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NEW APPROACH FOR CLASSIFYING UNSTRUCTURED DATA TO UNDERSTAND THE INFLUENCE OF NEW TECHNOLOGIES IN FUTURE ERP DEVELOPMENT

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Abstract

The rapid development of emerging technologies is changing the business world every day. Process automation, artificial intelligence (AI) consultants, mobile devices, cloud technologies, no-code programming, and many more are influencing the requirements for business systems. The current study aims to compare human experts and generative AI (GenAI) in classifying unstructured text to identify the emerging technologies that will have the greatest impact on the future development of enterprise resource planning systems. The basis for the comparison is statistical indicators such as the average Jaccard index and Krippendorff's alpha, which validate the classification from both approaches.The results indicate that GenAI holds potential for process automation, whereas human classification is more closely aligned with statistical indicators. GenAI has difficulties with contextual nuances and specific categories. Hence, a four-step funnel-based framework for the efficient classification of unstructured text was developed,

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which integrates GenAI for initial structuring and training while emphasizing the indispensable role of human supervision for quality assurance to leverage automation while maintaining the validity of the results. This approach significantly reduces manual effort while maintaining reliable analysis.

Key Words

Enterprise resource planning (ERP) systems; text classification; generative artificial intelligence (GenAI); technological advancements; business administration

INTRODUCTION

Enterprise resource planning (ERP) systems have emerged as one of the most critical enterprise software platforms within the contemporary business landscape. Being aware of prevailing technological developments and keeping an eye on future trends is crucial, for example, when selecting a suitable ERP system or making investment decisions in innovative technologies. Therefore, it is essential to scientifically analyze the current literature, journal articles, and expert discussions to remain current.

Researchers who want to investigate which relevant technologies may influence the further development of ERP systems must first gather different types of source material and analyze it. These texts are typically unstructured, such as books, research papers, and expert interviews. The second step is to transform this unstructured data into a format that enables the extraction of valuable, actionable insights.

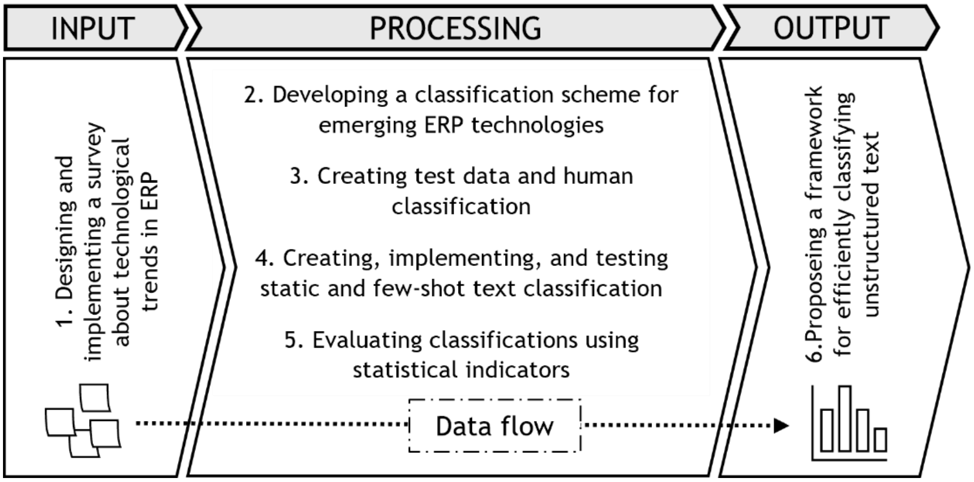
Unstructured data usually requires significant effort for researchers to perform data classification and evaluation, in contrast to structured data, which are often directly quantifiable. Reading texts carefully, performing comprehension, taking notes, and conceptually linking the sources are time-consuming tasks, especially when the sources are, for example, expert interviews, which integrate subjective opinions, assessments, future prognoses, and personal experiences. As a result, the context is often dynamic and interactive. Thus, classifying data can be exceptionally demanding, which often poses a problem for researchers, who must invest considerable time in classifying and analyzing it before they can obtain relevant findings.

Therefore, this article presents a new and up-to-date approach for minimizing the time spent classifying data without compromising quality. This novel approach aims to assist researchers in classifying unstructured texts by understanding the impact of modern technologies on future ERP development. The proposal integrates current technologies such as generative AI (GenAI) and provides recommendations for action, as well as concrete assistance for researchers.

METHODS AND RESEARCH APPROACH

This article follows the research design shown in Figure 1, as explained in the conceptual overview section below.

Figure 1: Research design



Conceptual overview

The sequence of six tasks, presented in Figure 1, forms the conceptual and logical framework of this article and is grouped into three stages: input, processing, and output. Firstly, the input stage encompasses the design and implementation of a survey about technological trends in ERP. Second, the processing stage comprises several important steps, which start with developing a classification scheme for emerging ERP technologies, followed by creating testing data and human classification. Third, the creation, implementation, and testing of static and few-shot text classification are conducted, which culminates in the evaluation of these classifications by applying statistical indicators. Fourth, the output stage delivers a comprehensive outcome built on the preceding stages and their relevant findings. A proposal for a novel methodology is subsequently presented. This methodology seeks to combine GenAI with traditional methods to achieve better and faster results for classifying non-structured text.

Designing and implementing a survey about technological trends in ERP

The survey aimed to confirm the importance of technologies expected to be significant in the ERP environment both now and in the future. These technologies were validated by a literature analysis encompassing 35 papers published between 2020 and 2024. These studies specifically examined the impact of at least three distinct technologies on ERP systems. Table 1 shows some of the survey participants' characteristics.

Table 1: Survey participants (*n* = 37)

ERP experience	
1–2	10
2–5	11
>5 years	16
Company size	
<50	8
50–100	2
100–500	9
> 500 employees	18

The participants' engagement with ERP software was also investigated beyond ensuring a balanced distribution while considering both experience and company size. Approximately one-third of the participants were traditional ERP system users. In addition, various other experts, including ERP system administrators, developers, and project managers, participated in the survey. The outcome was a well-balanced mix of ERP experience with varying company sizes and areas of responsibility. Consequently, gathering relevant domain knowledge and practical experience to develop a relevant and functional classification scheme in the ERP context was ensured through precise survey questions.

The survey was conducted online and designed to gather comprehensive expert opinions for the development of a classification scheme for emerging ERP technologies. Structured questions with Likert scales were used to identify trends regarding the influence of specific technologies on ERP.
In addition, binary questions (Yes/No) were used for specific decisions, supplemented by free-text questions to capture detailed opinions and additional perspectives.

The questions were grouped thematically, with both mandatory and optional questions to allow the participants to have flexibility in their responses while ensuring high data quality.

Several factors influenced the design and scope of the survey. Since the process of assessing free-text responses, understanding, and accurate labeling key technologies is inherently time-consuming, this constraint consequently necessitated a pragmatic reduction in the number of participants. Secondly, to ensure the representativeness of the findings, it was imperative to identify the appropriate target audience of experts. These individuals needed to possess the prerequisite knowledge to provide insightful answers regarding the future of ERP. Thirdly, the selection process itself demanded considerable effort to identify suitable individuals from each relevant group to participate in the questionnaire.

Overall, the chosen sample size was deemed sufficient to generate a qualitatively rich and diverse dataset despite these challenges. This dataset was intended for the exploratory development of a classification scheme while maintaining the practicality of both data collection and subsequent analysis.

Developing a classification scheme for emerging ERP technologies

The findings derived from the study served as the input for subsequent stages. Upon commencing the processing stage, the study results were thoroughly screened, and key technologies and keywords were extracted. Particular attention was paid during this process to ensuring the comprehensive integration of expert knowledge, with the aim of deriving precise category definitions and pertinent keywords. Subsequently, the findings pertaining to each identified technology were consolidated and clearly presented.

Figure 2: Classification scheme for emerging ERP technologies

The results of this work are presented in Figure 2, which provides a structured overview of a wide range of key technologies and concepts. In the context of this paper and due to its great importance in the ERP area, user experience is considered a technology that utilizes design principles, methods, and tools to create intuitive, efficient, and pleasant interfaces that increase acceptance and usability. These categories and technologies are shown, along with a brief description of the category. In addition, the gray boxes contain a list of keywords that indicate the technology. This classification scheme provided a guideline for recognizing the most important technologies in the domain of ERP systems. It facilitated the assignment of specific codes to text passages in the following sections of this research. The codes referred to the 20 relevant emerging technologies in the field of ERP systems.

Subsequently, a literature analysis was conducted to validate the relevance of the technologies outlined in the classification scheme for emerging ERP technologies. This analysis encompassed 35 papers, exclusively drawn from German and English literature published between 2020 and 2024, which specifically examined the impact of at least three distinct technologies on ERP systems.

Creating test data and human classification

A compilation of 100 examples from various sources was created to test the classification scheme with different approaches. Below are excerpts from texts dealing with technological trends in the field of ERP. The sources were written down sentence by sentence and numbered from 1 to 100, as shown in Table 2.

Table 2: Test dataset

No.	Sentence	Source
1	"Recent advancements in machine learning (ML), especially deep learning and ensemble techniques, have significantly improved the accuracy of predictive models."	(Mhaskey, 2025)
...	…	
25	"The transformative impact of AI-powered invoice automation on financial operations demonstrates the significant potential of intelligent technology integration in modern business environments."	(Onteddu, 2025)
…	…	
38	"The evidence available suggests that massive data and analytics are currently at the core of ERP systems and many related sectors."	(Kaulwar, 2025)
…	…	
85	"Enterprise Resource Planning (ERP) systems are universally used to automate and manage business processes."	(Sunmola and Lawrence 2024)
…	…	
100	"Previous research has been focused on critical success factors of ERP or critical success factors of blockchain."	

Three text classifications were conducted within the scope of this article. The first was performed by a human evaluator who assigned the test data to categories sentence by sentence using the previously created classification scheme for emerging ERP technologies, as shown in Figure 2.

The human evaluator in such research must be an ERP expert with a professional background of more than five years. Additionally, the verification of human work can be achieved through peer review. Ensuring the validity of human classification, particularly when considering the time investment required for thorough review, necessitates careful attention to selecting suitable individuals. Furthermore, it is advisable to assess or test potential evaluators prior to assigning them classification tasks.

Creating, implementing, and testing static and few-shot text classification

Another classification method was created using the Python programming language and the Pandas library: an “open-source data analysis and manipulation tool built on top of the Python programming language” (Pandas, 2025). The logic checks for the keywords are shown in Figure 2. Additionally, the program ensured that only relevant excerpts of the keywords were identified. For example, for the code Artificial Intelligence and Machine Learning, “AI” would be recognized as a term in the sentence “AI is an important feature.” Conversely, the terms “training” and “gain,” which also contain the keyword “AI,” would not result in a positive result. In summary, this form of evaluation statically checked for existing keywords.

A third classification was performed using a few-shot text classification by GenAI. The term is “particularly pertinent in text classification” and can be defined as “a specialized branch of machine learning, [which] tackles the challenge of constructing accurate models with minimal labelled data” (Aljehani et al., 2025).

However, GenAI must be trained with data before it can be used for classification. Thus, another dataset consisting of 100 sentence examples was created to implement this task, which comprised statements from the study conducted and classified by a human evaluator. Finally, the training and testing data were fed into an instance of ChatGPT5, and the results of the classification were documented and prepared.

Notably, a multi-label rating was possible when a sentence contained multiple technologies simultaneously. For example, the first sentence in Table 2 contains both Artificial Intelligence and Machine Learning, as well as Data Analytics/Science. There was also the option to classify a sentence as “uncategorized” if none of the technologies applied. The results of the classifications appear in Table 3.

A total of 11 of 20 technologies appeared in the test file. GenAI assigned the most codes with 148, followed by the human evaluator (138) and static classification (134).

Table 3: Test dataset classification results

Categories (technologies)	(I) Static classif.	(II) Classif. with GenAI	(III) Human class.
Distr. Ledger Tech. and Blockchain	21	23	25
Data Analytics/Science	15	21	23
AI and ML	21	29	25
Uncategorized	37	17	25

Data/Information Security	12	10	14
Cloud Computing	10	12	10
(Hyper-)Automation	11	13	10
Internet of Things	5	7	5
Digitalization and Digital Transf.	2	11	1
Business Process Mining	0	1	0
Microservices	0	1	0
User Experience	0	3	0
Other categories	0	0	0
Sum of Category Assignments	**134**	**148**	**138**

Evaluating classifications using statistical indicators

Statistical indicators were used to scientifically evaluate the data sets and determine the differences and similarities between the three evaluators. Statistical analysis was performed as part of this research by creating three different evaluation parameters. First was general statistical data, which included easily observable parameters, such as the sum of matching codes, partial matches, and non-matching codes.

Second, the average Jaccard coefficient was calculated by dividing the sum of the individual Jaccard coefficients by the number of sentences. Jaccard index *J* was defined according to Formula 1 below:

$$(1)\, J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

Here, *J* is calculated by dividing the union of sets A and B by the number of elements that differ between the sets. Consequently, the index values range from 0 to 1. As the index approaches 1, the degree of similarity between the sets increases. Specifically, the value of *J* = 1 indicates perfect congruence, which signifies that the sets are identical.

An illustrative example of the coding process is essential to ensure the index is comprehensible in the context of the article. Table 4 provides this concrete illustration.

Table 4: Example for category assignment

No.	Evaluator 1	Evaluator 2
1	A = {Artificial Intelligence and Machine Learning[1]}	A = {Artificial Intelligence and Machine Learning [1]}, B = {Data Analytics/Science[2]}

In this example, evaluator 1 assigned exactly one technology, while evaluator 2 assigned two. Both agreed on the category Artificial Intelligence and Machine Learning, but Data Analytics/Science was only assigned by evaluator 2.

A single Jaccard index *J* is calculated as follows:

$$(2)\ J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|\{1\}|}{|\{1,2\}|} = \frac{1}{2} = 0.5$$

Summing up the individual Jaccard indices and dividing them by the number of examples from the test dataset (i.e., 100 in this case) delivers the average Jaccard index.

Third, a more complex metric must be selected that also considers, for example, random agreement between categories. There are several possible agreement statistics, such as Cohen's kappa, Fleiss's kappa, and Krippendorff's alpha.

In this research project, Krippendorff's alpha was chosen as a "standard reliability statistic for content analysis and similar data making efforts" (Krippendorff, 2007). Unlike Cohen's kappa, which is limited to two evaluators, and Fleiss's kappa, which is primarily designed for exclusive categories, Krippendorff's alpha offers the necessary flexibility and robustness to accurately assess agreement under these more complex conditions and substantiate the credibility of qualitative analysis.

