Analysis of relationships of technology decision factors

Letícia Pekk[1,2*], Zoltán Kovács[1], András Háry[3]

[1]University of Pannonia, Veszprém, Hungary
[2]Széchenyi István University, Győr, Hungary
[3]ZalaZONE Science Park Ltd., Zalaegerszeg, Hungary
[*]Corresponding author, e-mail: pekk.leticia@sze.hu

Received: 1 August 2025; accepted: 9 March 2026

Summary

The study examines how company goals, forecasting practices and technology's value interact in strategic decision-making. Data were collected from 102 Hungarian high-tech companies. A triangulated methodology combined residual analysis, Fisher's exact test, and Association Rule Mining (ARM) to identify statistical and practically relevant relationships. Results show segment-specific decision patterns rather than uniform trends. Strong links appear between "Profit" and "Business performance monitoring," "Asset retention" with both "Manufacturing parameter analysis" and "Size-appropriate technology," and "Modernisation" with "Strategic market advantage." Findings highlight that effective technology decisions arise when forecasting practices align with goal-specific decision logics.

Keywords: technology management, technology forecast, business goals, technology decisions

A technológiai döntési szempontok összefüggéseinek elemzése

Pekk Letícia[1,2], Kovács Zoltán[1], Háry András[3]

[1]Pannon Egyetem, Veszprém, Magyarország
[2]Széchenyi István Egyetem, Győr, Magyarország
[3]ZalaZONE Tudományos Park Kft., Zalaegerszeg, Magyarország

Összefoglalás

A tanulmány célja a vállalati célok, az előrejelzési gyakorlatok és a technológiai döntési szempontok közötti összefüggések feltárása, különös tekintettel arra, hogy ezek a tényezők mennyiben támogatják egymást a stratégiai döntéshozatalban. A kutatás alapját 102 hazai, technológiaorientált vállalkozás válaszai képezték, amelyekben a vállalati célok (pl. „Profit", „Vagyonmegtartás", „Korszerűsödés"), az alkalmazott előrejelzési célok (pl. „Üzleti eredmények elemzése", „Gyártási paraméterek elemzése", „Technológiai lehetőségek vizsgálata") és a technológiai döntési szempontok (pl. „Stratégiai piaci előny", „Cégmérethez illeszkedő technológia", „Integrált technológiai költség") kerültek vizsgálatra.

A módszertan három egymást kiegészítő eljárást ötvözött: (1) reziduál-elemzés, amely a gyakorisági táblázatokban megfigyelt és a függetlenség mellett elvárt gyakoriságok eltérését vizsgálta, lehetővé téve a pozitív és negatív irányú kapcsolatok azonosítását, (2) Fisher-féle egzakt próba a statisztikai összefüggések erősségének értékelésére, valamint (3) asszociációs szabálybányászat (ARM) a rejtett, gyakorlati szempontból releváns mintázatok azonosítására. A teljes táblázatokra végzett vizsgálatok általában nem mutattak ki erős, általános érvényű kapcsolatokat, ami arra utal, hogy a vállalati célok, az előrejelzési és technológiai szempontok nem képeznek egységes mintázatot. Ugyanakkor a válaszpáronkénti elemzések és az ARM-szabályok több specifikus és gyakorlati szempontból fontos összefüggést tártak fel.

Az eredmények szerint a „Profit" cél kiemelten kapcsolódik az „Üzleti eredmények elemzéséhez", ami logikusan tükrözi a pénzügyi fókuszú vállalatok előrejelzési gyakorlatát. A „Vagyon megtartására" törekvő cégek gyakrabban végeznek „Gyártási paraméterek elemzést", és technológiai döntéseikben előnyben részesítik a „Cégmérethez illeszkedő technológiát", ami a kockázatcsökkentés és költséghatékonyság iránti igényre utal. A „Korszerűsödés", mint vállalati cél erős kapcsolatot mutat a „Stratégiai piaci előny" technológiai szemponttal, ami a modernizáció- és az innovációtudatos versenyelőny-teremtő szerepét jelzi.

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC

Összességében a vizsgált vállalatok döntéshozatala szegmens-specifikus, azaz bizonyos célkombinációkhoz illeszkedő tudatosabb előrejelzési és technológiai logika figyelhető meg. A kutatás hozzájárul a technológiai előrejelzés és menedzsment gyakorlati megértéséhez azzal, hogy rávilágít: a stratégiai célok és a technológiai döntések közötti kapcsolat gyakran nem általános érvényű, hanem szűkebb vállalati csoportokra jellemző.

