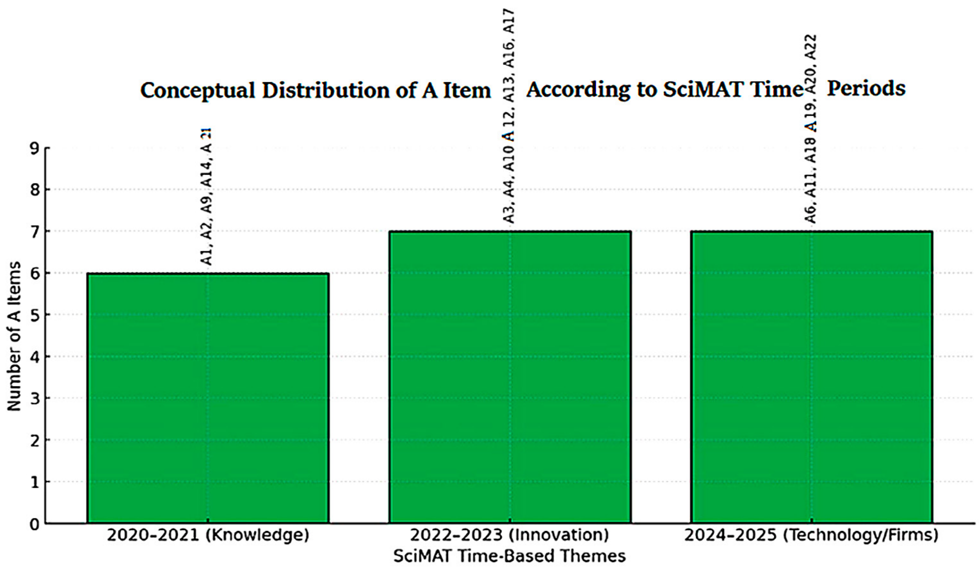

Figure 2. Distribution of items in the survey (Part A) according to their conceptual overlap with the periodic themes identified in the SciMAT analysis

In the period 2022–2023, centered around "*innovation*," the literature shifts toward more dynamic and functional competencies such as creativity, adaptability, and problem-solving. The survey questions in this phase (i.e., A3, A4, A10, A12, A13, A16, A17) address skills related to creative thinking, cognitive flexibility, and taking initiative in situations of uncertainty. For example, A10 ("generating more than one solution") and A12 ("adapting to new conditions") clearly reflect innovative and adaptive attitudes, which are recognized as key in shaping entrepreneurial intentions.

The third period, 2024–2025 (up to May), shows a shift toward practical applications, with dominant themes such as "*technology*" and "*firms*." The questions assigned to this stage (i.e., A6, A11, A18, A19, A20, A22) relate to the application of acquired competencies in the context of action, both individual and organizational. For example, A6 ("The setbacks I experience provide me with lessons for the future") reflects a learning-from-difficulty and resilience-oriented mindset. The item emphasizes meaning-making and adaptive learning from negative experiences rather than perceived capability to perform tasks. Accordingly, A6 is interpreted as an indicator of resilience and learning orientation rather than a measure of self-efficacy. The even distribution of questions across the three thematic periods suggests that the studied traits and competencies of students align with the main axes of knowledge development in literature. This indicates that bibliometric analysis and the developed survey questionnaire complement each other, creating a coherent picture of how various psychological, cognitive, and behavioral aspects jointly shape students' entrepreneurial intentions.

Rough sets approach to incomplete data

Lack of response or refusal to respond is a cause of incompleteness. The simplest way to handle incomplete data is to choose the most frequent answer when the domain is discrete, or the average when the domain is continuous. More advanced approaches estimate the most probable values based on available data. In consequence, the completed data set may be inconsistent i.e. if there exist two cases with all values identical but belonging to different decisions.

Rough sets theory describes a decision in the form of a decision table (Pawlak, 1982) made under certain conditions. An example of an incomplete decision table is presented in Table 6. The rows of the decision table represent cases i.e. the answers given by the respondent. The finite set of all respondents is called the universe and is denoted by U. In Table 6, U = {1, 2, 3, 4, 5, 6, 7, 8, 9}. The independent variables (questions) are called Attributes. In Table 6, Employment status, Level of study and Mode of study are the attributes.

The dependent variable Business start is called a Decision. The set of all cases with the same decision value is called a concept. In Table 6, there are two concepts: the set {1, 2, 3, 6} of all cases for which the value of Business start is yes, and the set {4, 5, 7, 8, 9} for which the value of Business start is no.