Although Krippendorff's alpha is generally unsuitable for multi-label data (Li et al., 2023), the value can be calculated for each category or technology. Generally, the value is calculated by the difference between 1 and the result of the quotient of the observed disagreement D_o and the disagreement expected by chance D_e, as shown in Formula 3:

$$(3)\ \alpha = 1 - \frac{D_O}{D_e}$$

Krippendorff (2011) described D_o as "the observed disagreement among values assigned to units of analysis" and D_e as "the disagreement one would expect when the coding of units is attributable to chance rather than to the properties of these units." In Krippendorff's article referenced in this research, he provided a detailed account of how to compute his index for reliability while elaborating on mathematical methodology and inherent properties. Hence, no further discussion is needed concerning the formula, while reference is made to Krippendorff's original work.

An applicable and straightforward solution for calculating the statistical alpha value was sought within the scope of this research article, so invaluable code libraries were leveraged for this purpose. Krippendorff's alpha was calculated with minimal effort using the Python programming language and a suitable library (Castro, 2017).

The characteristics of each category were translated into a series of binary values to achieve this aim. For example, each sentence to be coded was checked and compared to see whether evaluator 1 and 2 agreed in the category "Data Analytics/Science." This approach allowed the individual categories to be evaluated separately while determining which categories the evaluators agreed on (i.e., a high alpha value) and where there were significant differences of opinion (i.e., a low alpha value).

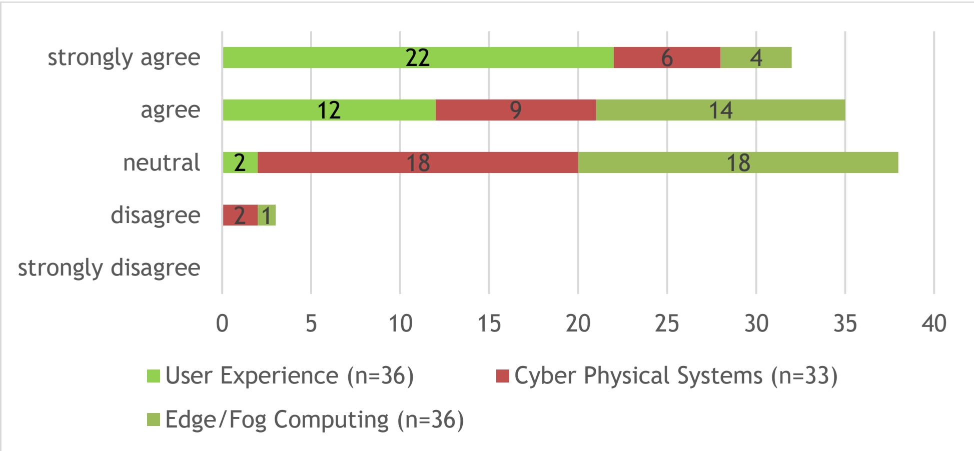
FINDINGS

This section presents the findings from the survey on technological trends in ERP, as well as the evaluation of classifications using statistical indicators. Additionally, a proposal is presented for a new approach to combine GenAI with traditional methods to achieve better and faster results for classifying non-structured text, informed by these findings.

Survey findings concerning technological trends in ERP

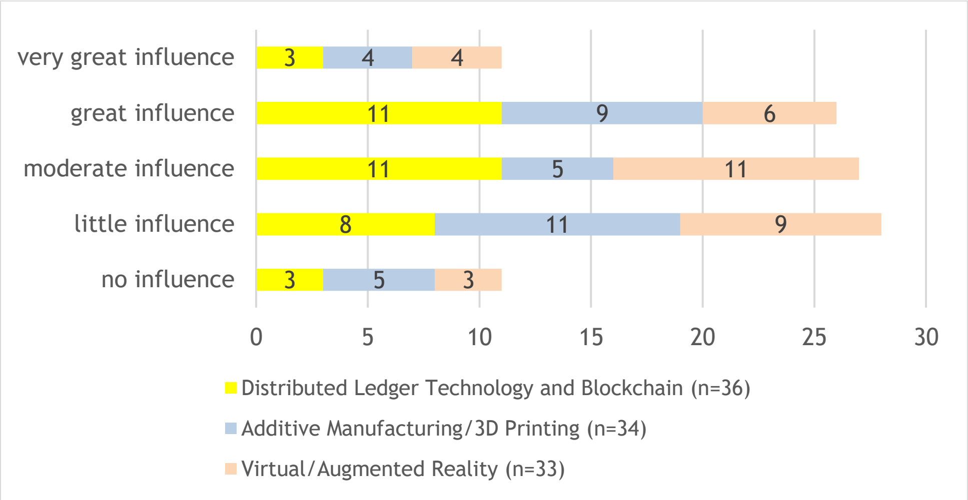
The first technologies the survey participants evaluated were cyber-physical systems and edge/fog computing. User experience, considered in the context of this paper as a technology that utilizes design principles, methods, and tools to design intuitive, efficient, and pleasant interfaces, was also evaluated here. All three technologies were considered to be important for ERP. Their significance is evident in Figure 3, particularly in the strong approval ratings for User Experience, with 22 of the 36 participants (60%) answering this specific question by expressing very strong agreement on its importance. Although approximately one-third of the participants were neutral about the technologies (in the cyber-physical systems category, this figure was as high as 18/33, ~ 55%), only three votes were cast against them.

Figure 3: Importance of user experience, cyber-physical systems, and edge/fog computing (*n* = 105)



Moreover, Figure 4 shows three other technologies: distributed ledger technology and blockchain, additive manufacturing/3D printing, and virtual/augmented reality. Most of the survey participants believed that these three technologies would have a moderate to significant impact on ERP. While approximately 38% (39/103) saw little or even no influence from these technologies, their impact was indeed difficult to deny.

Figure 4: Importance of distributed ledger technology and blockchain, additive manufacturing/3d printing, and virtual/augmented reality (*n* = 103)

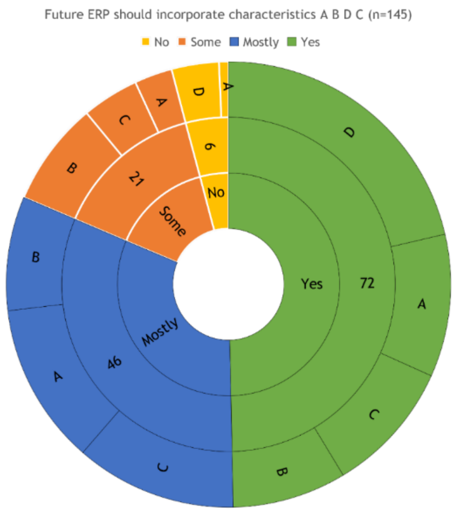


Finally, Figure 5 shows four desirable characteristics of ERP systems from the participants' perspectives (i.e., A to D), which reflect characteristics from four technological areas: (A) Microservices, (B) In-Memory Computing, (C) Business Process Mining, and (D) Low/No-Code. Approximately 81% (118/145) of the respondents would consider an ERP system with these four characteristics, depicted in Table 5, to be useful. Conversely, only 21 respondents considered these attributes important to some degree, while only six deemed them entirely unimportant.

Table 5: Requirements for ERP systems

Req.	Description
A	The future architecture of ERP software should be based on innovative cloud architecture with microservices and open APIs.
B	ERP systems should use the latest technology (e.g., fast in-memory computing) with the ability to process large volumes of data instantly.
C	ERP should offer more extensive analysis and monitoring functions to exploit potential for process improvements, which can be implemented directly in the ERP system or via preconfigured connectors for process mining tools.
D	ERP should provide stable interfaces to external NC/LC platforms so that the ERP system remains the central instance of data sovereignty.

Figure 5: Desirable requirements for ERP systems according to the survey participants



The survey included an optional free-text question that asked the respondents about their opinions on technologies affecting ERP that were not previously mentioned in this article. Many answers included AI. Moreover, 5G and quantum computing were addressed three times each, which suggested that these technologies were highly regarded by the experts and relevant to the classification scheme.

Findings from evaluating classifications using statistical indicators

Table 6 presents various statistical indicators, which are explained below. They were useful for evaluating the implemented classification options. The key figures refer to the data set of the human evaluator, which serves as a benchmark.

Table 6: Statistical indicators

Statistical Indicators	(I) Static Classification	(II) Classif. with GenAI
General Data		
Matching codes	77	61
Partial matches	9	25
Non-matching codes	14	16
Average Jaccard Index	0.81	0.73
Krippendorff's Alpha		
Cloud Computing	1.0	0.90
Distr. Ledger Tech. and Blockchain	0.89	0.95
AI and ML	0.89	0.85
Digitalization and Digital Transf.	1.0	0.12

Internet of Things	1.0	0.82
Data/Information Security	0.91	0.72
Data Analytics/Science	0.75	0.69
(Hyper-)Automation	0.74	0.66
Uncategorized	0.67	0.64
Business Process Mining	-	0.0
Microservices	-	0.0
User Experience	-	0.0

First, general data is displayed, which shows the sum of matching codes, partial matches, and non-matching codes. Notably, the static classification corresponds to 77% (77/100) of the authors' classification, a very good result, whereas GenAI achieved only 61% (61/100). In contrast, there were nine sentences in which the codes of the static classifier partially matched, compared to 25 for GenAI. There was complete disagreement in 16 cases with AI, and 14 cases with static classification. Therefore, the general statistical indicators showed that the static classification provided more absolute matching codes (77 vs. 61) and fewer absolute non-matching codes (14 vs. 16) than GenAI.

Furthermore, a comparison of the average Jaccard index of the two data sets also yielded a better value of 0.81 for static classification than 0.73 for classification with ChatGPT. The closer the value was to 1, the higher the agreement between the data sets. When considering all text passages, the codes assigned by the Python script overlapped 81% on average with those of the human evaluator, based on the total number of unique labels.

Nonetheless, Krippendorff's alpha values in the individual categories provided a differentiated picture. Krippendorff recommended "rely[ing] only on variables with reliabilities above a = .800" while "consider[ing] variables with reliabilities between a = .667 and a = .800 only for drawing tentative conclusions" (Krippendorff, 2004). Using these thresholds as an approximate guide, some notable differences between the two evaluators (i.e., static classification and classification with GenAI) were seen.

The results of the static classification indicated that the "uncategorized" category was only slightly above the threshold of 0.667 due to the insufficient performance of the Python script. In Table 7, Example 2 illustrates that static classification only recognized the string "pattern recognition," which would have resulted in classification in the category "Data Analytics/Science" but not the term "patterns." Example 9 showed a similar result, where "analysis of these vast datasets" was not recognized as a string. However, a human evaluator familiar with the technologies should be able to classify one easily.

Table 7: Wrong example category – Uncategorized

Nr.	Sentence	(I) Static	(III) Human
2	"These sophisticated methods can analyze complex datasets and uncover *patterns* that traditional	Uncategorized	Data Analytics/ Science

	statistical techniques might miss, resulting in more reliable forecasts" (Mhaskey 2025: 6).		
9	"They deliver extensive storage options and robust computing resources, allowing for the efficient processing and *analysis of these vast datasets*—capabilities often unattainable for many small and mid-sized businesses" (Mhaskey 2025: 6).	Uncategorized	Data Analytics/ Science

The results of classification with GenAI were particularly interesting, as some categories stood out clearly. One anomaly was the very poor score of 0.12 for Digitalization and Digital Transformation. According to the number of classifications in Table 3, GenAI assigned this category 11 times. Compared to (I) and (III), this deviation was significant. Moreover, examining sentence 20 in Table 8, GenAI might interpret the string "transformative effect" as referring to the category Digitalization and Digital Transformation. In addition, example 48 suggests that GenAI assumes institutional change also requires digital components.

Table 8: Wrong example category – Digitalization and Digital Transformation

Nr.	Sentence	(II) GenAI	(III) Human
20	"Exploring ERP analytics has illuminated its *transformative effect* on organizational performance, facilitating enhanced decision-making, operational efficiency, and strategic financial management" (Mhaskey 2025: 7).	Data Analytics/Science, Digitalization and Digital Transformation	Data Analytics /Science
48	"Current predictions also suggest that the future path of ERPs is a movement towards adaptation to revolutionize service co-production or value co-creation, necessitating organizations and institutional change" (Kaulwar 2025: 33).	Digitalization and Digital Transformation	Uncategorized

Observing the alpha values for the categories Business Process Mining, Microservices, and User Experience revealed that AI consistently failed to classify them correctly, which resulted in alpha values of 0.0. Although these were only assigned a total of five times (see Table 3), two examples are provided in Table 9. Sentence 74 revolves around "organizing workflows efficiently," which GenAI may associate with business processes. The second example, sentence 75, describes how a "high-quality degree of service" satisfies the customer. In this case, one could certainly speak of a good "user experience" if the description refers to the interaction with the ERP system. However, since this idea could only be assumed, the category shows a difference.

Table 9: Wrong example categories – Business Process Mining and User Experience

Nr.	Sentence	(I) Static C	(III) Human

74	"*Organizing workflows efficiently* can result in rapid or almost immediate real-time decisions and therefore quick responses" (Kaulwar 2025: 34).	(Hyper-) Automation, Business Process Mining	Uncategorized
75	"This operational speed can be transposed to customers and internal clients who could benefit from an immediate and high-quality degree of service" (Kaulwar 2025: 34).	User Experience	Uncategorized

Two categories, (Hyper-)Automation (0.66) and Uncategorized (0.64), also fell below the threshold when evaluated using Krippendorff's alpha, so they had to be adjusted. However, the analysis was similar to the previous ones, so further discussion is unwarranted here.

Finally, another striking pattern was noteworthy. In some sentences, it was debatable whether the AI correctly recognized the context of the sentences. Two of these examples are shown in Table 10. Example 26 refers to the fact that the implementation of "these solutions" (i.e., automation and AI) calls for certain requirements. In Example 57, "these innovations" refer to AI and Big Data Analytics, mentioned in the previous sentence. These examples illustrate the challenges that non-human evaluators face in this context.