Kulcsszavak: technológiamenedzsment, technológiai előrejelzés, vállalati célok, technológiai döntések

Introduction

Technology decision-making is a central component of corporate strategy because the selection and integration of new technologies fundamentally determine long-term competitiveness and sustainability (*Kim 2022; Ghonim et al. 2022*). In the context of rapid technological change and Industry 4.0, companies face increasingly complex decision environments, where uncertainty and the fast pace of innovation require systematic evaluation and forecasting (*Firat–Woon–Madnick 2008; Haleem–Javaid–Khan 2019; Feng et al. 2022*). Prior studies emphasise that effective technology decisions depend not only on the assessment of technological alternatives but also on their alignment with corporate goals and strategic priorities (*Heikkilä–Bouwman–Heikkilä 2018; Iwu–Johnson–Onyekachi 2024*). Strategic information system planning (SISP) and data-driven decision-making approaches facilitate this alignment, enabling firms to integrate IT investments and analytics into strategic planning (*Han–Kamber–Pei 2011; Szukits & Móricz 2024*). Multi-criteria decision-making methods, such as the Analytic Hierarchy Process (AHP), and models like Adjustable Fuzzy Data Envelopment Analysis (AFDEA) support the ranking and selection of technological solutions, reducing the risk of misaligned investments (*Awasthi & Varman 2003; Peykani–Namazi–Mohammadi 2022*). The literature also highlights the role of complementary practices, such as technology transfer and quality management systems, which enhance the effectiveness of strategic planning and the utilisation of new technologies (*Bolatan et al. 2022; Gandrita 2023*). Moreover, emerging technologies – such as AI, IoT, and robotic process automation – reshape business processes, requiring firms to maintain dynamic capabilities for sensing, adapting, and transforming their operations (*Kitsios & Kamariotou 2021; Teece 2019; Trivedi–Singh–Gupta 2023; Pekk et al. 2021*). Despite these advancements, many companies still experience fragmented decision-making processes. A lack of integration between corporate goals, forecasting methods, and technology evaluation reduces the efficiency of strategic planning and the practical value of technological investments (*Machado & Davim 2020; Ibeh–Okoro–Eze 2024; Szukits et al. 2024*).

The present study addresses this gap by examining the relationships among company goals, forecasting methods, and technology decisions. The research involved 102 companies – based in Hungary – from the automotive, electronics, machinery, and other high-tech industries. Statistical and network-based approaches were applied, including Fisher's exact test and association rule mining (ARM), to reveal how forecasting practices and company goals jointly shape technology decisions. The novelty of this research lies in demonstrating that technology decisions are not isolated events but are embedded in an interconnected system of company strategy, forecasting, and evaluation. The results provide practical guidance for managers aiming to enhance the effectiveness of strategic technology decisions and to strengthen long-term competitiveness.

Research goal and method

Research design and data collection

This study aims to explore the relationships between key factors that influence technology decision-making in companies. Specifically, the research focuses on three areas:

(A) company goals,
(B) forecasting areas, and
(C) technology decision considerations.

The analysis investigates the connections among these factors in all three possible pairings (A–B, B–C, A–C). Figure 1 illustrates the conceptual focus of the study.

Data were collected through structured face-to-face interviews with executive leaders of technology-oriented manufacturing firms operating in Hungary.

Sample characteristics

The final sample consists of 102 companies. The ownership structure is nearly balanced, with 49% domestically owned and 51% foreign-owned firms.

In terms of firm size, medium-sized (39.2%) and large enterprises (36.3%) dominate the sample, while small

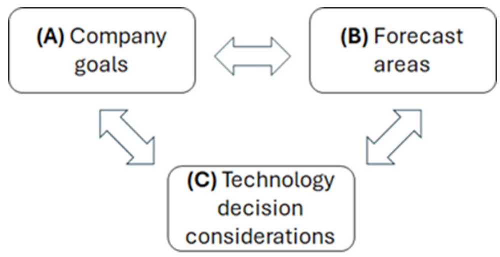

Figure 1 Subject of the analysis

Source: own editing

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC

(17.6%) and micro firms (5.9%) are represented to a lesser extent.

Sectoral distribution follows the TEÁOR'08 classification and reflects a strong industrial-technological orientation, with metal processing, machinery-related activities, engineering services, and R&D forming the largest groups.

Operationalisation of variables

Data were collected through semi-structured personal interviews with executive leaders. A predefined set of questions guided the discussions, while allowing flexibility to capture additional relevant insights. Responses were documented as written notes, coded, and entered into Excel spreadsheets for further analysis. Each company selected relevant options from predefined categories for the three factor groups (Table 1). Multiple responses were allowed, providing a detailed mapping of company priorities, forecasting activities, and technology-related considerations.