Table 6. Example of incomplete data set

Case	Attributes			Decision business start
	Employment status	Level of study	Mode of study	
1	full-time	bachelor		yes
2	full-time		part-time	yes
3	full-time		part-time	yes
4	unemployed	master		no
5	unemployed		full-time	no
6	unemployed	bachelor	full-time	yes
7	inactive		full-time	no
8	inactive	master	part-time	no
9	inactive	bachelor		no

Bachelor is the most common value of *Level of study* variable. Therefore, it should be selected for all the unknown values of this attribute. Result is presented in Table 7 (inserted values are italicized). Table 7 is inconsistent. Cases {5, 6} with all identical response values belonging to different concepts of decision. This approach to handling missing values does not account for the relationship between attribute values and decisions.

Table 7. Example of inconsistent data set

Case	Attributes			Decision business start
	Employment status	Level of study	Mode of study	
1	full-time	bachelor		yes
2	full-time	*bachelor*	part-time	yes
3	full-time	*bachelor*	part-time	yes
4	unemployed	master		no
5	unemployed	*bachelor*	full-time	no
6	unemployed	*bachelor*	full-time	yes
7	inactive	*bachelor*	full-time	no
8	inactive	master	part-time	no
9	inactive	bachelor		no

The most common attribute value method can be restricted to the concept (Kononenko et al., 1984). The most common value of the *Level of studies* variable for the concept *yes* is *bachelor*, while for the concept *no* it is *master.* Similarly, by completing the missing values in the Study Path attribute, the results areresented in Table 8.

Table 8. The result of the concept's most common attribute value method

Case	Attributes			Decision business start
	Employment status	Level of study	Mode of study	
1	full-time	bachelor	part-time	yes
2	full-time	*bachelor*	part-time	yes
3	full-time	*bachelor*	part-time	yes
4	unemployed	master	full-time	no
5	unemployed	*master*	full-time	no
6	unemployed	bachelor	full-time	yes
7	inactive	*master*	full-time	no
8	inactive	master	part-time	no
9	inactive	bachelor	full-time	no

Taking into account causes of incompleteness, such as accidental deletion, missed insertions, or refused responses, rough set theory also provides an interpretation of missing attribute values. Missing attribute values can be interpreted as *lost* values or *"do not care" conditions* (Grzymala-Busse, 1991; Kryszkiewicz, 1998). *Lost* values are denoted by question marks and are considered unavailable for the process of data mining. *"Do not care" conditions* denoted by star are interpreted as any specified value of the same attribute. In our research, we considered missing attribute values as "do not care" conditions, asresented in Table 9.

Table 9. Incomplete data set

Case	Attributes			Decision business start
	Employment status	Level of study	Mode of study	
1	full-time	bachelor	*	yes
2	full-time	*	part-time	yes
3	full-time	*	part-time	yes
4	unemployed	master	*	no
5	unemployed	*	full-time	no
6	unemployed	bachelor	full-time	yes
7	inactive	*	full-time	no
8	inactive	master	part-time	no
9	inactive	bachelor	*	no

To find the missing value of an attribute, we repeatedly add a case with the "*do not care*" conditions to the data, replacing it with subsequent attribute values from cases belonging to the same concept as the analyzed case. However, this approach does not account for relationships in the data. First of all, the maximal collection of cases, in which all cases are indiscernible in terms of available information, should be defined. Following Mroczek (2023) and Clark et al. (2024), maximal consistent blocks (MCB), as a maximal collection of indiscernible objects, for Table 7 are: {{1, 2, 3}, {4, 5}, {5, 6}, {7, 9}, {8}}. Consequently, upper and lower approximation are determined, as follows (Leung & Li, 2003):

$$\underline{appr_A}(X) = \{x \in U \mid MCB_A(x) \subseteq X\}$$
$$\overline{appr_A}(X) = \{x \in U \mid MCB_A(x) \cap X \neq \emptyset\}$$

The lower approximation consists of all objects that *certainly* belong to the set, while the upper approximation contains all objects that *possibly* belong to the set. In Table 9, for concept *yes* X = {1, 2, 3, 6} $\underline{appr}(X) = \{1,2,3\}$ and $\overline{appr}(X) = \{1,2,3,5,6\}$, while for the concept *no* X = {4, 5, 7, 8, 9} $\underline{appr}(X) = \{4,5,7,8,9\}$ and $\overline{appr}(X) = \{4,5,6,7,8,9\}$. Only certain sets are considered; therefore, case 6 is not included in the further analysis. The complete data set is presented in Table 10.