Table 10: Wrong example – Missing context

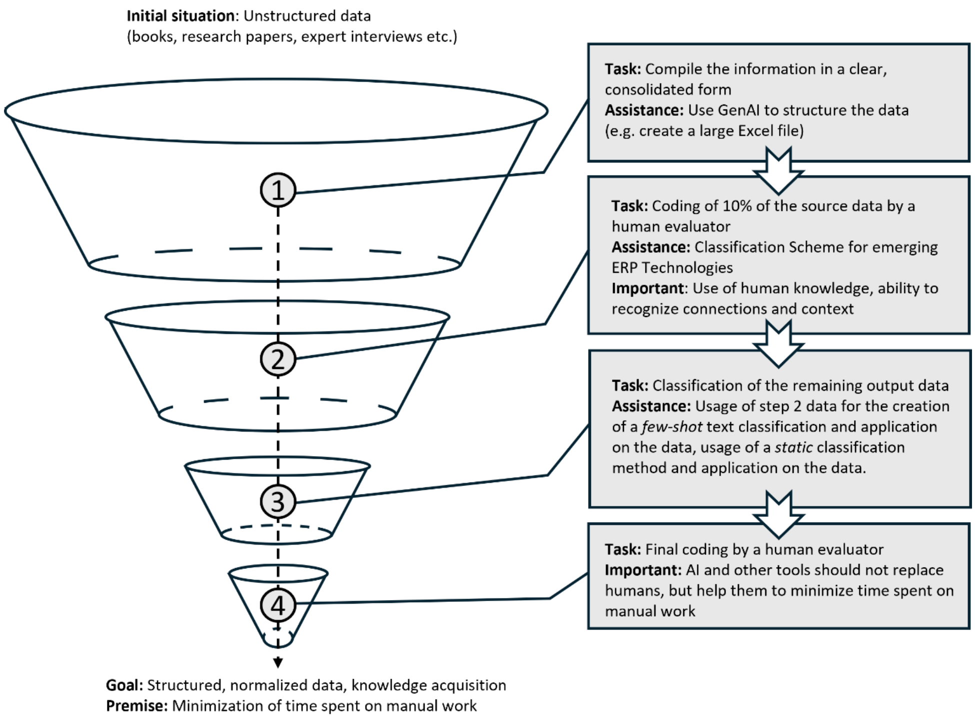
Nr.	Sentence	(II) GenAI	(III) Human
6	"The successful implementation *of these solutions* requires careful consideration of both technical integration requirements and organizational change management strategies" (Onteddu 2025: 596).	Digitalization and Digital Transformation	Artificial Intelligence, (Hyper-)Automation
57	"*These innovations* will change the perspective of ERP systems considerably" (Kaulwar 2025: 33).	Digitalization and Digital Transformation	Artificial Intelligence and Machine Learning, Data Analytics/Science

Proposed framework for efficiently classifying unstructured text

This scientific work proposes a novel approach that combines GenAI with traditional methods for achieving better and faster results in classifying non-structured texts. Figure 6 presents a four-step funnel-based framework for efficiently classifying unstructured text. It presents recommendations derived from the findings of this research and outlines how to obtain structured, normalized data and acquire knowledge in four steps from a large amount of unstructured data (e.g., books, research papers, and expert interviews).

This approach can significantly reduce the time spent on manual work while maintaining the best accuracy achieved through classification by a domain expert. The steps are presented in the form of an analogy to a funnel. Just as a funnel diverts a liquid into a controlled stream by means of ever-increasing narrowing, the proposed process is intended to convert a large amount of unstructured data into usable information and deliver structured, normalized data.

Figure 6: Four-step funnel-based framework for efficient classification of unstructured text



The first recommended task is to organize the material into a structured, consolidated form. GenAI is used to structure the source material. In this work, whole sentences were chosen as the smallest classifiable units. As a result, the unstructured source material is presented in a table in which the quotations are listed sequentially.

Secondly, at least 10% of the source material should be classified by a human evaluator. The classification scheme for emerging ERP technologies, illustrated in Figure 2, should be used here. This classification guidance can be expanded and adapted to new keywords during a research project.

The third step can involve either the static classification method or a few-shot text classification approach. In the case of the static classification method, the logic must then be expanded to include any new keywords that may have been created in Step 2. In the case of few-shot text classification, the data used in Step 2 can be utilized as training data for GenAI. The result is a table with classified units, which may resemble the excerpts in Tables 7–10. Notably, these results only correspond to those of a human evaluator to a limited extent.

As a final step, this table must be reviewed by a competent researcher. Although this work presents arguments for a correlation between the tools and a “real” human evaluator that can at least be substantiated by statistical indicators, these tools cannot replace or even substitute for human researchers. However, using this approach is based on a solid framework and can save considerable additional effort.

CONCLUSIONS AND FURTHER RESEARCH

The classification task for determining the categories of new technologies that will affect the functionality and future development of ERP systems is of the unstructured text processing type. The best results can be achieved with manual classification by a specialist in the field, but the task is time-consuming. Increasing efficiency can be achieved through various approaches for natural language automation using AI techniques, which involves building a knowledge base with code words in a specific domain for training a classification model and then continuously improving it for multiple uses within the same discipline. This approach is effective when processing text data in a specific field. The bases are used repeatedly and enriched with each new set of data.

The task of the present study was classification in a new domain for which there was no established baseline. Hence, a new approach is proposed to achieve a qualitative and rapid assessment of technologies that impact the development of ERP systems. By training GenAI in the new domain and optimizing the classification process, this innovative approach follows a few consecutive steps. The classification framework of the approach describes in detail the stages of processing unstructured text. GenAI is applied to approximately define the main categories and significantly reduce the classification time. The data is verified by static logic and refined by a domain expert. The proposed approach preserves the quality of the classification result while increasing the operational speed. The classification framework is suitable for processing unstructured data in a new domain for which there is no existing code base, yet fast and high-quality analysis is required.

The method developed in the study can be expanded in future work to larger and more diverse source materials (e.g., detailed expert interviews) to further demonstrate its practicality. Additional surveys and literature analyses in the field of ERP may reveal recently unknown ERP trends and developments that must be integrated into the process.

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REFERENCES

Aljehani, A., Hamid Hasan, S., & Ali Khan, U. (2025). Advancing text classification: A systematic review of few-shot learning approaches. *International Journal of Computing and Digital Systems, 17*(1), 1–21. https://doi.org/10.12785/ijcds/1571027526

Castro, S. (2017). Fast Krippendorff: Fast computation of Krippendorff's alpha agreement measure. GitHub repository. https://github.com/pln-fing-udelar/fast-krippendorff

Kaulwar, P. (2025). Enhancing ERP systems with big data analytics and AI-driven cybersecurity mechanisms. *Journal of Artificial Intelligence and Big Data Disciplines, 2*(1), 27–35. https://doi.org/10.70179/32w32914

Krippendorff, K. (2011). Computing Krippendorff's Alpha-Reliability. https://repository.upenn.edu/asc_papers/43

Li, S., Yan, R., Wang, Q., Zeng, J., Zhu, X., Liu, Y., & Li, H. (2023). Annotation quality measurement in multi-label annotations. In F. Liu, N. Duan, Q. Xu, & Y. Hong (Eds.), *Natural Language Processing and Chinese Computing: 12th National CCF Conference, NLPCC 2023, Foshan, China, October 12–15, 2023, Proceedings, Part II, Lecture Notes in Computer Science* (pp. 30–42). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-44696-2_3

Mhaskey, S. (2025). Unlocking business potential: The transformative impact of ERP analytics. *Journal of Advances in Developmental Research, 16*(1), 1–9. https://doi.org/10.5281/zenodo.15155165

Onteddu, K. (2025). AI-powered invoice automation in ERP systems: Revolutionizing accounts payable. Journal of Computer Science and Technology Studies, 7(5), 588–597. https://doi.org/10.32996/jcsts.2025.7.5.64

Pandas. (2025). *Pandas documentation*. https://pandas.pydata.org/

Sunmola, F., & Lawrence, G. (2024). Key success factors for integration of blockchain and ERP systems: A systematic literature review. *Procedia Computer Science, 232*, 775–782. https://doi.org/10.1016/j.procs.2024.01.077

THE DISTORTED PATH TO HIGH-GROWTH ENTREPRENEURSHIP: THE COMPLEX ROLE OF HIGH-GROWTH ENTREPRENEURIAL SELF-EFFICACY IN GENERATION Z

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Abstract

This study investigates the relationship between growth opportunity recognition, ambitious proactivity, and high-growth entrepreneurial intention, with high-growth entrepreneurial self-efficacy as a mediating variable. A digital survey of 400 Generation Z individuals who have taken entrepreneurship courses in higher education was analyzed using structural equation modelling (SEM) with AMOS 26. The findings reveal that ambitious proactivity significantly enhances both high-growth entrepreneurial self-efficacy and high-growth entrepreneurial intention. In contrast, growth opportunity recognition exhibits a complex dynamic—while it positively influences high-growth entrepreneurial self-efficacy, its direct effect on high-growth entrepreneurial intention is negative, indicating that high-growth entrepreneurial self-efficacy functions as a distorter variable. This study highlights the complex interaction of psychological traits and opportunity

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recognition in shaping entrepreneurial ambition, offering new insights into high-growth entrepreneurship development.

Key Words

High-growth entrepreneurship; entrepreneurial intention; entrepreneurial self-efficacy; opportunity recognition; proactive personality.

INTRODUCTION

Previous studies have proven that entrepreneurship contributes to economic development in a country (Jian et al., 2021; Pradhan et al., 2020). Nonetheless, research has shown that growth-oriented entrepreneurship significantly boosts macroeconomic growth, particularly in the countries transitioning their status to high-income economies (Stam & Stel, 2011). Several countries have designed and implemented high-growth entrepreneurship policies such as the NIY and Tekes programs in Finland, Accelerace in Denmark, the High-Growth Programme and the International Growth Programme in Norway, among many others (Autio & Rannikko, 2016; Lilischkis, 2011). These initiatives stem from evidence showing how high-growth firms contribute more to economic growth by generating new jobs and increasing labor productivity (Stam, Suddle, et al., 2011). Therefore, encouraging people to pursue high-growth entrepreneurship is essential, requiring them to have the intention to launch a high-growth business. However, studies regarding the determinants of high-growth entrepreneurial intention remain insufficient.

In this broad landscape, Generation Z, born between 1997-2012, stands out as a critical demographic for the future of entrepreneurship who will drive Indonesia's economy forward as they already make up the majority (27.94%) of the population (Indonesia Central Bureau of Statistics, 2020). Generation Z exhibits various positive traits that could encourage entrepreneurship in the future, such as being visionary, modern, effective communicators through digital media, smart workers, and influential individuals with massive online followership (Dreyer & Stojanová, 2023). Despite being more individualistic (Pichler et al., 2021), this trait may actually drive them to have higher intention to become entrepreneurs, although they will only launch a business if they discover a highly potentially profitable opportunity (Liñán et al., 2016). Thus, Generation Z has an outstanding potential to create high-growth businesses in the future. By focusing on Generation Z, this study addresses a critical gap: understanding how psychological factors, such as ambitious proactivity and self-efficacy, interact with opportunity recognition to shape high-growth entrepreneurial intentions. This will not only enrich the general discussion on the importance of entrepreneurship, but also provide targeted insights that are essential for developing supportive policies and educational programs aimed at nurturing the next generation of high-growth entrepreneurs. However, the factors that drive their high-growth entrepreneurial intentions, particularly in terms of psychological traits and self-efficacy, also remain underexplored.

Prior research has highlighted the importance of opportunity in fostering the intention to become entrepreneurs (Hassan et al., 2020; Lim et al., 2023; Ryu & Kim, 2020). For high-growth ventures, this capability is even more critical, as it involves identifying market gaps through observation and connecting shifting markets, demographics, technology, governmental regulations, and other elements (Baron, 2006). Entrepreneurs who can effectively identify growth opportunities are more likely to engage in ventures with scalable potential. However, recognizing an opportunity alone may not suffice. Individuals also need to be proactive in order to engage in entrepreneurial activity, as proactive personalities encourage creativity and inspire people to adopt new approaches to issues and challenges (Kumar & Shukla, 2022). In high-growth entrepreneurship, proactive personalities may translate into more ambitious growth objectives and a stronger drive to overcome obstacles.

The rest of the paper is structured as follows: The next section discusses the relationship between this study and earlier research. Section 3 explains the data and measurement strategy. Section 4 presents the results, including descriptive statistics and the measurement and structural models. Section 5 interprets the findings and discusses the significance of high-growth entrepreneurial self-efficacy as a distorter. The findings and implications are summarized in the concluding section.

LITERATURE REVIEW

High-Growth Entrepreneurial Intention

Previous research has identified three types of entrepreneurial intention: general entrepreneurial intention, lifestyle entrepreneurial intention, and high-growth entrepreneurial intention (Drost & Mcguire, 2011). High-growth entrepreneurial intention refers to the interest in building or creating a business and rapidly expanding that business, which could potentially become an international business, an industry leader, or a public company through an IPO (Prabhu et al., 2012). This type of entrepreneurial intention is crucial, as individuals with high-growth entrepreneurial intention will create rapidly growing businesses that are expected to contribute more to the economic development of a country by generating job opportunities, having a lower failure rate, yielding higher profits, paying higher wages, increasing opportunities for product exports, and investing more in research and development (Buss, 2002). High-growth businesses have been found to contribute more to job creation in OECD countries, thus playing a significant role in developing policies to reduce unemployment and encourage economic development (Audretsch, 2012).

According to Gundry & Welsch (2001), high-growth entrepreneurs share several traits, including strategic intentions that prioritize technological advancement and market expansion, a stronger commitment to business success, a greater willingness to make sacrifices for the company, early planning for business growth, the use of a team-based organizational structure, concern for reputation and quality, adequate capitalization, strong leadership, and the utilization of a wider range of financing sources for expansion. These characteristics suggest recognizing growth opportunities and being ambitiously proactive.

Growth opportunity recognition, high-growth entrepreneurial self-efficacy, and high-growth entrepreneurial intention

Opportunity recognition is defined as a cognitive process that involves identifying potential business venture ideas, involving the individual's ability to discover or construct patterns and concepts (Hassan et al., 2020). Therefore, it is accurate to state that growth opportunity recognition refers to the ability to recognize business ideas that have potential to expand, rather than merely being general business ideas. A study regarding new venture growth (X. Kang et al., 2023) stated that entrepreneurs often talked about their "eureka" moments, when they saw market gaps or creative solutions to existing problems. An entrepreneurial venture often grows as a result of taking advantage of and exploiting environmental opportunities (Petrović & Leković, 2019). These findings show the importance of growth opportunity recognition for building a high-growth business. Entrepreneurs who can effectively recognize promising business opportunities tend to pursue ventures with significant growth potential (Baron, 2006; Shane & Venkataraman, 2000). Prior studies emphasize that opportunity recognition is not just a passive observation but an active cognitive process that drives the entrepreneurial mindset (Ardichvili et al., 2003; Mitchell et al., 2002). Thus, when individuals clearly identify viable growth opportunities, they are more likely to develop a strong intention to launch and grow a business.

H1: Growth opportunity recognition has a significant influence on high-growth entrepreneurial intention.

The ability to recognize opportunities plays a pivotal role in building entrepreneurs' confidence in their capabilities (Mcgee et al., 2009). Dinh et al. (2021) found that opportunity recognition affects entrepreneurial self-efficacy. However, another study by J.-H. Kang & Yang (2016) found that recognition of entrepreneurial activities has a significant positive effect on entrepreneurial self-efficacy among college students, which indicates that the more they can identify entrepreneurial opportunities, the more confident they become in starting a business. These studies showed the possibility of a reciprocal relationship between opportunity recognition and entrepreneurial self-efficacy. Another study about women entrepreneurs in high-growth startups found that people with a strong discovery mindset act and think in ways that support opportunity perception, and when combined with a belief in their abilities, they are more likely to move from opportunity perception to the creation of a new venture (Neill et al., 2015). This finding indicates that developing skills in opportunity recognition can enhance an individual's confidence in starting a high-growth business. Therefore, effective opportunity recognition enhances high-growth entrepreneurial self-efficacy, reinforcing the belief that one can successfully execute the venture.