Table 1 | Surveyed factor areas

(A) Company goals	(B) Forecast areas	(C) Technology decision considerations
• Profit • Maintaining assets • Growth • Development • Improve market positions • Modernisation • Developing new capabilities • Other	• Monitoring business performance • Monitoring production parameters • Analysing technology opportunities • No forecasting used	• Strategic market advantage • Impact on other existing technologies • Integrated technology cost • Finding the right technology for the size of the company • Cost advantage for competition

Source: own editing

Analytical methods

The relationship analysis followed a three-method approach to provide complementary insights:

- Residual analysis: Cross-tabulation of the three factor groups was used to calculate standardised residuals, identifying where answer combinations occurred more or less frequently than expected. This method allowed for directional interpretation of relationships, as positive and negative residuals indicate higher or lower co-occurrence than expected under independence.
- Fisher's exact test: To statistically verify whether the observed co-occurrences were non-random, Fisher's exact test was applied to the cross-tabulated data. This test is suitable for datasets with multiple small cell values and determines significant relationships between categorical variables.
- Association Rule Mining (ARM): ARM was applied to identify frequent patterns and hidden connections among the responses. Rules were evaluated based on three standard indicators:
  - Support – the frequency of co-occurrence in the dataset.
  - Confidence – the conditional probability of co-occurrence.
  - Lift – the strength of the relationship compared to random occurrence. (Bubble area is proportional to Lift values.)
    - Note1: Larger bubbles in the upper-right quadrant indicate rules with both higher confidence and stronger-than-random associations.
    - Note2: In the ARM scatterplots (Figures 2–4), the x-axis represents support, the y-axis represents confidence, and bubble size is proportional to the Lift value. Larger bubbles therefore indicate stronger-than-random associations between the respective factor combinations.
  - Only rules with support > 0.1 and lift > 1 were considered for interpretation, with confidence levels around 50% accepted as meaningful in the context of exploratory analysis (*Han–Kamber–Pei 2011*).

When the full-table Fisher's exact test did not reach conventional significance, the analysis continued at the level of individual response pairs. This approach made it possible to detect practically relevant associations that could remain hidden in the aggregated table. Pairwise evaluation was applied consistently in all subsequent analyses. This ensured that meaningful patterns were captured, even when no strong overall statistical signal was present.

Among the three approaches, residual analysis was the only method providing an indication of relationship direction, while Fisher's test and ARM revealed existence and strength of connections.

This combined methodology enables a triangulated understanding of how company goals, forecasting areas, and technology decision considerations are interrelated in practice, without implying causality.

Instead of presenting all possible combinations, detailed tables for all three analytical methods are provided only for the first factor pair, while for the remaining analyses the results are summarised to highlight the key patterns and support the overall interpretation.

Results and discussion

The analyses aim to uncover how company goals, forecasting objectives, and technology decision considerations are related in practice. Residual analysis, Fisher's exact test, and Association Rule Mining (ARM) were applied to detect both general statistical patterns and practically relevant pairwise associations. The discussion highlights where significant or meaningful connections

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC

emerge, and how these patterns reflect segment-specific decision-making logics rather than uniform, generalisable trends across all companies.

Statistical analysis of company goals and forecast areas

The objective of this study is to determine whether significant relationships exist between companies' general strategic goals (e.g., profit, asset retention, growth) and their applied forecasting objectives. Although emerging technologies and forecasting methods have become increasingly important in today's competitive environment, it remains uncertain how closely aligned the deliberate use of forecasts is with companies' overarching strategic aims. The analysis begins with the evaluation of residual values calculated from frequency cross-tabulations *(Table 2)*, followed by interpreting the outcomes of Fisher's exact test and the Association Rule Mining (ARM) method *(Table 3)*.

Table 2 | Residual analysis – Company goals and forecast areas

	Business performance monitoring	Manufacturing parameter analysis	Technological potential analysis	Does not use forecasting
Profit	0.089	–0.064	–0.023	–0.076
Asset retention	0.096	0.706	–0.659	–0.946
Growth	0.173	–0.039	0.4	–1.527
Development	–0.311	–0.127	0.214	1.039
Improvement of market position	0.136	–0.424	0.568	–0.589
Modernisation	–0.105	0.119	–0.097	0.263
Development of new capabilities	–0.675	–0.559	0.685	2.598
Other	0.435	0.516	–1.018	–0.725

Source: own editing

Based on the results of the residual analysis *(Table 2)*, the highest positive residual (2.598) appears in the pairing of "Development of new capabilities" and "Does not use forecasting." This indicates that, compared to the average, there is a higher frequency of companies placing importance on developing new capabilities, yet simultaneously refraining from using any forecasting methods. This finding presents an interesting contradiction, as analysing future trends and technological opportunities would typically be essential for successfully developing new corporate capabilities.

In contrast, the largest negative residual (–1.527) was observed for the pairing of "Growth" and "Does not use forecasting." This suggests that companies aiming for growth are significantly less likely than expected to avoid forecasting methods, indicating a clear tendency among growth-oriented businesses to actively use some form of forecasting in their strategic planning.