Table 10. Complete data set

Case	Attributes			Decision business start
	Employment status	Level of study	Mode of study	
1	full-time	bachelor	part-time	yes
2	full-time	bachelor	part-time	yes
3	full-time	bachelor	part-time	yes
4	unemployed	master	full-time	no
5	unemployed	master	full-time	no
7	inactive	master	full-time	no
8	inactive	master	part-time	no
9	inactive	bachelor	full-time	no

Patterns discovering

The purpose of survey analysis is to establish patterns in the form of a set of frequently occurring responses. Finding the most frequent and relevant subsets X occurring in a data set requires discovering a set of items and estimating the probability of their occurrence, as follows: $\frac{|X|}{|U|}$ where |X| is the number of transactions containing the set X and |U| is the number of cases in the data set. For Table 10 the most frequent and relevant subsets are: {(**Level of study**, master), (**Mode of study**, full-time)}, {(**Employment status**, full-time), (**Level of study**, bachelor), (**Mode of study**, part-time)}. Selecting only the highest frequency subsets reduces the large, analyzed set and allows for a more detailed exploration of the relationships.

Decision tree classifier

C5.0, as an extension of the published algorithm in (Quinlan, 1993), is an advanced decision tree algorithm widely used in machine learning for classification tasks. Developed by Quinlan (1993), it predicts categorical outcomes by constructing decision trees based on input features. The algorithm follows a top-down, recursive process, selecting the most suitable feature at each step to split the data. It evaluates the quality and size of the resulting subgroups using metrics such as information gain and gain ratio to determine optimal splits. Pruning techniques are applied to prevent overfitting and enhance the model's ability to generalize to new data. C5.0 effectively handles categorical and numerical variables as well as missing values. The resulting decision trees provide clear, interpretable classification results, making the algorithm a popular choice across various fields.

EXPERIMENTS & RESULTS

Our main goal was to determine the relationship between entrepreneurial competencies and entrepreneurial intentions. To achieve this, a hybrid approach, including several of the machine learning methods mentioned above, was employed to plan the research process, conduct the research, and interpret the results.

First of all, the survey data was incomplete. For this reason, the maximal collection of cases, in which all cases are indiscernible in terms of available information, was identified. Then, the lower approximation of concepts based on maximal consistent blocks was determined. In this way, a complete, consistent data set was prepared for further analysis. It should be noted that the incompleteness of the dataset was below 1% of all observations, with missing values in six cases affecting the dependent variable (the decision). The decision variable was not imputed, as its imputation could introduce bias and distort the relationships between variables. Additionally, the applied method for handling missing data does not account for the decision variable, as it is intended solely for imputing values in explanatory variables.

The analysis used a one-hot encoder because it allows each possible Likert-scale response to be represented as a separate binary variable, ensuring that item sets are defined unambiguously without making assumptions about the level of agreement. In the following step the most frequent and significant subsets of responses were discovered in the complete data set. The subsets for which the probability of occurrence is above 30% are presented in Table 11. It should be noted that 30% is more than 456 responses in the set. The most significant subsets of responses involved either consistent "Rather agree" or consistent "Rather disagree" selections; in each case, both answers within a pattern fell into the same category. No mixed combinations were observed. This indicates a clear and decisive stance among the respondents.

The discovered patterns in the data allowed for the reduction of the data set. Demographic information (such as gender, age, employment status, mode, level and field of study) was added to the reduced data. In the C5.0 model, only the most significant variables for each metric were used.

Table 11. The most significant subsets of responses

[A10. In difficult and complex situations, I always find a few alternatives to solve the problem, A12. I can easily adapt to new circumstances]
[A10. In difficult and complex situations, I always find a few alternatives to solve the problem, A13. I am able to look at a situation from different points of view]
[A10. In difficult and complex situations, I always find a few alternatives to solve the problem, A19. I try to cope with solving problems no matter how difficult they are]
[A13. I am able to look at a situation from different points of view, A12. I can easily adapt to new circumstances]
[A13. I am able to look at a situation from different points of view, A19. I try to cope with solving problems no matter how difficult they are]
[A14. I like to find out about things even if it means handling some problems while doing so, A19. I try to cope with solving problems no matter how difficult they are]
[A18. I make a determined effort to achieve the goals I set for myself, A19. I try to cope with solving problems no matter how difficult they are]
[A19. I try to cope with solving problems no matter how difficult they are, A12. I can easily adapt to new circumstances]
[A22. I am open to new experiences, A20. Dealing with difficult situations strengthens and develops me]
[A20. Dealing with difficult situations strengthens and develops me, A6. The setbacks I experience provide me with lessons for the future]