H2: Growth opportunity recognition has a significant influence on high-growth entrepreneurial self-efficacy.

Ambitious proactivity, high-growth entrepreneurial self-efficacy, and high-growth entrepreneurial intention

Proactive people see possibilities and seize them; they take charge, act, and persist until they achieve significant change (Crant, 1996). This trait is crucial for aspiring entrepreneurs to identify market opportunities and act swiftly upon them (Bateman & Crant, 1993). Proactive personality has been discovered to be a significant predictor of entrepreneurial intention, since it encourages creativity and inspires people to alter how they handle difficulties and issues (Kumar & Shukla, 2022). Meanwhile, ambitious entrepreneurs are defined as those who engage in the entrepreneurial process with the intention of producing the greatest possible value (Stam et al., 2012). In startups and newly formed companies, ambitious entrepreneurship has a positive effect on economic growth (Stam, Hartog, et al., 2011). Ambitious proactivity involves taking the initiative, setting high goals, and actively seeking opportunities, which all are the fundamental traits of successful entrepreneurs (Baum & Locke, 2004; Crant, 1996; Shane & Venkataraman, 2000). Ambitious proactive individuals are more driven to pursue ventures that promise rapid expansion and substantial impact (Autio & Acs, 2010; Ucbasaran et al., 2010). Therefore, ambitious proactivity may directly drive the intention to start high-growth businesses by inspiring an opportunity-driven mindset.

H3: Ambitious proactivity has a significant influence on high-growth entrepreneurial intention.

Proactive personality has also been found to be a strong predictor of entrepreneurial self-efficacy (Nawaz et al., 2023; Yu, 2021). Proactive personality and entrepreneurial self-efficacy have been identified as the cognitive process foundations of entrepreneurial feasibility (Fuller et al., 2018). Proactive people are more aware of environmental opportunities, and their self-efficacy may have a greater influence on their plans to launch a business (Travis & Freeman, 2017). Some of the traits of high-growth entrepreneurs include a strong commitment to a company's success and a willingness to make sacrifices (Gundry & Welsch, 2001), which shows the ambitious characteristics of entrepreneurs. Ambitious proactivity fosters greater entrepreneurial self-efficacy, forming a foundation for effective business execution (Drnovšek et al., 2010; Zhao et al., 2005). Therefore, we can conclude that ambitious proactivity is crucial for increasing high-growth entrepreneurial self-efficacy, which in turn increases the intention to start a high-growth business.

H4: Ambitious proactivity has a significant influence on high-growth entrepreneurial self-efficacy.

High-growth entrepreneurial self-efficacy and high-growth entrepreneurial intention

Since starting a new firm is a difficult and risky endeavour that requires confidence and courage in one's talents, the idea of self-efficacy is highly relevant to entrepreneurial studies (Kumar & Shukla, 2022). Self-efficacy has long been identified as a critical determinant of entrepreneurial behaviour (Bandura et al., 1999; Chen et al., 1998). Entrepreneurial self-efficacy has also been identified as a mediating variable between proactive personality and high-growth entrepreneurial intention (Prabhu et al., 2012; Sidratulmunthah et al., 2018). Sweida & Reichard (2013) proposed that increasing high-growth entrepreneurial self-efficacy through proper education and training could boost the intention to create high-growth ventures.

H5: High-growth entrepreneurial self-efficacy has a significant influence on high-growth entrepreneurial intention.

While recognizing growth opportunities is essential, its effect on entrepreneurial intention may be indirect, operating through the enhancement of self-efficacy (Newman et al., 2019; Zhao et al., 2005). Studies indicate that when individuals perceive opportunities, this perception strengthens their confidence in handling entrepreneurial tasks, which in turn shapes their intent to pursue high-growth ventures (Krueger & Carsrud, 1993; Romero-Galisteo et al., 2022). Thus, self-efficacy may act as a mediating mechanism, showing the positive impact of opportunity recognition on entrepreneurial intention (Chen et al., 1998; Wardana et al., 2020).

H6: High-growth entrepreneurial self-efficacy mediates the relationship between growth opportunity recognition and high-growth entrepreneurial intention.

Similarly, ambitious proactivity is thought to influence entrepreneurial intention partly by bolstering self-efficacy (Newman et al., 2019; Zhao et al., 2005). Research has found that individuals with a proactive and ambitious nature tend to develop stronger confidence in their ability to navigate the uncertainties of entrepreneurship (Chen et al., 1998; Krueger & Carsrud, 1993). Hence, self-efficacy may also mediate the relationship between ambitious proactivity and high-growth entrepreneurial intention, meaning that a proactive mindset enhances self-belief, which in turn drives the intention to engage in high-growth entrepreneurship.

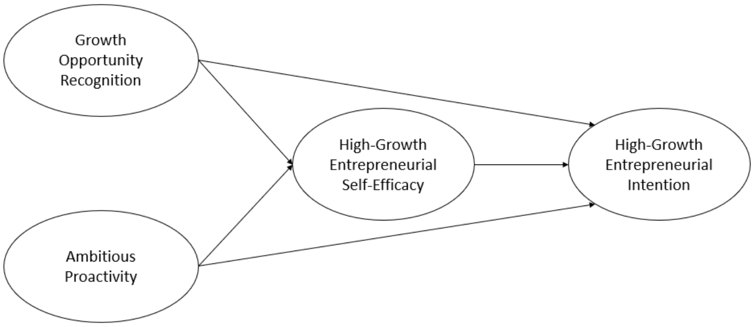
H7: High-growth entrepreneurial self-efficacy mediates the relationship between ambitious proactivity and high-growth entrepreneurial intention.

RESEARCH METHODS AND DESIGN

Research design

This study's quantitative and empirical nature was made possible by its adoption of a positivist paradigm. The purpose of this study was to investigate the relationship between growth opportunity recognition and ambitious proactivity towards high-growth entrepreneurial intention, mediated by high-growth entrepreneurial self-efficacy, as shown in Figure 1.

Figure 1: Research model



Sample and data collection

This study employed a purposive sampling technique with the respondents of Generation Z who had taken an entrepreneurship course at a university. Participants were chosen using clear criteria to ensure they were well-suited for the study. First, they had to belong to Generation Z (born between 1997 and 2012). Second, they needed to have taken an entrepreneurship course at a recognized higher education institution, ensuring that each participant had a basic understanding of entrepreneurship. Lastly, only those who agreed to complete the digital survey were included. This demographic was chosen due to its potential in shaping the future entrepreneurial landscape and its unique characteristics, such as digital savviness and an innovative communication style (Smith & Cawthon, 2017; Turner, 2015). However, it is important to note that most of the respondents were likely in the early stages of their careers, meaning that they had limited practical experience (Gielnik et al., 2018). Consequently, their responses regarding high-growth entrepreneurial intention may tend to show their theoretical knowledge rather than practical experience in the real world (Nabi et al., 2017). This selection process helped us gather responses from individuals who were both knowledgeable about entrepreneurship and interested in sharing their insights on high-growth entrepreneurial intentions. The primary data were collected through digital questionnaires that were used to distribute the survey. In total, 400 qualified respondents participated, exceeding the minimum required number of respondents of 385 for an unknown population with a 95% confidence level, based on Lemeshow et al. (1988).

Measurement

A 5-point Likert scale ranging from strongly disagree to strongly agree was used. The research questionnaire included 24 items designed to assess five key variables. These variables included growth opportunity recognition and ambitious proactivity as the independent variables, high-growth entrepreneurial self-efficacy as the proposed mediating variable, and high-growth entrepreneurial intention as the dependent variable. There were 5 items adapted from Hassan et al. (2020) to measure growth opportunity recognition, 10 items adapted from SEIBERT et al. (2001) to measure ambitious proactivity, 4 items adapted from Zhao et al. (2005) to measure high-growth entrepreneurial self-efficacy, and 7 items adapted from Drost & Mcguire (2011) to measure high-growth entrepreneurial intention.

Data analysis tool

The study used structural equation modelling (SEM) using AMOS software version 26 to analyze the intricate interactions between these factors. While AMOS may provide a strong framework to analyze complex relationships, it may also come with several limitations, such as dependence on the normality and linearity of data (Kline, 2023). Moreover, its effectiveness may also be influenced by the size and variance of the sample (Wolf et al., 2013). Confirmatory factor analysis was then performed to ensure that all indicators were grouped into factors associated with the author's attempts to connect them with latent variables. The validity and reliability were then assessed using an AVE and construct reliability tests. In order to determine if the sample data originated from a population that was normally distributed, multiple tests were performed, including the normality test. Before determining the outcome using maximum likelihood estimation, the model fit was also assessed to ensure that the structural equation model (SEM) accurately represented the observed data.

RESULTS

Descriptive statistics

This study examined 400 people categorized as Generation Z (born 1997-2012) who have taken an entrepreneurship course at a university or similar higher education program. Age, gender, social economy status, and domicile were some of the demographic data collected. Based on Table 1, the majority of the respondents were female (81.5%), within the age group 18-24 (70.5%), belonged to the middle social economy status (40.5%), and were located in Java (78%).

Table 1: Demographic characteristics

Profile	Classification	Frequency	%
Gender	Male	74	18.5%
	Female	326	81.5%
Age group	18-24	282	70.5%
	25-28	118	29.5%
Social economy status	Lower	125	31.25%
	Middle	162	40.5%
	Higher	111	27.75%
Domicile	Sumatra	45	11.25%
	Java	312	78%
	Bali & Nusa Tenggara	9	2.25%
	Kalimantan	14	3.5%
	Sulawesi	17	4.25%
	Maluku & Papua	3	0.75%

Validity and reliability test

By examining the loading factor values for each item and the average variance extracted (AVE), with a threshold value of 0.50, tests for convergent validity and construct reliability were conducted to verify the quality of the data (Hair et al., 2021). The construct reliability value was above 0.7 and the AVE > 0.5, demonstrating the validity and reliability of the data. Table 2 shows the loading factor values and AVE for each item.

Table 2: Convergent validity and construct reliability

Variable & Indicator	Std. Loading	Convergent Validity (AVE) ≥ 0.50	Construct Reliability ≥ 0.70
Growth Opportunity Recognition		0.580	0.872
GOR1	0.612		
GOR2	0.761		
GOR3	0.729		
GOR4	0.845		
GOR5	0.836		
Ambitious Proactivity		0.583	0.933
AP1	0.717		
AP2	0.796		
AP3	0.628		
AP4	0.763		
AP5	0.722		
AP6	0.834		
AP7	0.791		
AP8	0.804		
AP9	0.744		
AP10	0.813		
High-Growth Entrepreneurial Self-Efficacy		0.748	0.922
HGSE1	0.888		
HGSE2	0.885		
HGSE3	0.859		

HGSE4		0.827		
High-Growth Intention	Entrepreneurial		0.668	0.961
HGEI1		0.788		
HGEI2		0.825		
HGEI3		0.802		
HGEI4		0.853		
HGEI5		0.831		
HGEI6		0.803		
HGEI7		0.791		

Normality analysis

To determine whether the data had a normal distribution, a normality test was performed. A number of indicators, as shown in Table 3, had critical ratios higher than 2.5, indicating that certain data were not provided frequently. Consequently, the data was standardized using bootstrap. The Bollen-Stine bootstrap showed that the model fit 3000 bootstrap samples more closely. Table 4 shows the distributions with a bell-shaped distribution after a bootstrap.

Table 3: Assessment of normality

Variable	min	max	skew	c.r.	kurtosis	c.r.
GOR5	2.000	7.000	-.664	-5.424	-.285	-1.164
HGEI7	1.000	7.000	-1.291	-10.544	1.392	5.683
HGEI6	1.000	7.000	-.933	-7.621	.209	.855
HGEI5	2.000	7.000	-1.019	-8.322	.425	1.735
HGEI4	2.000	7.000	-.870	-7.107	.031	.126
HGEI3	2.000	7.000	-.898	-7.336	.117	.478
HGEI2	1.000	7.000	-.834	-6.813	.189	.773
HGEI1	3.000	7.000	-.854	-6.973	.049	.199
HGSE4	1.000	7.000	-.714	-5.833	-.053	-.217
HGSE3	2.000	7.000	-.565	-4.613	-.387	-1.581
HGSE2	2.000	7.000	-.548	-4.477	-.400	-1.634
HGSE1	2.000	7.000	-.476	-3.884	-.398	-1.625
AP10	2.000	7.000	-.562	-4.585	-.499	-2.036
AP9	1.000	7.000	-.745	-6.087	.430	1.757
AP8	1.000	7.000	-.656	-5.360	-.071	-.289
AP7	1.000	7.000	-.523	-4.270	-.275	-1.121
AP6	2.000	7.000	-.630	-5.143	-.396	-1.617
AP5	2.000	7.000	-.844	-6.894	-.130	-.532
AP1	1.000	7.000	-.660	-5.387	.227	.925
AP2	1.000	7.000	-.435	-3.552	-.360	-1.471
AP3	3.000	7.000	-.919	-7.501	-.042	-.172
AP4	1.000	7.000	-.947	-7.729	.775	3.162
GOR1	1.000	7.000	-1.158	-9.454	1.168	4.766
GOR2	1.000	7.000	-.120	-.977	-.540	-2.204
GOR3	1.000	7.000	-.745	-6.080	.610	2.490
GOR4	1.000	7.000	-.314	-2.560	-.642	-2.622
Multivariate					330.376	86.582

Table 4: Bootstrap distribution

243.189	|*

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                         275.060   |*
                         306.930   |**
                         338.800   |******
                         370.671   |**********
                         402.541   |*******************
                         434.412   |********************
N = 3000                 466.282   |*****************
Mean = 440.755           498.152   |************
S. e. = 1.128            530.023   |******
                         561.893   |***
                         593.764   |*
                         625.634   |*
                         657.504   |*
                         689.375   |*
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Goodness of fit

Table 5 shows the results of goodness of fit test. The NFI and RFI values of 0.899 and 0.887, respectively, suggest that the model is a moderately good fit. However, the IFI, TLI, and CFI values all exceeded the cut-off of 0.90, and the RMSEA was less than 0.8, suggesting a good model fit and confirming the appropriateness of the collected data for analysis.