Table 3 | Fisher-exact test results – Company goals vs. forecast areas

	Business performance monitoring	Manufacturing parameter analysis	Technological potential analysis	Does not use forecasting
Profit	0.971	0.386	0.378	0.379
Asset retention	0.795	0.927	0.446	0.409
Growth	0.438	0	0.164	0.956
Development	0.250	0	0.180	0.633
Improvement of market position	0.248	0.495	0.345	0.330
Modernisation	0.822	0.660	0	0.334
Development of new capabilities	0.969	0.711	0.466	0.993
Other	0.607	0.459	0.986	0.761

Source: own editing

Based on the results of the comprehensive Fisher's exact test *(Table 3)*, no significant overall relationship was found across the entire table ($1 – p = 0.168$). However, several individual response pairs displayed notably strong associations based on their individual $1 – p$ values. Despite the generally weak Fisher's exact test value, the matrix reveals multiple values approaching 1, indicating selective yet meaningful connections. Overall, the limited number of strong relationships suggests that forecasting objectives may depend largely on individual or firm-specific decisions rather than being systematically aligned with broader company goals.

Nevertheless, several notable exceptions and partial relationships emerge, highlighting that specific strategic objectives (such as profit orientation or growth) often coincide with more deliberate forecasting practices. An intriguing anomaly appears in the combination of "Development of new capabilities" and "Does not use forecasting," suggesting that some companies do not fully recognise the importance of forecasting future trends when building new capabilities. On the other hand, companies aiming for modernisation – which typically implies technological innovation – appear to be more consciously engaged in analysing technological opportunities.

Regarding the ARM analysis, the support threshold was initially set at 0.2. However, since most rules with high confidence values were found in the support range of 0–0.1, this lower support interval was also examined.

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC

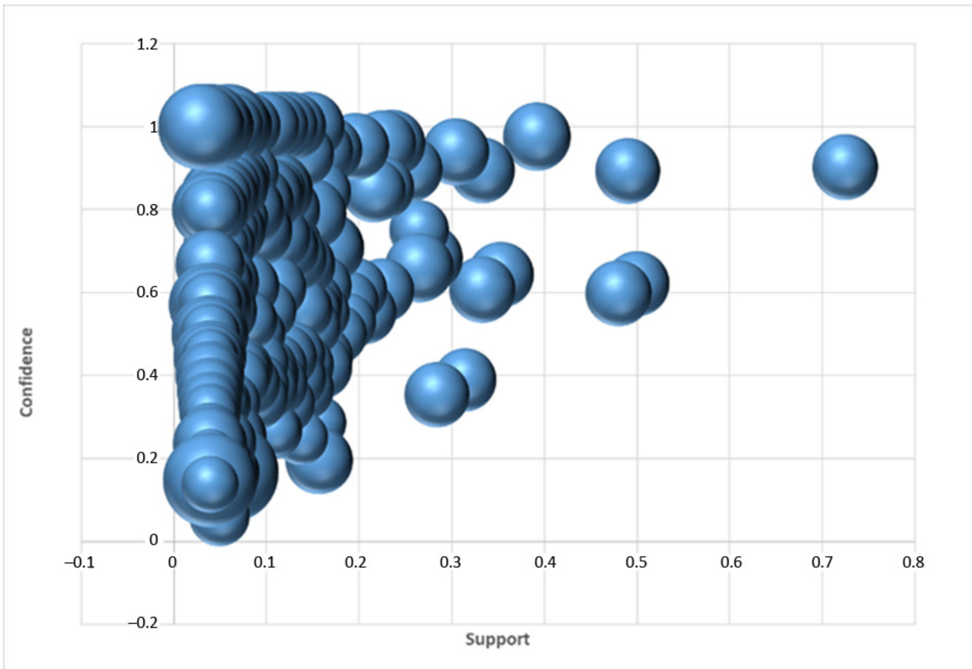

Figure 2 | The ARM scatterplot of company goals and forecast area
Source: own editing

Decreasing the support threshold generally reduces the absolute occurrence frequency of rules, potentially distorting confidence and lift values. Therefore, a subsequent support interval of 0.1–0.2 was also analysed, as rules in this range appeared with relatively higher frequency, ensuring more reliable outcomes (Table 4).

While several rules exhibit high confidence values, the most structurally relevant association is the rule linking "Asset retention" with "Manufacturing parameter analysis" (Lift = 1.488). This combination is visually identifiable in Figure 3 through its comparatively larger bubble size and is also supported by the residual and Fisher

Table 4 | ARM rules – Company goals vs. forecast areas

Left side	Right side	Support	Confidence	Lift
Rules according to settings				
[‚Profit']	[‚Business perform. mon.']	0.725	0.902	1.046
[‚Other']	[‚Business perform. mon.']	0.49	0.893	1.035
[‚Profit', ‚Other']	[‚Business perform. mon.']	0.392	0.976	1.131
[‚Other']	[‚Manufact. param. analysis']	0.353	0.643	1.058
[‚Growth']	[‚Business perform. mon.']	0.333	0.895	1.037
[‚Other']	[‚Business perform. mon.', ‚Manufact. param. analysis']	0.333	0.607	1.068
[‚Profit', ‚Other']	[‚Manufact. param. analysis']	0.275	0.683	1.124
[‚Profit', ‚Improv. of market pos.']	[‚Business perform. mon.']	0.235	0.96	1.113
[‚Modernisation ‚]	[‚Business perform. mon.']	0.225	0.958	1.111
Additional rules				
[‚Modernisation']	[‚Manufact. param. analysis']	0.167	0.708	1.165
[‚Profit', ‚Improv. of market pos.', ‚Other']	[‚Business perform. mon.']	0.147	1	1.159
[‚Profit', ‚Development']	[‚Business perform. mon.', ‚Manufact. param. analysis']	0.118	0.706	1.241
[‚Asset retention]	[‚Business perform. mon.', ‚Manufact. param. analysis']	0.108	0.846	1.488