The obtained models were subjected to semantic analysis to determine the dependencies between the values of variables and demographic metrics. To clarify the analytical scope, the decision-tree models were not designed to predict entrepreneurial intention nor to estimate the moderating role of demographic variables. Instead, the models identify group-differentiating response patterns, showing how entrepreneurial competencies and intention-related attributes cluster within specific demographic categories. This pattern-based approach aligns with the exploratory nature of the study and complements the earlier pattern-mining results. In the C5.0 decision-tree models, demographic categories (e.g., gender, age group, nationality, field of study) were treated as dependent variables to identify the response patterns that differentiate these groups. This approach enables the extraction of group-differentiating configurations of entrepreneurial competencies and intention-related attributes, rather than predicting intention outcomes or modelling causal relationships. The main goal of this analysis was to identify which features and conditions in the models have the greatest impact on demographic indicators and what conclusions can be drawn from them in the context of students' entrepreneurial competencies. The accuracy of the developed models, evaluated through 10-fold cross-validation, was approximately 70% when employing the classifier's default parameters. The identified dependencies were visualized in Figure 3 to Figure 8. Darker colors symbolize stronger dependencies, while lighter colors symbolize weaker ones.

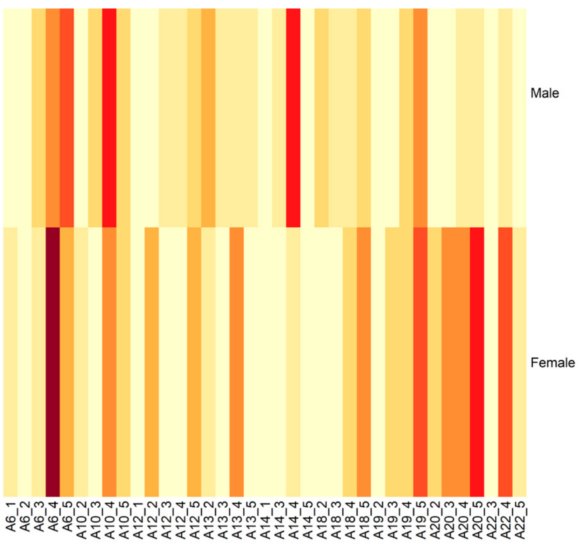

Figure 3. Dependencies: Attributes and the gender[4]

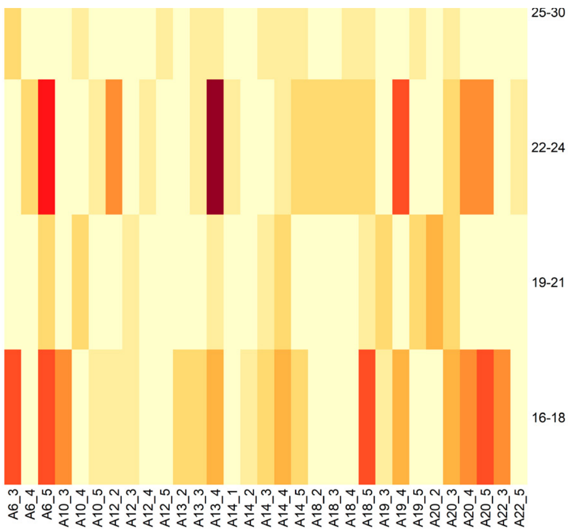

Figure 4. Dependencies: Attributes and the age

4 A6. The setbacks I experience provide me with lessons for the future. A10. In difficult and complex situations, I always find a few alternatives to solve the problem. A12. I can easily adapt to new circumstances. A13. I am able to look at a situation from different points of view. A14. I like to find out about things even if it means handling some problems while doings so. A18. I make a determined effort to achieve the goals I set for myself. A19. I try to cope with solving problems no matter how difficult they are. A20. Dealing with difficult situations strengthens and develops me. A22. I am open to new experiences. The answers to each question were on a Likert scale. They were as follows: 1) Definitely agree, 2) Rather agree, 3) Neither agree or disagree, 4) Rather disagree, 5) Definitely disagree. Hence, on the 0X axis, each question is accompanied by a resolution referring to the answer chosen by the students.