Table 5: Goodness of fit

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI	RMSEA
Default model	.899	.887	.929	.921	.929	.072
Saturated model	1.000		1.000		1.000	
Independence model	.000	.000	.000	.000	.000	.257

Structural equation modelling analysis

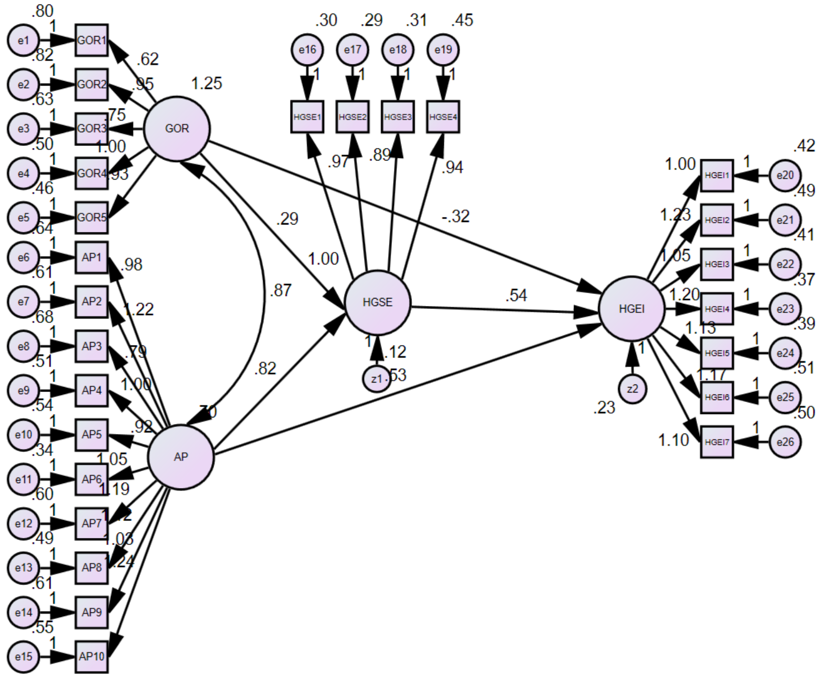
By integrating the measurement model (confirmatory factor analysis) with the structural model through structural equation modelling, we might simultaneously develop a statistical test. Growth opportunity recognition was found to negatively affect high-growth entrepreneurial intention but positively affect high-growth entrepreneurial self-efficacy, rejecting H1 and supporting H2. Ambitious proactivity was found to positively affect both high-growth entrepreneurial self-efficacy and high-growth entrepreneurial intention, supporting H3 and H4. High-growth entrepreneurial self-efficacy was found to positively affect high-growth entrepreneurial intention, supporting H5. This result also means that high-growth entrepreneurial self-efficacy partially mediated the relationship between ambitious proactivity and high-growth entrepreneurial intention, supporting H7. Table 6 summarizes the statistical test, and the structural equation model can be seen in Figure 2.

Table 6: Regression weights

	Estimate	S.E.	C.R.	P	Conclusion
GOR → HGSE	.291	.090	3.249	.001	Accepted

	Estimate	S.E.	C.R.	P	Conclusion
AP → HGSE	.818	.123	6.633	***	Accepted
HGSE → HGEI	.536	.129	4.160	***	Accepted
GOR → HGEI	-.323	.113	-2.862	.004	Rejected
AP → HGEI	.533	.174	3.057	.002	Accepted

Figure 2: Structural equation model



Although growth opportunity recognition positively affected high-growth entrepreneurial self-efficacy, and high-growth entrepreneurial self-efficacy positively affected high-growth entrepreneurial intention, it cannot be concluded that high-growth entrepreneurial self-efficacy mediates the relationship between those variables, because growth opportunity recognition had a negative relationship with high-growth entrepreneurial intention. This result also indicates that high-growth entrepreneurial self-efficacy may act as a distorter variable. To prove this, the analysis was conducted once more, considering only growth opportunity recognition and high-growth entrepreneurial intention. Based on the analysis shown in Table 7, the analysis revealed that in a simple model, growth opportunity recognition positively affected high-growth entrepreneurial intention. This result indicates that the original relationship between opportunity recognition and high-growth entrepreneurial intention was positive but turned negative with the existence of high-growth entrepreneurial self-efficacy.

Table 7: Regression weight for growth opportunity recognition and high-growth entrepreneurial intention

	Estimate	S.E.	C.R.	P
Growth Opportunity Recognition → High-Growth Entrepreneurial Intention	.511	.041	12.330	***

Mediating effect

Table 8 shows that ambitious proactivity and high-growth entrepreneurial intention through high-growth entrepreneurial self-efficacy were significantly correlated (Sobel z = 3.524, p<0.05), proving that H7 is indeed accepted. There is no need to test the mediating effect of high-growth entrepreneurial self-efficacy of growth opportunity recognition and high-growth entrepreneurial intention, since the direct relationship between these variables was negative, despite the positive relationship between growth opportunity recognition, high-growth entrepreneurial self-efficacy, and high-growth entrepreneurial intention. For mediation to be categorized as positive, the signs of both the direct and indirect pathways should be consistent. This means that if the pathway between the independent variable and the dependent variable is positive, then the pathways from independent variable to mediating variable and from the mediating variable to the dependent variable should also be positive. If these signs are inconsistent, the mediation effect can become ambiguous or even lead to a distortion effect (MacKinnon et al., 2012).

Table 8: Sobel test for the mediating effect

	Hypotheses	Z	p	Result
H7	HGSE mediated AP and HGEI	3.524	0.000	Accepted

DISCUSSION

Interpretation of key findings

The results of this study revealed a complex relationship between growth opportunity recognition, ambitious proactivity, and high-growth entrepreneurial intention, especially when high-growth entrepreneurial self-efficacy is included as a mediating variable. Ambitious proactivity consistently demonstrated a positive effect on high-growth entrepreneurial self-efficacy. This aligns with previous studies emphasizing the important role of a proactive individual in identifying opportunity, determining ambitious goals, and encouraging entrepreneurial success (Biswas, 2024; Hirschi & Spurk, 2021; Neneh, 2019). This finding affirmed that a proactive and aspirational approach tends to increase one's belief in their capabilities and determination to pursue high-growth entrepreneurship.

However, the relationship between growth opportunity recognition and high-growth entrepreneurial intention showed an unexpected dynamic. Although growth opportunity recognition positively affected high-growth entrepreneurial self-efficacy, its direct effect on high-growth entrepreneurial intention was negative. This result challenged the conventional assumption that opportunity recognition is always beneficial (Baron, 2006; Patzelt & Shepherd, 2011). On the contrary, this result also showed that psychological factors like high-growth entrepreneurial self-efficacy may intervene in an unexpected way to shape the final outcomes.

The role of high-growth entrepreneurial self efficacy as a distorter variable

Our findings confirm previous research highlighting the role of self-efficacy in driving entrepreneurial intention (Prabhu et al., 2012; Zhao et al., 2005). However, most of the studies examined the role of general entrepreneurial self-efficacy rather than its specific role in high-growth entrepreneurship. This study found that high-growth entrepreneurial self-efficacy did not function as a mediating variable but as distorter variable in the relationship between growth opportunity recognition and high-growth entrepreneurial intention. When high-growth entrepreneurial self-efficacy was included in the analysis, the direct relationship between growth opportunity recognition and high-growth entrepreneurial intention changed from positive to negative. This showed that high-growth entrepreneurial self-efficacy not only changed the strength of the relationship, but also its direction.

One possible explanation for this distortion is the overemphasize on the self-efficacy, which may lead individuals to overestimate their capabilities and focus too much on the internal factors while overlooking the external market factors (Camerer & Lovallo, 1999; Moore et al., 2007). This overconfidence can hinder their decision-making and decrease the possibility of pursuing opportunity in high-growth entrepreneurship (Farsi et al., 2014; Taktak & Triki, 2015). Conversely, individuals with high self-efficacy might be too cautious and perceive opportunity as risky and complex. This finding highlighted the importance of maintaining balance between confidence and decision-making, while providing a new perspective on how self-efficacy interacts with opportunity recognition.

Theoretical contributions

This study made a significant contribution to the theoretical understanding of high-growth entrepreneurship by showing that growth opportunity recognition does not always have a direct positive relationship with entrepreneurial intention. The finding that high-growth entrepreneurial self-efficacy acts as a distorter variable broadens the theoretical perspective on mediators in entrepreneurship, challenging the traditional assumption of a linear relationship between variables. Moreover, this study integrates the theory of proactive personality and social cognitive theory, highlighting the importance of the interaction between personal characteristics, such as ambitious proactivity and self-efficacy, in influencing entrepreneurial intention. Thus, this study offers a new foundation for further study that may explore the role of psychological variables in high-growth entrepreneurship.

Practical implications

This study has crucial implications for education and entrepreneurship policy. Educational institutions may develop programs that not only teach technical skills like opportunity recognition but also train students to balance their self-efficacy with critical analysis regarding market risk and opportunity. Educational intervention should aim to balance the self-confidence building and critical market analysis, given that high-growth entrepreneurial self-efficacy appears to distort rather than mediate the relationship between growth opportunity recognition and high-growth entrepreneurial intention. For instance, entrepreneurship curricula could integrate case studies and simulation practices that highlight the pitfalls of overconfidence, allowing students to experience firsthand how overconfidence may hinder growth opportunity recognition. Additionally, policy makers could design programs that provide access to training, mentoring, and real-world simulations to encourage young entrepreneurs, especially Generation Z, in developing their capabilities and realistic confidence in starting a high-growth business. For example, entrepreneurship programs could include mentorship initiatives and peer review sessions to provide constructive feedback on the business ideas and strategic planning. These steps would help to ensure that future entrepreneurs are psychologically prepared and equipped with the practical skills to succeed in high-growth businesses.

Limitations

One of the notable limitations of this study is the dependence on the self-assessment of a relatively inexperienced group. Generation Z, who are in their late teens to mid-twenties, may not have faced the full spectrum of challenges associated with managing a high-growth business, such as operational complexity, failure, and limited resources (Goh & Lee, 2018). As entrepreneurial self-efficacy is generally built through experiential learning, the speculative nature of self-efficacy may affect the reliability of these insights (Bandura et al., 1999; Nabi et al., 2017). This limitation shows that it is necessary to interpret the findings with caution, as they may not fully reflect the realities experienced by more experienced entrepreneurs.

Another limitation lies in the regional context of this study. This study was conducted in Indonesia, which is still a developing country (Tambunan, 2011). This means that the respondents may face unique socio-economic challenges such as limited access to capital, limited entrepreneurial networks, and underdeveloped infrastructure in less developed areas (Sandee & Rietveld, 2001; Suryahadi et al., 2009). These limitations may influence respondents’ perceptions of entrepreneurial opportunity and self-efficacy, reflecting the wider constraint of their environment. In less developed areas, the absence of a supportive ecosystem, such as strong financial institutions, skilled labor markets, and innovative networks, may restrict high-growth entrepreneurial intention (Ács et al., 2014; Bruton et al., 2013). Consequently, the findings of this study may be less applicable in a more developed economy, where entrepreneurs usually benefit from a more comprehensive support system (Stenholm et al., 2013).

Another critical limitation of this study is the low number of male respondents that could affect the overall findings. The survey sample was highly imbalanced, with 81.5% of the respondents being female and only 18.5% being male. This gender imbalance is significant because entrepreneurial intention and self-efficacy may vary by gender due to variations in social norms, risk perception, and access to resources (Gupta et al., 2009; Wilson et al., 2007). This composition may reflect the cultural factors from the surveyed area, where women tend to operate smaller-scale or home-based businesses, potentially affecting their perception of high-growth entrepreneurial intention (Brush et al., 2009; Jennings & Brush, 2013).

Future research

Future research could address one of the limitations by including a more diverse sample across various age groups or adopting a longitudinal design to track the evolution of entrepreneurial self-efficacy over time. Including respondents with various levels of entrepreneurial experience may enable a deeper investigation on how practical experience would affect high-growth entrepreneurial intention. Such studies could provide a more comprehensive understanding of the dynamic interaction between theoretical knowledge and practical experience in shaping entrepreneurial self-efficacy.

Future studies could also consider including samples from more economically developed countries to explore how contextual support might affect high-growth entrepreneurial intention. A comparative study in various socio-economy settings might help clarify the extent to which regional factors shape entrepreneurial self-efficacy and entrepreneurial intention, compared to individual capacities, thereby increasing the generalizability of the findings.

Achieving a more balanced gender distribution in future research would also be beneficial in understanding the nuances of entrepreneurial self-efficacy and high-growth entrepreneurial intention. Including a more proportional representation of male respondents could facilitate a deeper investigation into gender-related socio-cultural factors. A comparative study could determine whether the observed patterns hold universally or are context-specific, shaped by differing gender norms.

CONCLUSION

This study provided notable insights into the complex dynamics between growth opportunity recognition, ambitious proactivity, and high-growth entrepreneurial self-efficacy in shaping high-growth entrepreneurial intention. While ambitious proactivity emerged as an absolute driver for high-growth entrepreneurial intention, the role of growth opportunity recognition was proven to be more complex. The results showed that high-growth entrepreneurial self-efficacy acted as a distorter variable, changing the relationship between growth opportunity recognition and high-growth entrepreneurial intention. This finding highlighted the need for a deeper understanding of psychological dynamics in entrepreneurship.

Future studies should investigate contextual factors such as cultural influences or socio-economic status that may influence how high-growth entrepreneurial self-efficacy functions as a distorter variable. Moreover, a longitudinal study could also reveal how these relationships develop over time. By exploring these aspects, scholars can continuously refine theoretical frameworks and provide practical insights to encourage high-growth entrepreneurship.

REFERENCES

Ács, Z. J., Autio, E., & Szerb, L. (2014). National Systems of Entrepreneurship: Measurement issues and policy implications. *Research Policy*, *43*(3). https://doi.org/10.1016/j.respol.2013.08.016

Ardichvili, A., Cardozo, R., & Ray, S. (2003). A theory of entrepreneurial opportunity identification and development. *Journal of Business Venturing*, *18*(1). https://doi.org/10.1016/S0883-9026(01)00068-4

Audretsch, D. B. (2012). Determinants of High-Growth Entrepreneurship. *High-Growth Firms: Local Policies and Local Determinants*, *March*.

Autio, E., & Acs, Z. (2010). Intellectual property protection and the formation of entrepreneurial growth aspirations. *Strategic Entrepreneurship Journal*, *4*(3). https://doi.org/10.1002/sej.93

Autio, E., & Rannikko, H. (2016). Retaining winners: Can policy boost high-growth entrepreneurship? *Research Policy*, *45*(1). https://doi.org/10.1016/j.respol.2015.06.002

Bandura, A., Freeman, W. H., & Lightsey, R. (1999). Self-Efficacy: The Exercise of Control. *Journal of Cognitive Psychotherapy*, *13*(2). https://doi.org/10.1891/0889-8391.13.2.158

Baron, R. A. (2006). Opportunity Recognition as Pattern Recognition: How Entrepreneurs "Connect the Dots" to Identify New Business Opportunities. *Academy of Management Perspectives*, *20*(1), 104–119. https://doi.org/10.5465/amp.2006.19873412

Bateman, T. S., & Crant, J. M. (1993). The proactive component of organizational behavior: A measure and correlates. *Journal of Organizational Behavior*, *14*(2), 103–118. https://doi.org/10.1002/job.4030140202

Baum, J. R., & Locke, E. A. (2004). The relationship of entrepreneurial traits, skill, and motivation to subsequent venture growth. In *Journal of Applied Psychology* (Vol. 89, Issue 4). https://doi.org/10.1037/0021-9010.89.4.587

Biswas, A. (2024). From passion to profit: unveiling the strengths of proactive mindset, perseverance, excellence and education in the entrepreneurial success of MSMEs. *International Journal of Productivity and Performance Management*, *73*(8), 2530–2557. https://doi.org/10.1108/IJPPM-05-2023-0269

Brush, C. G., de Bruin, A., & Welter, F. (2009). A gender-aware framework for women's entrepreneurship. *International Journal of Gender and Entrepreneurship*, *1*(1). https://doi.org/10.1108/17566260910942318

Bruton, G. D., Ketchen, D. J., & Ireland, R. D. (2013). Entrepreneurship as a solution to poverty. *Journal of Business Venturing*, *28*(6). https://doi.org/10.1016/j.jbusvent.2013.05.002

Buss, T. F. (2002). Emerging High-Growth Firms and Economic Development Policy. *Economic Development Quarterly*, *16*(1), 17–19. https://doi.org/10.1177/0891242402016001002

Camerer, C., & Lovallo, D. (1999). Overconfidence and Excess Entry: An Experimental Approach. *American Economic Review*, *89*(1), 306–318. https://doi.org/10.1257/aer.89.1.306

Chen, C. C., Greene, P. G., & Crick, A. (1998). Does entrepreneurial self-efficacy distinguish entrepreneurs from managers? *Journal of Business Venturing*, *13*(4). https://doi.org/10.1016/S0883-9026(97)00029-3

Crant, J. M. (1996). The proactive personality scale as a predictor of entrepreneurial intentions. In *Journal of Small Business Management* (Vol. 34, Issue 3).