Source: own editing

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC

analyses. The result suggests a stabilisation-oriented logic, where firms aiming to preserve assets rely more strongly on operational forecasting mechanisms.

Among the forecasting objectives, "Business performance monitoring", "Manufacturing parameter analysis" appear to serve as a supplementary focus, occurring most often alongside "Other" goals. However, its highest confidence values are associated with the company objectives of "Modernisation" and "Asset retention."

Overall, the findings indicate a positive relationship between company goals and the application of forecasting objectives. Companies emphasising goals such as "Profit," "Other" (e.g., specialised or unique objectives), "Growth," and "Modernisation" tend to employ business performance forecasting with notably higher frequency.

Certain pairings of company goals and forecasting methods deviate notably from a random distribution, suggesting that specific underlying decisions might be influencing these associations. However, caution is necessary in interpreting these results, as many pairings exhibit relatively low residual values. A notable exception is the relationship between the company goal of "Asset retention" and the forecasting method of "Manufacturing parameter analysis," a connection consistently supported by all three analytical methods. This particular association likely reflects an emphasis on risk reduction or cost efficiency.

Statistical analysis of forecast areas and technology decision considerations

The analysis of the relationship between technology selection and forecasting aims to provide insight into how these two elements may reinforce each other and, in turn, support corporate strategic decision-making. In the residual analysis, which examines the extent to which observed frequencies deviate from those expected under the assumption of independence, no extreme or highly significant values were identified. Most residuals fall within the ±1 range, indicating that the actual distributions are generally very close to the statistically expected frequencies.

The Fisher's exact test for the full table did not reveal a statistically strong association ($1 - p = 0.045$); however, a pairwise evaluation was conducted to extract insights of practical relevance. The highest value in the table is observed for the pair "Manufacturing parameter analysis" and "Finding technology suitable for company size" (0.920), suggesting that companies employing this type of forecasting tend to seek size-appropriate, long-term sustainable solutions. This association is also moderately reflected in relation to "Cost advantage for competitiveness."

The next notable relationship is between "Technological potential analysis" and "Strategic market advantage" (0.894), although the residual value here remains relatively low.

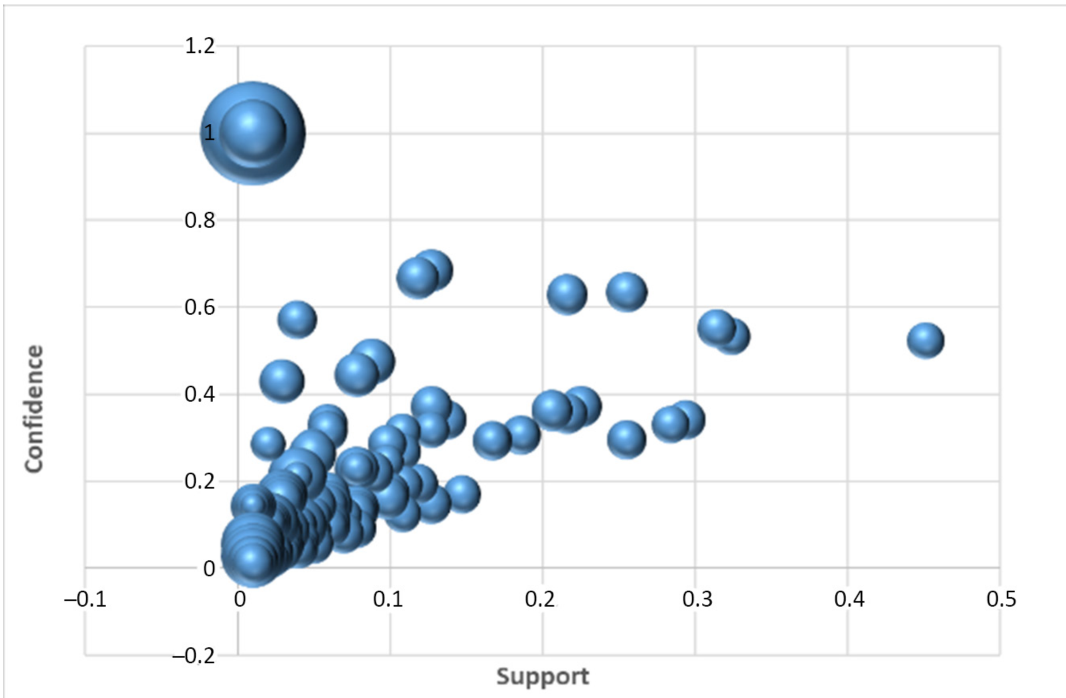

Figure 3 The ARM scatterplot of forecast areas and technology decision considerations

Source: own editing

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC

The connection between "Does not use forecasting" and "Integrated technology cost" (0.815) is also reflected in the residual analysis with a negative value. This implies that companies inclined to apply forecasting objectives are more likely to consider integrated technology costs.