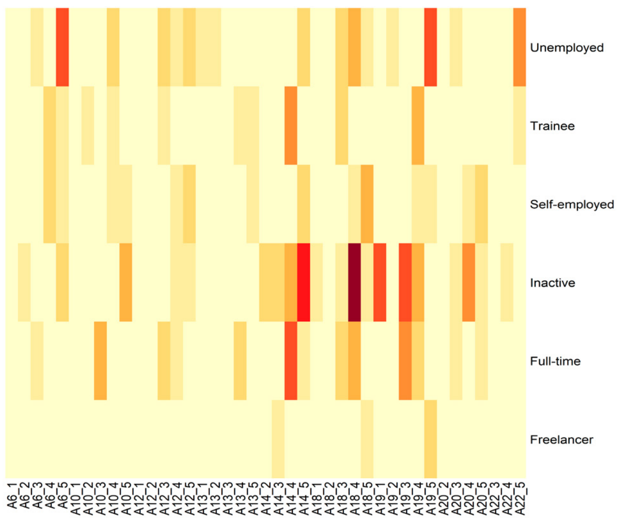

Figure 5 Dependencies: Attributes and employment status

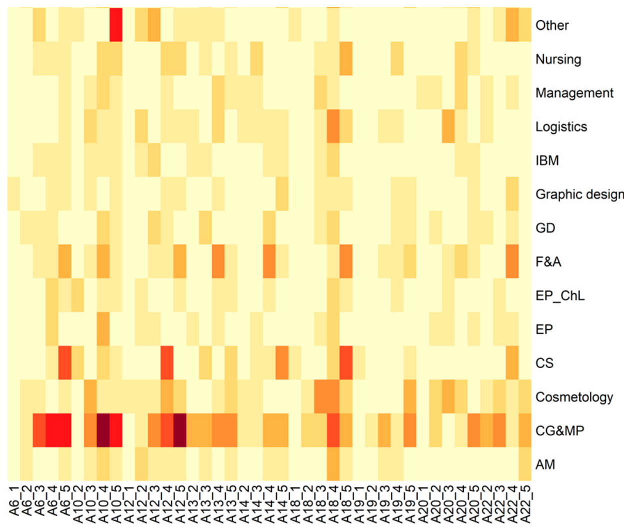

Figure 6. Dependencies: Attributes and field of study

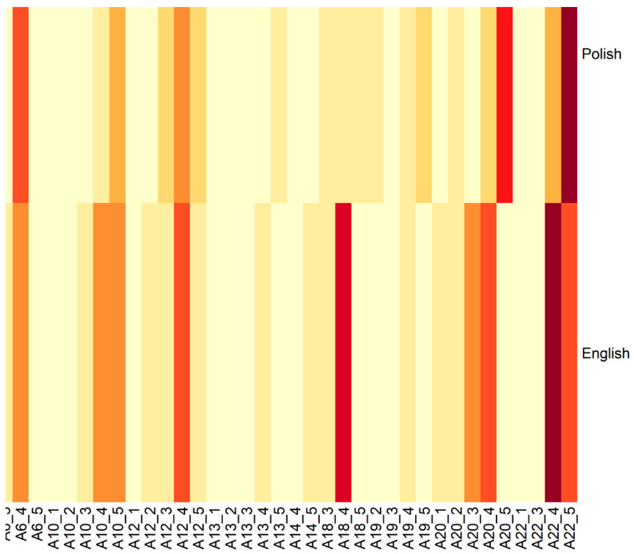

Figure 7. Dependencies: Attributes and mode of study

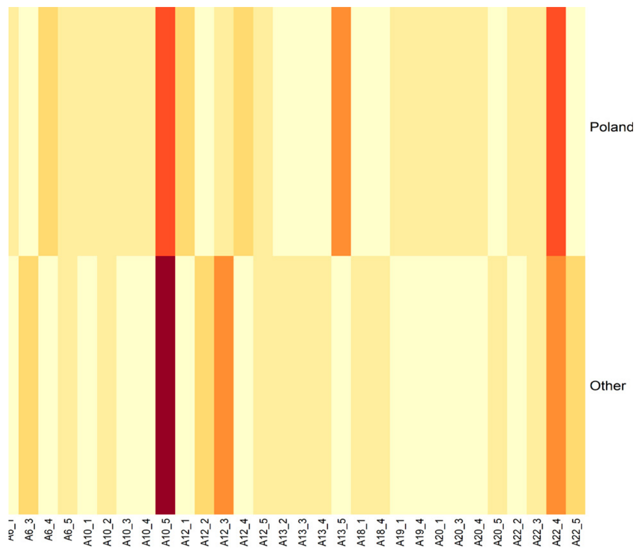

Figure 8. Dependencies: Attributes and country-of-origin

DISCUSSION

Students who readily adapt to new circumstances (A12) are more likely to find alternative solutions in difficult situations (A10). Adaptation, understood as cognitive, behavioral, and emotional adjustment to change (Sheriston et al., 2019), supports problem-solving and resilience (Feraco et al., 2023b). This ability is conceptually associated with entrepreneurial readiness, enabling individuals to cope with business-related challenges (Salas Tuanama et al., 2024; Indhirapratha & Thavaraj, 2024).