Dinh, A., Oberrauch, L., & Liening, A. (2021). The Window of Entrepreneurial Opportunity: Investigation of the Antecedents of Opportunity Recognition. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3911287

Dreyer, C., & Stojanová, H. (2023). How entrepreneurial is German Generation Z vs. Generation Y? A Literature Review. *Procedia Computer Science*, *217*, 155–164. https://doi.org/10.1016/j.procs.2022.12.211

Drnovšek, M., Wincent, J., & Cardon, M. S. (2010). Entrepreneurial self-efficacy and business start-up: Developing a multi-dimensional definition. *International Journal of Entrepreneurial Behaviour and Research*, *16*(4). https://doi.org/10.1108/13552551011054516

Drost, E. A., & Mcguire, S. J. J. (2011). Fostering Entrepreneurship among Finnish Business Students : Antecedents of Entrepreneurial Intent and Implications for Entrepreneurship Education. *International Review of Entrepreneurship*, *9*(2).

Farsi, J. Y., Nouri, P., Kafeshani, A. A., & Toghraee, M. T. (2014). Identifying the Main Factors Influencing the Formation of Overconfidence Bias in Entrepreneurs: A Qualitative Content Analysis Approach. *International Journal of Academic Research in Business and Social Sciences*, *4*(4). https://doi.org/10.6007/IJARBSS/v4-i4/815

Fuller, B., Liu, Y., Bajaba, S., Marler, L. E., & Pratt, J. (2018). Examining how the personality, self-efficacy, and anticipatory cognitions of potential entrepreneurs shape their entrepreneurial intentions. *Personality and Individual Differences*, *125*, 120–125. https://doi.org/10.1016/j.paid.2018.01.005

Gielnik, M. M., Zacher, H., & Wang, M. (2018). Age in the entrepreneurial process: The role of future time perspective and prior entrepreneurial experience. *Journal of Applied Psychology*, *103*(10). https://doi.org/10.1037/apl0000322

Goh, E., & Lee, C. (2018). A workforce to be reckoned with: The emerging pivotal Generation Z hospitality workforce. *International Journal of Hospitality Management*, *73*. https://doi.org/10.1016/j.ijhm.2018.01.016

Gundry, L. K., & Welsch, H. P. (2001). The ambitiou s entrepreneur: High growth strategies of women-owned enterprises. *Journal of Business Venturing*, *16*(5). https://doi.org/10.1016/S0883-9026(99)00059-2

Gupta, V. K., Turban, D. B., Wasti, S. A., & Sikdar, A. (2009). The role of gender stereotypes in perceptions of entrepreneurs and intentions to become an entrepreneur. *Entrepreneurship: Theory and Practice*, *33*(2). https://doi.org/10.1111/j.1540-6520.2009.00296.x

Hassan, A., Saleem, I., Anwar, I., & Hussain, S. A. (2020). Entrepreneurial intention of Indian university students: the role of opportunity recognition and entrepreneurship education. *Education + Training*, *62*(7/8), 843–861. https://doi.org/10.1108/ET-02-2020-0033

Hirschi, A., & Spurk, D. (2021). Ambitious employees: Why and when ambition relates to performance and organizational commitment. *Journal of Vocational Behavior*, *127*, 103576. https://doi.org/10.1016/j.jvb.2021.103576

Indonesia Central Bureau of Statistics. (2020). *Jumlah Penduduk menurut Wilayah, Klasifikasi Generasi, dan Jenis Kelamin, INDONESIA, 2020*. Https://Sensus.Bps.Go.Id/Main/Index/Sp2020. https://sensus.bps.go.id/main/index/sp2020

Jennings, J. E., & Brush, C. G. (2013). Research on Women Entrepreneurs: Challenges to (and from) the Broader Entrepreneurship Literature? *The Academy of Management Annals*, *7*(1). https://doi.org/10.1080/19416520.2013.782190

Jian, J., Fan, X., Zhao, S., & Zhou, D. (2021). Business creation, innovation, and economic growth: Evidence from China's economic transition, 1978–2017. *Economic Modelling*, *96*, 371–378. https://doi.org/10.1016/j.econmod.2020.03.019

Kang, J.-H., & Yang, D.-W. (2016). A Study on Effect of the University Student's Entrepreneurship on Entrepreneurial Self-efficacy and Entrepreneurial Intention : Focusing on Mediating Effect of Opportunity Recognition. *Journal of the Korea Academia-*

Industrial Cooperation Society, *17*(1), 493–507. https://doi.org/10.5762/KAIS.2016.17.1.493

Kang, X., Chaivirutnukul, K., & Zeng, Y. (2023). Entrepreneurial Bricolage and New Venture Growth: The Mediating Effect of Opportunity Recognition and the Moderating Role of Environmental Dynamism. *Cuadernos de Economia*, *46*(131). https://doi.org/10.32826/cude.v2i131.1102

Kline, R. B. (2023). Principles and practice of structural equation modelling (5th Ed.). *Guilford Press*.

Krueger, N. F., & Carsrud, A. L. (1993). Entrepreneurial intentions: Applying the theory of planned behaviour. *Entrepreneurship and Regional Development*, *5*(4). https://doi.org/10.1080/08985629300000020

Kumar, R., & Shukla, S. (2022). Creativity, Proactive Personality and Entrepreneurial Intentions: Examining the Mediating Role of Entrepreneurial Self-efficacy. *Global Business Review*, *23*(1), 101–118. https://doi.org/10.1177/0972150919844395

Lemeshow, S., Hosmer, D. W., & Klar, J. (1988). Sample size requirements for studies estimating odds ratios or relative risks. *Statistics in Medicine*, *7*(7), 759–764. https://doi.org/10.1002/sim.4780070705

Lilischkis, S. (2011). Policies in support of high-growth innovative SMEs. *Policy*, *2*.

Lim, W., Lee, Y., & Mamun, A. Al. (2023). Delineating competency and opportunity recognition in the entrepreneurial intention analysis framework. *Journal of Entrepreneurship in Emerging Economies*, *15*(1), 212–232. https://doi.org/10.1108/JEEE-02-2021-0080

Liñán, F., Moriano, J. A., & Jaén, I. (2016). Individualism and entrepreneurship: Does the pattern depend on the social context? *International Small Business Journal: Researching Entrepreneurship*, *34*(6), 760–776. https://doi.org/10.1177/0266242615584646

MacKinnon, D. P., Cheong, J., & Pirlott, A. G. (2012). Statistical mediation analysis. In *APA handbook of research methods in psychology, Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological.* (pp. 313–331). American Psychological Association. https://doi.org/10.1037/13620-018

Mcgee, J. E., Peterson, M., Mueller, S. L., & Sequeira, J. M. (2009). Entrepreneurial self-efficacy: Refining the measure. *Entrepreneurship: Theory and Practice*, *33*(4). https://doi.org/10.1111/j.1540-6520.2009.00304.x

Mitchell, R. K., Busenitz, L., Lant, T., McDougall, P. P., Morse, E. A., & Smith, J. B. (2002). Toward a Theory of Entrepreneurial Cognition: Rethinking the People Side of Entrepreneurship Research. *Entrepreneurship Theory and Practice*, *27*(2). https://doi.org/10.1111/1540-8520.00001

Moore, D. A., Oesch, J. M., & Zietsma, C. (2007). What Competition? Myopic Self-Focus in Market-Entry Decisions. *Organization Science*, *18*(3), 440–454. https://doi.org/10.1287/orsc.1060.0243

Nabi, G., LiñáN, F., Fayolle, A., Krueger, N., & Walmsley, A. (2017). The impact of entrepreneurship education in higher education: A systematic review and research agenda. In *Academy of Management Learning and Education* (Vol. 16, Issue 2). https://doi.org/10.5465/amle.2015.0026

Nawaz, T., Hashim, S., Javed, A., Ali, A., & Khan, M. K. (2023). Proactive Personality and Emotional Intelligence as determinants of Entrepreneurial Self-efficacy among University Students: An Evidence from KP Public Sector Universities. *Research Journal for Societal Issues*, *5*(2), 121–132. https://doi.org/10.56976/rjsi.v5i2.98

Neill, S., Metcalf, L., & York, J. L. (2015). Seeing What Others Miss: A Study of Women Entrepreneurs in High-Growth Startups. *Entrepreneurship Research Journal*, *5*(4). https://doi.org/10.1515/erj-2014-0009

Neneh, B. N. (2019). From entrepreneurial alertness to entrepreneurial behavior: The role of trait competitiveness and proactive personality. *Personality and Individual Differences*, *138*, 273–279. https://doi.org/10.1016/j.paid.2018.10.020

Newman, A., Obschonka, M., Schwarz, S., Cohen, M., & Nielsen, I. (2019). Entrepreneurial self-efficacy: A systematic review of the literature on its theoretical foundations, measurement, antecedents, and outcomes, and an agenda for future research. In *Journal of Vocational Behavior* (Vol. 110). https://doi.org/10.1016/j.jvb.2018.05.012

Patzelt, H., & Shepherd, D. A. (2011). Recognizing Opportunities for Sustainable Development. *Entrepreneurship Theory and Practice*, *35*(4), 631–652. https://doi.org/10.1111/j.1540-6520.2010.00386.x

Petrović, M., & Leković, B. (2019). Characteristics of ambitious entrepreneurs in Southeast Europe region: High-growth expectation concept. *Anali Ekonomskog Fakulteta u Subotici*, *41*, 55–66. https://doi.org/10.5937/AnEkSub1941055P

Pichler, S., Kohli, C., & Granitz, N. (2021). DITTO for Gen Z: A framework for leveraging the uniqueness of the new generation. *Business Horizons*, *64*(5), 599–610. https://doi.org/10.1016/j.bushor.2021.02.021

Prabhu, V. P., McGuire, S. J., Drost, E. A., & Kwong, K. K. (2012). Proactive personality and entrepreneurial intent. *International Journal of Entrepreneurial Behavior & Research*, *18*(5), 559–586. https://doi.org/10.1108/13552551211253937

Pradhan, R. P., Arvin, M. B., Nair, M., & Bennett, S. E. (2020). The dynamics among entrepreneurship, innovation, and economic growth in the Eurozone countries. *Journal of Policy Modeling*, *42*(5), 1106–1122. https://doi.org/10.1016/j.jpolmod.2020.01.004

Romero-Galisteo, R. P., González-Sánchez, M., Gálvez-Ruiz, P., Palomo-Carrión, R., Casuso-Holgado, M. J., & Pinero-Pinto, E. (2022). Entrepreneurial intention, exp ectations of success and self-efficacy in undergraduate students of health sciences. *BMC Medical Education*, *22*(1). https://doi.org/10.1186/s12909-022-03731-x

Ryu, P., & Kim, D. (2020). Moderating effect of gender on the opportunity recognition and entrepreneurial intention. *Entrepreneurship and Sustainability Issues*, *8*(1). https://doi.org/10.9770/jesi.2020.8.1(49)

Sandee, H., & Rietveld, P. (2001). Upgrading traditional technologies in small-scale industry clusters: Collaboration and innovation adoption in Indonesia. *Journal of Development Studies*, *37*(4). https://doi.org/10.1080/00220380412331322081

Seibert, S. E., Kraimer, M. L., & Crant, J. M. (2001). What do proactive people do? A longitudinal model linking proactive personality and career success. *Personnel Psychology*, *54*(4), 845–874. https://doi.org/10.1111/j.1744-6570.2001.tb00234.x

Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of Management Review*, *25*(1). https://doi.org/10.5465/AMR.2000.2791611

Sidratulmunthah, Hussain, S., & Imran Malik, M. (2018). Towards nurturing the entrepreneurial intentions of neglected female business students of Pakistan through proactive personality, self-efficacy and university support factors. *Asia Pacific Journal of Innovation and Entrepreneurship*, *12*(3), 363–378. https://doi.org/10.1108/APJIE-03-2018-0015

Smith, T., & Cawthon, T. W. (2017). Generation Z Goes to College. *College Student Affairs Journal*, *35*(1). https://doi.org/10.1353/csj.2017.0008

Stam, E., Bosma, N., van Witteloostuijn, A., de Jong, J. P. J., Bogaert, S., Edwards, N., & Jaspers, F. (2012). Ambitious entrepreneurship: A review of the academic literature and new directions for public policy. In *Awti.Nl* (Issue January).