The lack of formal statistical significance indicates that forecasting objectives and technology considerations cannot be claimed to be strongly or universally interconnected. Nevertheless, the pairwise findings highlight patterns that may be relevant in practical decision-making. These observations were further supported and explored using the ARM analysis.

The association rules were examined within a support range of 0.1–0.4, followed by 0.05–0.1. In these cases, the confidence levels were generally moderate rather than strong. However, several lift values exceeded the 1.2–1.3 threshold, indicating a moderate positive relationship between the forecasting objectives (left-side variables) and the technological considerations (right-side variables).

The "Technological potential analysis" forecasting objective frequently co-occurs with "Strategic market advantage," suggesting that identifying technological opportunities is perceived as an important source of competitive advantage—an intuitively logical link. Moreover, the combination of "Manufacturing parameter analysis" and "Technological potential analysis" shows a stronger association with "Cost advantage for competitiveness" compared to other pairings. This implies that detailed analysis of production and development processes supports the selection of cost-efficient technological solutions.

Overall, most ARM rules exhibit moderate confidence levels (around 0.4–0.6) and medium lift values (1.2–1.5). While the detected associations are not universally strong, they highlight practical patterns and point to specific combinations that may hold decision-making relevance.

Statistical analysis of company goals and technology decision considerations

The purpose of this analysis is to explore whether statistical relationships exist between company goals and the criteria used for technology selection. The research examines how the objectives defined by companies relate to the priorities behind their technology decisions, identifying frequency patterns, residual deviations, and pairwise associations.

Most residuals fall within the ±1 range, indicating no strongly deviant cells compared to expected values. The most notable deviation appears for the combination of "Other" and "Finding technology appropriate for company size" (–1.204), suggesting this pairing is less common in the dataset. In contrast, "Modernisation" and "Strategic market advantage" (0.902) show a slight positive deviation, as does "Other" with "Integrated technology cost" (0.899). This latter finding implies that companies pursuing non-traditional goals may be more sensitive to integrated technology costs than expected.

The Fisher exact test for the full contingency table again shows no strong overall association ($1 - p = 0.0002$). As in the previous analysis, pairwise Fisher tests were performed to highlight localised connections.

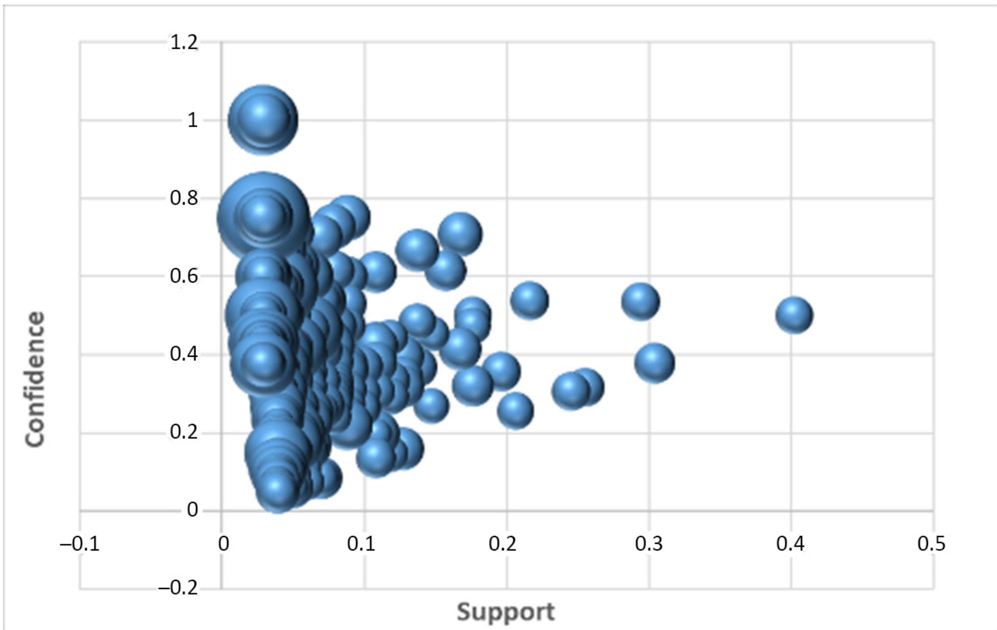

Figure 4 The ARM scatterplot of company goals and technology decision considerations

Source: own editing

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC

The residual analysis and Fisher results confirm several meaningful associations. The strongest link is between “Other” and “Finding technology appropriate for company size.” “Asset retention” also shows a notable relationship with technology choices tailored to company size, and “Modernisation” aligns with “Strategic market advantage.”