Students who are capable of viewing situations from multiple perspectives (A13) are more likely to generate a variety of solutions to problems (A10). Situational self-awareness (Govern & Marsch, 2001) and innovativeness (Gözükara & Çolakoğlu, 2016) support entrepreneurial intentions (Bae, 2024). Entrepreneurial alertness mediates the relationship between innovativeness and the readiness to start a business, indicating that creative students are more likely to take action (Gözükara & Çolakoğlu, 2016). Those who engage in solving complex problems (A19) often identify alternative solutions (A10) and demonstrate determination in pursuing their goals (A18). Their adaptability (A12) reflects both resilience and creativity. Perseverance contributes to solution generation (Merrill, 2003; Hidayati et al., 2022), while openness (Clarete et al., 2023), conscientiousness (Juhari et al., 2023), and autonomy enhance self-efficacy and entrepreneurial behavior (Brás et al., 2023).

Cognitive flexibility, stemming from perspective-taking (A13) and adaptability (A12), supports entrepreneurial intentions (Jiatong et al., 2021). Entrepreneurial self-efficacy and adaptability gain importance through education (Qiao & Hua, 2019; Zhang et al., 2022; Sun et al., 2023). The ability to take on challenges (A19) and creativity (A10) foster innovativeness and resilience (Zhao et al., 2014). Students with high cognitive flexibility are more likely to seize opportunities under uncertain conditions (Caputo et al., 2025).

Solving complex problems (A19) facilitates learning, even in the face of obstacles (A14). Action-based learning supports the development of competencies and entrepreneurial intentions (Atrup et al., 2023; Triansyah et al., 2023; Arifia et al., 2024). Resilience, understood as perceiving difficulties as opportunities (A20), is associated with openness (A22) and promotes entrepreneurial behavior (Cruz et al., 2022; Abdel-Kader et al., 2023). Moreover, students who believe that challenges strengthen them (A20) tend to view failure as a learning experience (A6). This mindset, linked to resilience, correlates with entrepreneurial intention (Cruz et al., 2022).

The dependencies between the values of variables and demographic metrics

The developed models enabled the identification of relationships between attribute values and demographic information (i.e., decisions and their corresponding classes), highlighting group-differentiating patterns in traits relevant to students' entrepreneurial intentions.

The „gender" decision revealed that within the „female" class, disagreement with the statement that failures are a source of future learning (A6) was associated with adaptability (A12), disagreement with the notion that difficulties strengthen (A20), and low openness to new experiences (A22). While women demonstrate adaptive capacity, fear of failure negatively impacts their entrepreneurial intentions (Rahman & Mahendran, 2025) and limits opportunities for experiential learning (He & Krähenmann, 2021). Among men, there is a lack of perception in the value of failure (A6), reluctance to engage in problem-solving (A14), a limited perception of alternatives (A10), and an avoidance of challenging situations (A19). These attitudes may be culturally driven and stem from social pressure to avoid showing vulnerability (Nikolić et al., 2020). This is supported by findings on the detrimental effect of fear of failure on entrepreneurial intentions (Wimer & Levant, 2011; Mutmainnah et al., 2024).

The analysis of the „age" decision revealed differing student approaches to failure, problem-solving, and motivation. The 16–18 age group does not perceive failure as a learning opportunity (A6), struggles to identify action strategies (A10), and shows weak goal-directed motivation (A18). They are reluctant to engage in learning through overcoming difficulties (A14), which aligns with low challenge readiness (A19), confirming the findings of Fournier et al. (1995). The 19–21 age group, consistent with Allan (2017), does not view difficult situations as developmental (A20), demonstrates low engagement in problem-solving (A19), denies the value of failure (A6), has difficulty identifying alternatives (A10), and shows ambiguous attitudes toward growth through adversity (A20). The 22–24 age group exhibits three patterns: rejection of learning from failure (A6), weaker opposition to development through difficulty (A20), cognitive flexibility (A13), and a willingness to act despite challenges (A19). Moderate agreement is observed only for adaptability (A12), in line with Stephens & Gehlbach (2007). The 25–30 age group displays two distinct patterns. The first includes a negative attitude toward learning through problem-solving (A14), identifying alternatives (A10), and goal pursuit (A18), with no clear stance on learning from failure (A6) or growth through adversity (A20). The second pattern reflects reluctance to act under challenging conditions (A19), low motivation (A18), and a lack of openness to change (A12), alongside moderately negative cognitive flexibility (A13) and an undefined view on learning through overcoming difficulties (A14). These findings are supported by Lee (2009).