Stam, E., Hartog, C., van Stel, A., & Thurik, R. (2011). Ambitious Entrepreneurship, High-Growth Firms, and Macroeconomic Growth. In *The Dynamics of Entrepreneurship: Evidence from Global Entrepreneurship Monitor Data*. https://doi.org/10.1093/acprof:oso/9780199580866.003.0011

Stam, E., & Stel, A. van. (2011). Types of Entrepreneurship and Economic Growth. In *Entrepreneurship, Innovation, and Economic Development* (pp. 78–95). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199596515.003.0004

Stam, E., Suddle, K., Hessels, S. J. A., & van Stel, A. J. (2011). High Growth Entrepreneurs, Public Policies and Economic Growth. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1019429

Stenholm, P., Acs, Z. J., & Wuebker, R. (2013). Exploring country-level institutional arrangements on the rate and type of entrepreneurial activity. *Journal of Business Venturing*, *28*(1). https://doi.org/10.1016/j.jbusvent.2011.11.002

Suryahadi, A., Suryadarma, D., & Sumarto, S. (2009). The effects of location and sectoral components of economic growth on poverty: Evidence from Indonesia. *Journal of Development Economics*, *89*(1). https://doi.org/10.1016/j.jdeveco.2008.08.003

Sweida, G. L., & Reichard, R. J. (2013). Gender stereotyping effects on entrepreneurial self-efficacy and high-growth entrepreneurial intention. *Journal of Small Business and Enterprise Development*, *20*(2), 296–313. https://doi.org/10.1108/14626001311326743
Taktak, S., & Triki, M. (2015). The Importance of Behavioral Factors: How Do Overconfidence Affect Entrepreneurial Opportunity Evaluation ? *Journal of Behavioural Economics, Finance, Entrepreneurship, Accounting and Transport*, *3*(1).
Tambunan, T. T. H. (2011). Development of small and medium enterprises in a developing country: The Indonesian case. *Journal of Enterprising Communities*, *5*(1). https://doi.org/10.1108/17506201111119626
Travis, J., & Freeman, E. (2017). Predicting entrepreneurial intentions: Incremental validity of proactive personality and entrepreneurial Self-Efficacy as a moderator. *Journal of Entrepreneurship Education*, *20*(1).
Turner, A. (2015). Generation Z: Technology and Social Interest. *The Journal of Individual Psychology*, *71*(2). https://doi.org/10.1353/jip.2015.0021
Ucbasaran, D., Westhead, P., Wright, M., & Flores, M. (2010). The nature of entrepreneurial experience, business failure and comparative optimism. *Journal of Business Venturing*, *25*(6). https://doi.org/10.1016/j.jbusvent.2009.04.001
Wardana, L. W., Narmaditya, B. S., Wibowo, A., Mahendra, A. M., Wibowo, N. A., Harwida, G., & Rohman, A. N. (2020). The impact of entrepreneurship education and students' entrepreneurial mindset: the mediating role of attitude and self-efficacy. *Heliyon*, *6*(9). https://doi.org/10.1016/j.heliyon.2020.e04922
Wilson, F., Kickul, J., & Marlino, D. (2007). Gender, entrepreneurial self-efficacy, and entrepreneurial career intentions: Implications for entrepreneurship education. *Entrepreneurship: Theory and Practice*, *31*(3). https://doi.org/10.1111/j.1540-6520.2007.00179.x
Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample Size Requirements for Structural Equation Models: An Evaluation of Power, Bias, and Solution Propriety. *Educational and Psychological Measurement*, *73*(6). https://doi.org/10.1177/0013164413495237
Yu, M. (2021). Analysis on the Influencing Factors of College Students' Entrepreneurial Self-efficacy Based on Factor Analysis. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3511716.3511748
Zhao, H., Hills, G. E., & Seibert, S. E. (2005). The mediating role of self-efficacy in the development of entrepreneurial intentions. *Journal of Applied Psychology*, *90*(6). https://doi.org/10.1037/0021-9010.90.6.1265

DRIVING GROWTH: EXPLORING THE INFLUENCE OF DIGITALIZATION AND SUSTAINABILITY ON THE GROWTH OF SMALL AND MEDIUM ENTERPRISES

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Abstract

Small and medium-sized enterprises (SMEs) are central to economic development, yet their growth is increasingly shaped by digitalization and sustainability. This study examines how these determinants influence SME growth in Slovenia through a qualitative design with triangulated data. A systematic review of peer-reviewed literature, policy reports, and statistical sources (Scopus, Web of Science, Google Scholar, Eurostat, OECD) was combined with ten semi-structured interviews conducted in March and April 2025 with SME owners and managers across diverse industries in Slovenia. Thematic analysis revealed that digitalization enhances efficiency, innovation, and market expansion, while sustainability drives cost savings, brand differentiation, and competitiveness. Importantly, synergies, such as AI-enabled emission reduction and ERP-supported waste minimization, amplify benefits. However, SMEs also face financial constraints, generational resistance, and regulatory complexity. The findings demonstrate that digital and green transitions are not only complementary but interdependent, underscoring the need for policymakers to integrate both into targeted SME support strategies.

Key Words

SMEs, digitalization, sustainability, growth determinants, qualitative research.

INTRODUCTION

Entrepreneurship is widely recognized as a cornerstone of economic development, reflecting its growing relevance for global economies. Bygrave, Zacharakis, Wise, and Corbett (2024) stress that this is the entrepreneurial age, with more than 300 million people worldwide starting or managing new ventures in 2021.

Entrepreneurship is a complex phenomenon that spans a variety of contexts. The varied definitions in entrepreneurship literature reflect this complexity (Autio, 2007). SMEs are a policy priority worldwide because of their role in economic development and societal well-being (Harash, Al-Timimi & Alsaadi, 2014). Lowrey (2003) conceptualizes entrepreneurship as an economic system consisting of three components: (1) entrepreneurs, who pursue survival and advancement; (2) the social constitution that grants enterprise rights; and (3) government institutions that shape the environment for entrepreneurial activity.

While entrepreneurship is frequently associated with the establishment of new ventures, its scope is much broader. Entrepreneurial thinking and practice are equally critical for the ongoing management and renewal of established SMEs, where innovation, flexibility, and responsiveness to changing markets determine survival and growth. As Duarte (2004) argues, entrepreneurship must be seen as a continuous practice embedded in enterprise management rather than a one-time act of firm creation. From this perspective, the study of SMEs and the factors that drive their growth becomes both meaningful and necessary.

Shane and Venkataraman (2000) define entrepreneurship as the study of how, by whom, and with what effects opportunities to create future goods and services are discovered, evaluated, and exploited. Resources, however, remain limited, while societal expectations increasingly demand technological advancement, job creation, and sustainable development. This implies not only efficient use of renewable resources but also careful stewardship of non-renewable ones (Hall, Daneke & Lenox, 2010). Sustainability and the circular economy will therefore be essential in the coming decades. The Europe 2020 Strategy positioned smart, inclusive, and sustainable growth at the heart of European competitiveness, actively supporting businesses, administrations, and consumers in transitioning to a resource-efficient, green, and low-carbon economy (European Commission, 2023a).

In 2024, SMEs represented 99.8% of all EU enterprises, employing nearly 90 million people (Schulze et al., 2024). SMEs (firms with 250 or fewer employees) also constitute the largest business sector globally and remain central to national development strategies (Algan, 2019). They are disproportionately large creators of employment, particularly in countries with strong labor market performance (OECD, 2017).

Research has consistently shown that the growth and competitiveness of SMEs are determined by a complex interaction of internal capabilities and external conditions. Growth brings opportunities but also new challenges, such as financing, market competition, and regulatory adaptation

(Kindström, Carlborg & Nord, 2024). A conducive business environment is therefore essential for SME development (Acs, Estrin, Mickiewicz & Szerb, 2018; Nkwabi & Mboya, 2019). Yet despite significant policy support, a large number of newly established firms fail in the first years of operation. According to a CB Insights (2021) study, 95 percent of start-ups fail, and 42 percent of them fail when they realize there is no market for their product or service. Understanding why so many SMEs fail and how they can be supported to survive and grow remains a pressing challenge for both scholars and policymakers.

The research from Smallbone and Welter (2001) is concerned with the role of government in relation to SME development in economies at different stages of market reform. It demonstrates that, as in mature market economies, the state is a major factor influencing the nature and pace of SME development, although more through its influence on the external environment in which business activity can develop than through direct support measures or interventions. The logical question here is how the government with its policy decisions is influencing the growth of SMEs.

In this context, rather than attempting to construct an all-encompassing model of SME growth this study focuses on two determinants increasingly relevant in both academic and policy debates: digitalization and sustainability. By integrating a systematic literature review with qualitative insights from Slovenian SMEs, the paper highlights how these factors shape growth trajectories in practice. The evidence generated here is intended to inform policymakers, encouraging them to consider digitalization and sustainability not as optional enhancements but as strategic priorities when designing SME support frameworks and national development policies.

DIGITALIZATION

Among the wide range of factors influencing SME performance, digitalization has emerged as one of the most transformative and empirically supported drivers. Recent studies provide robust evidence that the adoption of digital technologies significantly enhances SME performance, productivity, and innovation capacity. According to Quinton et al. (2018), businesses can strategically navigate the utilization of developing digital technologies to enhance their competitive advantage and capitalize on chances for innovation-driven growth. Similarly, research on German SMEs indicates that digitalization in areas such as production, logistics, value chains, and big data analytics stimulates both product and process innovations, even in firms without formal R&D departments (Becker & Schmid, 2023).

European industry is firmly committed to integrating the concept of digitalization in order to be more competitive in the context of globalization (Kádárová, Lachvajderová & Sukopová, 2023). The economy of the 20th and 21st century has a different set of rules than Smith‘s economy of the 19th century. The new ideology of neo-liberalism and globalization emphasizes the role of SMEs as promoters of a healthy business climate, economic efficiency and power for economic development, especially in developing countries (Keskġn, Ġentürk, Sungur & Kġrġġ, 2010). Together, these perspectives highlight that the competitive role of SMEs in a globalized economy is inseparable from their ability to adapt through digitalization, which provides the foundation for this study's focus on the intersection of technological transformation and SME growth.

From a strategic perspective, digitalization is not only a source of competitive advantage but also a buffer against external shocks. By enabling flexibility, remote operations, and data-driven decision-making, digital tools strengthen SMEs' resilience in volatile environments. The theoretical relevance of digital transformation is further emphasized by Nambisan, Lyytinen, Majchrzak, and Song (2017), who describe how digital technologies reshape innovation processes, while Schallmo, Williams & Boardman (2017) highlight their role in opening new problem–solution pathways. Policy frameworks also reinforce this view, in line with the European Commission's "Digital Decade" strategy, which sets targets for 90% of SMEs to achieve basic digital intensity by 2030, reflects the recognition of digitalization as a cornerstone of long-term competitiveness (European Commission, 2022).

The phenomenon of Industry 4.0 demonstrates how digital technologies are embedded into enterprise-level strategy. Known as the Fourth Industrial Revolution, it has been described as a comprehensive transformation where digital tools are used to enhance production, supply chains, and customer interactions (Grabowska & Saniuk, 2022). Germany's leadership in this area, particularly in digitalizing its manufacturing sector, has drawn global attention and provides an example of how SMEs can leverage national strategies for competitiveness (Kilimis, Zou, Lehmann & Berger, 2019). Beyond productivity, digitalization also interacts with sustainability goals: it is increasingly seen as an enabler of environmentally responsible business practices, for instance through resource efficiency and reduced material consumption (Isensee, Teuteberg, Griese & Topi, 2020).

To move beyond general statements, it is important to examine the specific mechanisms through which digitalization supports SME growth. Several dimensions can be distinguished:

- Efficiency gains: The implementation of digital programs such as customer relationship management (CRM) systems or project management tools allows SMEs to base decisions on systematic data analysis rather than intuition, improving accuracy and reducing waste (Telukdarie, Dube, Matjuta & Philbin, 2023). By automating routine tasks, employees can redirect their efforts toward creative and innovative activities.
- Innovative capacity: Emerging technologies including artificial intelligence, augmented reality, blockchain, and the Internet of Things equip SMEs with new opportunities for product and service development. Many global startups that have grown into unicorns or decacorns achieved their position precisely by leveraging such digital tools to outperform incumbents (AlMujaini, Hilmi, Abudaqa & Alzahmi, 2021).

- Market access and internationalization: Digital platforms enable SMEs to overcome geographical boundaries. Through e-commerce, social media, and online marketplaces, firms can expand into new markets even without a physical presence abroad (Matalamäki & Joensuu-Salo, 2022; HTTPOOL, 2023).
- Customer loyalty and engagement: Digital channels provide cost-effective means to build direct relationships with customers. SMEs can maintain continuous communication through social media, chatbots, or automated marketing tools, fostering stronger loyalty and repeat business (Shabani, Behluli, Qerimi, Pula & Dalloshi, 2022).

Taken together, the literature review suggests that digitalization is far more than a technological upgrade; it represents a strategic reorientation of SMEs toward efficiency, innovation, and global competitiveness. At the same time, it lays the groundwork for sustainable practices by reducing reliance on material resources and enabling smarter energy management. For these reasons, this study positions digitalization as one of the two focal determinants of SME growth, linking theoretical insights with qualitative evidence from Slovenian firms to illustrate how these mechanisms operate in practice.

SUSTAINABILITY

In the era of economic globalization, SMEs are recognized as an engine of sustainable economic development in both the developed and developing world (Prasanna et al., 2019). For SMEs, sustainability involves striking a balance between financial, human, and material resources on the one hand, and the social and economic environment in which they operate on the other (Burlea-Schiopoiu & Mihai, 2019). Growing ecological pressures, increasingly strict regulations, and shifting customer expectations encourage firms of all sizes to integrate responsible business practices into their operations (Yadav, Gupta, Rani & Rawat, 2018).

Over the past decades, sustainability has become a key dimension of competitiveness and corporate legitimacy. Organizations are now expđected not only to pursue profitability but also to improve their environmental and social performance (Siegel et al., 2019). Strategic integration of sustainability practices allows SMEs to save resources, reduce costs, and create added value for both employees and society at large (Grothe & Marke, 2012). Moreover, businesses that display strong sustainability performance often develop distinctive organizational cultures that support long-term resilience (Grayson, Coulter & Lee, 2018). Prior studies suggest that incorporating sustainability into SME strategies enhances their market positioning and creates opportunities to differentiate against larger enterprises (Fernandes, Raja & Whalley, 2006; Gelbmann & Baumgartner, 2012).

Despite these benefits, SMEs and societies remain at the early stages of fully adopting sustainability principles. Research in strategic management suggests that a strong digital orientation enables organizations to reconfigure structures and workflows, supporting more resource-efficient and sustainable operations (Kindermann et al., 2021). Such integration satisfies the long-term requirements of sustainable development and aligns with the broader vision of the European Commission, which positions sustainability as a critical foundation for competitiveness (Khrais & Alghamdi, 2022).

The importance of sustainability is evident in light of pressing global challenges. Journeault, Perron, and Vallières (2021) argue that, given the scale of challenges such as climate change, deforestation, biodiversity reduction, water pollution, and public health, sustainable development has come to be recognized as an issue of global concern. For SMEs, alignment with sustainability principles is increasingly vital not only for regulatory compliance but also for maintaining credibility with customers, partners, and investors. In B2B markets, especially commodities like energy and chemicals buyers who perceive suppliers as transparent and committed to sustainability are significantly more likely to remain loyal, even at a premium price. For instance, a Deloitte (2023) survey of 1,300 B2B buyers found such suppliers were 2.7 times more likely to draw long-term purchasing commitments and 1.7 times more likely to command price premiums. Trust formed through credible sustainability positioning directly influences buyer performance and relationship longevity (Casidy, 2022).

Another academic research indicates that sustainable HRM practices especially when combined with social capital enhance employee loyalty and retention within organizations, effectively reducing turnover intentions (Cachón-Rodríguez et al., 2022). Thus, some surveys report that over 70% of Gen Z and millennials consider an employer's green credentials important when selecting a job, with some even changing jobs for environmental reasons (Thomas, 2023; INAC Global Executive Search, 2023). In this sense, sustainability contributes not only to external reputation but also to internal employee motivation and talent retention.