Overall, the lack of broad statistical significance suggests that company goals and technology decisions do not form a uniform, generalisable pattern. However, the pairwise results reveal several relationships that may hold practical relevance for decision-making, particularly in industry-specific or strategic contexts.

As in the previous analysis, the identified association rules are not particularly strong. The support range was first examined from 0.1 and later extended to 0.05–0.1. The resulting rules also include some with lower confidence values (<0.6) but relatively high lift values.

The association between “Modernisation” as a company goal and “Strategic market advantage” as a decision criterion suggests that companies pursuing modernisation consciously aim to gain a market advantage. This finding aligns with the results of the Fisher exact test. Moreover, when “Modernisation” is combined with “Profit” and “Other” goals, the lift increases to 1.374, although the support decreases to 0.078, indicating that this pattern is specific to a smaller group of companies.

For companies prioritising “Asset retention,” the results show a higher-than-expected tendency to select technologies that are well-aligned with the company’s size and operational characteristics. In the case of “Development” as a company goal, the pursuit of market advantage is evident, and when paired with “Other” goals, the lift reaches a higher value. This pattern indicates that, within a narrower corporate segment, technology investment decisions emphasise both competitive advantage and system compatibility.

Conclusions

Strategic alignment between company objectives and technology-related decisions has long been emphasised in the literature on technology management and dynamic capabilities (*Teece 2019; Kim 2022*). Most existing studies, however, assume a relatively coherent relationship between strategic intent and technological action. The present findings suggest a more nuanced reality. The analysis of 102 technology-oriented Hungarian firms indicates that uniform alignment patterns are largely absent. Instead of a single, consistent decision logic, the data reveal segment-specific configurations, where certain goal–evaluation combinations appear meaningful only within narrower corporate groups. This finding partially contrasts with normative decision-support literature (e.g., AHP-based models), which typically presumes stable and structured criteria hierarchies. In practice, however, strategic-technological coherence appears fragmented and context-dependent.

From a methodological perspective, the combined application of residual analysis, Fisher’s exact test, and association rule mining enabled the identification of localised but practically interpretable associations, even in cases where overall table-level significance was weak. This multi-method triangulation contributes to empirical research on technology management by demonstrating that complex categorical decision systems may require layered statistical exploration rather than reliance on a single analytical approach.

Implications for researchers

For researchers, the results highlight three important aspects:

- Strategic–technological alignment should not be assumed as a structural characteristic of firms; it may exist only in specific segments.
- Pairwise and pattern-based analytical techniques can reveal meaningful micro-level configurations that remain hidden in aggregated statistical testing.
- Future studies may extend this framework by incorporating segmentation variables (e.g., firm size, ownership structure, performance indicators) to determine whether identified configurations are structurally embedded or context-specific.

The study thus contributes not by introducing new decision models, but by empirically demonstrating the fragmented nature of strategic-technological relationships in practice.

Implications for industry

For technology-oriented firms, the findings suggest that:

- Companies prioritising asset retention tend to follow a stabilising logic, connecting operational analysis with scale-appropriate technology choices.
- Firms emphasising modernisation are more likely to associate technology investments with strategic market positioning.
- However, several firms pursuing development-oriented goals do not consistently rely on structured forecasting or systematic evaluation mechanisms.

This indicates that strengthening internal coherence between strategic objectives and technology-related evaluations may reduce investment inefficiencies and improve long-term competitiveness.

Security relevance

From a security and risk-management perspective, the absence of consistent alignment patterns may represent a structural vulnerability. When technology selection, operational analysis, and strategic goals are weakly con-

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC

nected, firms may face increased exposure to strategic misinvestment, operational instability, or technological lock-in. Conversely, segment-specific coherent configurations may enhance organisational resilience by reducing uncertainty in technology adoption decisions.

The novelty of this study does not lie in the individual methods (residual analysis, Fisher's exact test, ARM), but in their combined application to explore directional, statistical, and pattern-based relationships within a three-dimensional strategic decision framework. This methodological triangulation enables the detection of segment-specific decision logics that remain hidden in traditional contingency analyses.

Overall, the findings underline that technology decision-making is not governed by universal rules, but by context-dependent strategic configurations. Recognising and consciously structuring these configurations may improve both competitiveness and organisational security.

Acknowledgements

Project no. C1010785 has been implemented with the support provided by the Ministry of Culture and Innovation of Hungary from the National Research, Development and Innovation Fund, financed under the kdp-2020 (kdp-11-3/paly- 2021) funding scheme.