Responses categorized by the "nationality" decision indicate that individuals of Polish nationality more frequently report learning from failure (A6) and identifying alternative solutions in difficult situations (A10), which may reflect a stronger growth mindset and a heightened sense of agency (Cieślik et al., 2024). Students from outside Poland are more likely to report ease in adapting to new conditions (A12) (Bartkowiak & Krugiełka, 2017), likely due to their international experiences (Słowińska, 2016). In contrast, Polish respondents more often indicate the ability to adopt multiple perspectives (A13) (Błaszczak & Klocek, 2022), higher engagement in goal pursuit (A18), and greater resilience when facing adversity (A19, A20) (Surzykiewicz et al., 2019). Both groups show similar levels of cognitive curiosity (A14); however, foreign students more frequently express openness to new experiences (A22), which may stem from greater mobility and functioning in diverse environments.

Relationships between attributes and the “employment status” decision revealed that individuals employed full-time and self-employed most frequently report the ability to learn from mistakes (A6), which may result from greater exposure to professional challenges (Wilhelm et al., 2019; Tao et al., 2023). Freelancers and self-employed individuals are equally likely to indicate the ability to find alternative solutions (A10), reflecting their flexibility (Becker et al., 2014). Unemployed and inactive individuals are less likely to agree with these statements, possibly indicating lower perceived agency (Justo et al., 2021). Employed individuals, especially full-time workers and freelancers, are more likely to report ease of adaptation (A12) and the capacity to adopt multiple perspectives (A13) (Justo et al., 2021). The highest cognitive curiosity and readiness to learn through difficulties (A14) are exhibited by trainees and working students (Tumin et al., 2020). Self-employed and full-time employees score highest on perseverance (A18), coping with difficulties (A19), and perceiving challenges as growth opportunities (A20) (Feraco et al., 2023a), whereas inactive and unemployed respondents are more likely to provide neutral or negative responses (Dunn et al., 2014). Freelancers and those with flexible work arrangements achieve the highest scores in openness to new experiences (A22), likely because of the need for continuous adaptation (Frie et al., 2024).

The study also revealed differences in attribute outcomes based on the “field of study” decision. A comparison of students across different disciplines highlights significant variations in approaches to adaptation, development, and problem-solving. Students of Psychology, Nursing, and Management more frequently learn from mistakes (A6) and adopt multiple perspectives (A13), which may be attributed to the humanistic orientation of these programs (Winarko & Budiwati, 2024; Hojat, 2016). In contrast, technical and IT-related fields (Programming, Computer Science, Data Science) promote the identification of alternatives (A10) and cognitive flexibility (A12) (Sim & Wright, 2002; Bhattacherjee & Kukreja, 2023). Students in Finance and Accounting in Management and International Business Management exhibit higher perseverance (A18) and better coping with difficult situations (A19, A20), suggesting a strong goal orientation (Séllei, 2021). Meanwhile, students from artistic disciplines (Graphic Design, Game Design and Development) stand out for their openness to new experiences (A22) and cognitive curiosity (A14), reflecting the creative nature of these fields (Feraco et al., 2023b).

Differences were also observed in responses related to the “mode of study” decision. Students studying in English more frequently report openness to new experiences (A22), ease of adaptation (A12) (Drozdova & Taulean, 2022), and the perception that challenging situations support their development (A20), which may result from functioning in an international environment (Guillén-Yparrea & Ramírez-Montoya, 2023; Dunworth et al., 2021). Conversely, Polish-speaking students more often indicate perseverance in goal attainment (A18) and effectiveness in problem-solving (A10), potentially reflecting a task-oriented approach to learning (Pharaoh & Li, 2022). Differences in reflection on failures (A6) and willingness to learn despite difficulties (A14) are minimal, with a slight advantage for students studying in Polish.

This work does not directly operationalize the TPB components; therefore, the results should not be interpreted as an empirical test of the TPB model. The study does not assess latent factor structure or cross-language measurement equivalence, as the analytical focus is on item-level pattern configurations rather than psychometric scale validation. Instead, the observed relationships represent conceptual patterns related to intention that emerge within the scope of entrepreneurial potential. In this study, the relationships among elements of adaptability, resilience, problem-solving, and initiative reflect conceptual coherence in students’ self-definitions and the internal clustering of these characteristics. These patterns are consistent with the dominant themes highlighted in the bibliometric structure. Direct analysis has not been performed to correlate item-level features with intention-specific responses; therefore, the findings are interpreted as thematic alignment and clustering rather than predictive evidence.

In this study, the internal structure of intention-related attributes among university students was examined using mining techniques and compared with the thematic evolution of entrepreneurship research. The study findings indicate that students’ adaptability, resilience, and initiative-related traits often converge and are conceptually aligned with the main knowledge areas in the field. These results provide an integrative perspective on how behavioral trends at the individual level relate to broader trends in entrepreneurship.

This study makes a methodological contribution by linking micro-level patterns with macro thematic development, while emphasizing practical aspects for entrepreneurship education and the enhancement of institutional support. Future research may expand on this study by incorporating longitudinal data, additional behavioral constructs, or multi-institutional datasets to further validate and expand on the insights presented here.

CONCLUSION

This study examined entrepreneurial intentions through a multilayered analytical framework that integrates bibliometric analysis (SciMAT) with machine learning–based decision tree classification. SciMAT was employed to situate survey items within the evolving thematic structure of the entrepreneurship literature, providing a conceptual and interpretative coherence check rather than a psychometric validation of the instrument (Cobo et al., 2012; Vila-Lopez & Küster-Boluda, 2021).

The bibliometric analysis highlighted resilience, initiative, adaptive thinking, problem solving, goal orientation, cognitive flexibility, and open-mindedness as dominant themes in recent entrepreneurship research. These themes have been widely discussed as foundational elements of entrepreneurial development (Dessyana, 2017; Feraco et al., 2023b). Their convergence with high-influence survey items identified in the decision tree analysis indicates conceptual alignment between the literature and observed student response patterns, rather than empirical validation or predictive inference.

Clarifying item interpretation was an important outcome of this study. Item A21, based on its actual wording ("I implement developed plans from start to finish"), was reclassified as an execution-oriented behavioral competency reflecting perseverance and follow-through, rather than causal reasoning. This refinement ensures internal consistency between item content and the thematic clusters derived from the bibliometric analysis. Similarly, Item A6 was interpreted as reflecting resilience and learning from adversity, consistent with prior conceptualizations of adaptive learning and growth-oriented mindsets (Feraco et al., 2023a; Rahman & Mahendran, 2025).

The temporal evolution identified in the SciMAT analysis suggests that entrepreneurial intentions are shaped by both individual attributes and changing thematic emphases in the literature. While knowledge-oriented themes dominated earlier periods, more recent years have emphasized innovativeness and technology-related competencies, reflecting broader shifts in entrepreneurship education and research agendas (Dessyana, 2017; Brás et al., 2023).

From a theoretical perspective, the findings indicate that key psychological attributes such as initiative, adaptability, and cognitive flexibility are reflected in students' behavioral patterns. These attributes cluster conceptually within intention-related configurations, rather than serving as direct indicators of perceived capability or predictive validity. In this sense, the results resonate with prior work emphasizing the multidimensional and context-sensitive nature of entrepreneurial attributes (Caliendo et al., 2023; Feraco et al., 2023b).

From a practical standpoint, the findings offer a data-driven basis for entrepreneurship education. Educational programs may benefit from focusing on the development of problem-solving ability (A19), adaptability (A12), goal-directed behavior (A18), and resilience-oriented learning, as suggested by recent studies on experiential and action-based entrepreneurship education (Qiao & Hua, 2019; Sun et al., 2023; Atrup et al., 2023). The integration of decision-support tools and AI-based analytical approaches can assist educators and policymakers in designing targeted and responsive learning environments that address diverse student profiles and evolving educational needs.

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Authorship contribution statement

Tomasz Skica: Conceptualization, Data Curation, Formal Analysis, Methodology, Project Administration, Validation, Visualization, Writing Original Draft Preparation, Writing Review & Editing. **Teresa Mroczek:** Methodology, Software, Validation, Visualization, Writing Original Draft Preparation, Writing Review & Editing. **Esra Sipahi Döngül**: Formal Analysis, Methodology, Validation, Visualization, Writing Original Draft Preparation, Writing Review & Editing.

Conflicts of interest

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