National Research, Development and Innovation Office
Hungary

PROJECT FINANCED
FROM THE NRDI FUND

References

Awasthi, A., & Varman, R. (2003) Investigating the influence of information technology on decision making. Journal of Advances in Management Research, Vol. 1. No. 1. pp. 74–87. https://doi.org/10.1108/97279810380000361

Bolatan, G. I. S., Kalkan, A., Alpkan, L., & Savrul, M. (2022) Unlocking the relationships between strategic planning, leadership and technology transfer competence: The mediating role of strategic quality management. Journal of Knowledge Management, Vol. 26. No. 11. pp. 89–113. https://doi.org/10.1108/JKM-12-2020-0897

Feng, L., Xie, X., Zhang, W., & Huang, Y. (2022) A review of technological forecasting from the perspective of complex systems. Entropy, Vol. 24. No. 6. 787. https://doi.org/10.3390/e24060787

Firat, A. K., Woon, W. L., & Madnick, S. (2008) Technological forecasting: A review. Composite Information Systems Laboratory (CISL), Massachusetts Institute of Technology.

Gandrita, D. M. (2023) Improving strategic planning: The crucial role of enhancing relationships between management levels. Administrative Sciences, Vol. 13. No. 10. 211. https://doi.org/10.3390/admsci13100211

Ghonim, M. A., Alyahya, M., Alshamari, M., & Al-Mutairi, A. (2022) Strategic alignment and its impact on decision effectiveness: A comprehensive model. International Journal of Emerging Markets, Vol. 17. No. 1. pp. 198–218. https://doi.org/10.1108/IJOEM-04-2020-0364

Haleem, A., Javaid, M., & Khan, I. H. (2019) Technology forecasting (TF) and technology assessment (TA) methodologies: A conceptual review. Benchmarking: An International Journal, Vol. 26. No. 1. pp. 48–72. https://doi.org/10.1108/BIJ-04-2018-0090

Han, J., Kamber, M., & Pei, J. (2011) Data mining: Concepts and techniques (3rd ed.). Morgan Kaufmann.

Heikkilä, M., Bouwman, H., & Heikkilä, J. (2018) From strategic goals to business model innovation paths: An exploratory study. Journal of Small Business and Enterprise Development, Vol. 25. No. 1. pp. 107–128. https://doi.org/10.1108/JSBED-03-2017-0097

Ibeh, C. V., Okoro, O. A., & Eze, S. C. (2024) Business analytics and decision science: A review of techniques in strategic business decision making. World Journal of Advanced Research and Reviews, Vol. 21. No. 2. pp. 1761–1769. https://doi.org/10.30574/wjarr.2024.21.2.0247

Iwu, I., Johnson, S., & Onyekachi, F. S. (2024) Strategic management practices as fundamental to the achievement of organizational performances. African Journal of Social Sciences and Humanities Research, Vol. 7. No. 1. pp. 106–118. https://doi.org/10.52589/AJSSHR-OQ22U7MS

Kim, S. (2022) Critical success factors evaluation by multi-criteria decision-making: A strategic information system planning and strategy-as-practice perspective. Information, Vol. 13. No. 6. 270. https://doi.org/10.3390/info13060270

Kitsios, F., & Kamariotou, M. (2021) Artificial intelligence and business strategy towards digital transformation: A research agenda. Sustainability, Vol. 13. No. 4. 2025. https://doi.org/10.3390/su13042025

Machado, C., & Davim, J. P. (eds 2020) Research methodology in management and industrial engineering. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-40896-1

Pekk L., Háry A., & Tóth C. (2021) Technology features of the different sectors. The 3rd International Conference on the Economics of the Decoupling (ICED). p. 72.

Peykani, P., Namazi, M., & Mohammadi, E. (2022) Bridging the knowledge gap between technology and business: An innovation strategy perspective. PLOS ONE, Vol. 17. No. 4. e0266843. https://doi.org/10.1371/journal.pone.0266843

Szukits Á., & Móricz P. (2024) Towards data-driven decision making: The role of analytical culture and centralization efforts. Review of Managerial Science, Vol. 18. No. 10. pp. 2849–2887. https://doi.org/10.1007/s11846-023-00694-1

Szukits Á., Sztrida L., & Szabó I. A. (2024) Információs folyamatok digitalizációjának Hatása a kontrolleri szakmára – szisztematikus Irodalomáttekintés. Vezetéstudomány, Vol. 55. No. 6. https://doi.org/10.14267/VEZTUD.2024.06.03

Teece, D. J. (2019) A capability theory of the firm: An economics and (strategic) management perspective. New Zealand Economic Papers, Vol. 53. No. 1. pp. 1–43. https://doi.org/10.1080/00779954.2017.1371208

Trivedi, P., Akhter, F., Khan, A., Shajrawi, A. A. I., Ratkovic, N., & Kausar, F. N. (2023). The role of technology in enhancing business processes. Journal of Management & Educational Research Innovation, 1(1). https://doi.org/10.5281/zenodo.10055077

This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited, a link to the CC License is provided, and changes – if any – are indicated. (SID_1)

Unauthenticated | Downloaded 07/01/26 10:49 AM UTC