Several mechanisms further illustrate how sustainability can directly foster SME growth:

– New market opportunities: Demand for sustainable products and services is expanding, enabling SMEs to diversify their offerings and strengthen differentiation. Positioning as a sustainable enterprise can create a competitive edge in markets where customers and business partners increasingly value ethical and ecological standards (Cezarino, Liboni, Hunter, Pacheco & Martins, 2022).
– Green transformation of operations: Investments in renewable energy, energy efficiency, and recycling technologies allow SMEs to reduce environmental impact while lowering costs in the long run. For instance, adopting solar panels, upgrading to energy-efficient machinery, or reusing materials not only improves ecological performance but also enhances competitiveness in tenders and procurement processes (Dzhioeva & Magomadov, 2023).
– Corporate social responsibility: Beyond environmental considerations, SMEs that engage with local communities and contribute to social well-

being generate reputational capital. Agu, Iyelolu, Idemudia and Ijomah (2024) present evidence from multiple industries that sustainable business practices strengthen brand loyalty through improved trust and customer retention.

Overall, sustainability ought to be conceptualized not merely as a regulatory obligation but as a strategic orientation that enables SMEs to pursue innovation, consolidate stakeholder relationships, and enhance their long-term resilience and competitiveness within increasingly dynamic markets. This study therefore examines sustainability not as an isolated concept but as a determinant of SME growth with strategic implications. By combining a literature review with qualitative interviews in Slovenia, it builds a foundation for understanding how sustainability is practiced, what challenges SMEs face, and why policymakers should take this dimension into serious consideration when shaping future business environments.

METHODOLOGY

Research Design

This study adopts a qualitative research design that combines two complementary components: (1) theoretical desktop research to build a comprehensive understanding of SME growth determinants, with a particular focus on digitalization and sustainability, and (2) semi-structured interviews with SME decision-makers in Slovenia to capture practical experiences and contextual insights. This dual approach ensures both conceptual grounding and empirical richness, providing a foundation for evaluating the relevance of digitalization and sustainability for SME growth in practice.

Desktop Research

The first stage of the research consisted of an extensive literature review and analysis of secondary sources. References were gathered through systematic searches in major academic databases, including Scopus, Web of Science, and Google Scholar, as well as policy documents and statistical data from Eurostat, OECD, and European Commission reports. Keywords included SME growth, digitalization, sustainability, innovation, competitiveness, and entrepreneurship. Selection criteria prioritized recent (2018–2024) peer-reviewed studies, high-quality policy reports, and statistical datasets to ensure both credibility and timeliness, while also incorporating earlier works that provide essential theoretical foundations for the research context.

The desktop research had two main objectives:

1. Theoretical foundation – mapping the existing knowledge on how digitalization and sustainability influence SME performance and competitiveness, guided by studies such as Acs et al. (2018), Isensee et al. (2020), and Journeault et al. (2021).

2. Contextual mapping – analyzing European and Slovenian data to situate SMEs within broader economic, technological, and environmental trends, drawing on Eurostat SME indicators, OECD entrepreneurship outlooks, and EU strategic frameworks.

In the contextual mapping stage, official statistics and strategic frameworks were systematically examined to situate Slovenian SMEs within the wider European environment. Eurostat indicators confirmed that SMEs account for 99.8% of enterprises and employ nearly 90 million people across the EU, underscoring their structural importance for the economy (European Commission, 2023b). Comparative insights from OECD entrepreneurship outlooks emphasized the disproportionate contribution of SMEs to job creation across member states, providing an international benchmark for evaluating Slovenian patterns (OECD, 2017). In addition, EU strategic frameworks such as the Europe 2020 Strategy and the Digital Decade 2030 roadmap demonstrated how digitalization and sustainability have been institutionalized as policy priorities, thereby validating the relevance of these determinants for SME growth in Slovenia (European Commission, 2022). This systematic review provided the conceptual lens and analytical categories used in the second research phase.

Qualitative Data Collection: Semi-Structured Interviews

To complement the theoretical findings, qualitative data were collected through semi-structured interviews with SME owners, managers, and industry experts. This method allowed for consistency across interviews while leaving room to explore unique firm-specific experiences and insights (Bryman, 2021).

Sampling Strategy

A purposive sampling approach was employed to ensure diversity across:

- Industry sectors (manufacturing, services, logistics, IT, hospitality, retail, construction, sports equipment, plastics, and furniture).
- Firm size within the SME category (micro, small, and medium).
- Levels of maturity in digitalization and sustainability adoption (from early-stage adopters to advanced implementers).

Ten interviews were conducted, a sample size sufficient to achieve thematic saturation while maintaining depth of analysis.

Interview Procedure

To guide the qualitative interviews, a structured questionnaire was developed, informed by the literature review and aligned with the study's research questions. The instrument consisted of two parallel interview guides one focusing on digitalization and the other on sustainability, each containing 9 open-ended questions for both determinants and one about the company at the beginning of the instrument. Questions were grouped into four thematic sections:

1. **Organizational context** (e.g., company profile, role of interviewee, strategic orientation).
2. **Adoption practices and drivers** (motivations, external pressures, and internal enablers).
3. **Impact on growth** (effects on sales, market reach, innovation, efficiency, and reputation).
4. **Strategic outlook** (future plans, long-term vision, and advice to other SMEs).

This structure ensured both consistency across interviews and the flexibility to probe deeper into emerging themes. The complete version of the questionnaire is provided in Appendix A.

Interviews were carried out either in person or via secure online platforms, depending on participant availability. Data collection took place in March and April 2025, ensuring that the findings reflect current SME experiences in the post-pandemic recovery and ongoing digital and green transition context.

Data Recording and Transcription

With participants' consent, all interviews were audio-recorded to ensure accurate data capture. Recordings were subsequently transcribed verbatim, providing a precise representation of participants' responses. To protect confidentiality, transcripts were anonymized by replacing identifying details with numbers, and audio files were permanently deleted once transcription was complete. Interviewees were explicitly assured that their contributions would never be reported as individual discussions but only as aggregated findings.

Data Analysis

The qualitative data collected through semi-structured interviews were analyzed using thematic analysis, following Braun and Clarke's (2023) six-phase framework. This approach was selected because it offers both structure and flexibility in identifying, organizing, and interpreting patterns across qualitative datasets, while remaining well-established in management and social science research.

The analysis proceeded through the following stages:

1. **Familiarization with the data:** Interview transcripts were read multiple times while also cross-checking with field notes to ensure immersion and the identification of preliminary impressions.
2. **Generating initial codes:** A hybrid coding approach was applied. **Deductive codes** were derived from the literature review (e.g., adoption drivers, innovation, sustainability drivers), while **inductive codes** emerged from the interview data (e.g., generational resistance to digital tools, client-driven sustainability demands). Coding was conducted using **Taguette** (open-source qualitative software).

3. **Searching for themes:** Codes were clustered into broader candidate themes such as "implementation practices," "challenges and barriers," and "impact on growth."
4. **Reviewing themes:** Themes were cross-checked against the coded extracts and the full dataset to ensure consistency and coherence.
5. **Defining and naming themes:** Each theme was refined, given a clear conceptual scope, and structured into seven overarching categories: organizational context, adoption drivers, implementation practices, challenges and barriers, impact on growth, strategic outlook, and cross-factor synergies.
6. **Producing the report:** The analysis was finalized by selecting illustrative quotations (anonymized) and integrating them with the literature review to triangulate findings.

Through this process, thematic analysis allowed not only the identification of convergent findings (e.g., efficiency gains from digital tools, reputation gains from sustainability practices) but also divergent and emergent themes (e.g., generational gaps in digital adoption, market resistance to paying premiums for sustainable products).

Ethical Considerations

Participation was voluntary, and all respondents were informed about the study's objectives, their right to withdraw at any time, and the measures taken to ensure confidentiality. Data were anonymized, and any potentially identifying details were removed from transcripts and analysis outputs.

Research questions:

RQ1: How does digitalization influence the growth of SMEs?

- Independent variable: digitalization (measured through adoption of digital tools such as ERP, CRM, e-commerce, AI, cloud services).
- Dimensions / Indicators: efficiency, innovation, new market entry, customer loyalty.
- Dependent variable: SME growth (measured through employment growth, market share, profit growth, process improvements).

RQ2: How does sustainability influence the growth of SMEs?

- Independent variable: sustainability practices (measured through adoption of renewable energy, waste reduction, recycling, eco-friendly product design, CSR initiatives).
- Dimensions / Indicators: market opportunities, cost savings, operational efficiency, brand reputation.
- Dependent variable: SME growth (employment, market share, profit, reputation, competitiveness).

RESULTS – QUALITATIVE INSIGHTS FROM SLOVENIAN SMES

This section synthesizes findings from ten semi-structured interviews with SMEs in Slovenia, complemented by insights from the literature review. The interviews were conducted during March and April 2025, providing a timely perspective on how SMEs are responding to digitalization and sustainability challenges in the current economic and policy environment. Participants represented diverse industries, including logistics, manufacturing, construction, IT, hospitality, retail, plastics, sports equipment, and furniture. The thematic analysis was structured according to the coding framework, allowing comparison across firms and highlighting common patterns as well as sector-specific insights.

Organizational Context and Strategic Orientation

All interviewees were either owners or senior managers, indicating that decisions on digitalization and sustainability are driven primarily at the leadership level. Several firms were family-owned and multi-generational (Interviewees 6, 7, 8), where long-term stability shaped decision-making. Younger or IT-oriented firms (Interviewees 5, 9) integrated digital tools and sustainability practices from inception, while traditional sectors (Interviewees 3, 10) adopted them gradually, often in response to rising costs or customer expectations.

Adoption Drivers

Digitalization was primarily motivated by efficiency gains, cost control, and customer demands for transparency. For instance, Interviewee 1 (logistics) adopted AI-based route optimization to reduce fuel consumption, while Interviewee 6 (plastics) introduced ERP systems to improve planning and reduce errors. Sustainability drivers combined environmental responsibility with market pressure: eco-conscious clients in Western Europe required compliance with environmental standards, while several interviewees emphasized personal values as a motivation for green practices.

Implementation Practices

Digitalization practices ranged from basic adoption of POS systems, e-commerce platforms, and CRM (Interviewees 8, 10) to advanced applications of AI, IoT, and predictive maintenance (Interviewees 1, 4, 5). Sustainability measures included renewable energy (solar panels at Interviewees 1, 4, 6), waste reduction and recycling (Interviewees 2, 3), and eco-friendly product innovations (Interviewee 7). Together, these practices illustrate how SMEs are embedding both determinants directly into their operational strategies.

Challenges and Barriers

Interviewees consistently reported three types of barriers:

- **Financial constraints:** High upfront costs for solar panels, electric vehicles, or ERP systems.
- **Human resource limitations:** Resistance from older employees (Interviewees 6, 10) and lack of expertise in digital tools.
- **Regulatory and integration issues:** Difficulty in obtaining permits for renewable energy projects (Interviewee 8) and challenges in aligning digital tools with legacy systems (Interviewee 4).

These findings mirror broader research, which identifies finance, skills, and regulatory complexity as recurring barriers to SME transformation (OECD, 2017; Kindström et al., 2024).

Impact on Growth

Both digitalization and sustainability contributed to measurable growth outcomes. Digital tools enhanced operational efficiency (e.g., Interviewees 1 and 3 achieved fuel savings; Interviewee 4 reduced downtime with predictive maintenance), expanded market reach (e.g., Interviewees 7 and 2 expanded internationally via online sales), and stimulated product innovation (e.g., Interviewees 5 and 7 developed customized solutions).

Sustainability initiatives reinforced brand differentiation**,** particularly in eco-sensitive markets. Firms like Interviewees 6 and 7 leveraged eco-certified products to win new contracts abroad, while Interviewee 1 expanded into Austria and Germany through green logistics services. Cost savings were also significant: solar panels reduced energy bills, electric vehicles lowered maintenance costs, and recycling reduced material expenses.

Strategic Outlook

Looking ahead, most SMEs view digitalization and sustainability as central to their future growth strategies. IT-based firms (Interviewees 5, 9) plan further AI-driven product development, while manufacturing and logistics firms (Interviewees 1, 4) focus on carbon tracking, energy management, and predictive analytics. Sustainability ambitions include carbon neutrality (Interviewee 1), expansion of eco-product lines (Interviewees 6, 7), and positioning as regional leaders in sustainable practices (Interviewee 2).

Cross-Factor Synergies

A key insight was the synergy between digitalization and sustainability. Digital technologies frequently enabled sustainability outcomes: AI-driven route optimization reduced both costs and emissions (Interviewee 1 and 3), ERP systems minimized material waste (Interviewees 4 and 6), and e-commerce reduced reliance on physical stores (Interviewees 7 and 8). This interplay confirms recent research suggesting that digitalization can act as an enabler of sustainability (Isensee et al., 2020). For SMEs, such integration yields compounded benefits.

DISCUSSION OF FINDINGS

Answering the research questions

RQ1: How does digitalization influence the growth of SMEs?
The findings confirm that digitalization is a critical driver of SME growth, consistent with prior research (Quinton et al., 2018; Becker & Schmid, 2023). From the Slovenian interviews, digitalization enabled firms to increase efficiency (e.g. route optimization and predictive maintenance reduced costs and downtime), expand markets (online sales allowed SMEs to reach international customers), and stimulate innovation (customizable products, client portals). These insights illustrate that digitalization not only improves operational processes but also enhances strategic positioning and competitiveness. Importantly, SMEs that adopted digital tools proactively, rather than reactively, reported stronger growth trajectories. This supports the argument that digitalization must be embedded as a core strategic practice rather than treated as an add-on.

RQ2: How does sustainability influence the growth of SMEs?
The results demonstrate that sustainability contributes to SME growth in multiple ways, aligning with previous studies (Burlea-Schiopoiu & Mihai, 2019; Cezarino et al., 2022). Slovenian SMEs showed that sustainability initiatives lead to cost savings (e.g., energy efficiency, recycling, renewable energy use), market opportunities (entry into eco-conscious international markets), and brand differentiation (enhanced reputation, certifications for tenders). While some customers remain price-sensitive, the long-term benefits of sustainability practices particularly in building trust with partners, investors, and employees were widely acknowledged. The data thus support the notion that sustainability is both an ethical commitment and a business growth strategy.

Cross-factor insights

An important contribution of this study is the identification of synergies between digitalization and sustainability**.** Digital technologies often acted as enablers of sustainable practices, such as using AI to reduce fuel consumption or ERP systems to minimize waste. This confirms the argument of Isensee et al. (2020) that digitalization can facilitate environmentally responsible business models. For SMEs, this integration generates compounded benefits: efficiency gains, market expansion, and reputational advantages. For SMEs, such integration yields compounded benefits, including efficiency gains, market expansion, and reputational advantages, aligning with the view that digitalization, sustainability, and internationalization represent three interrelated strategic trajectories for firm growth (Denicolai, Zucchella, & Magnani, 2021).

These findings underline that SME growth cannot be explained by digitalization or sustainability in isolation, but rather by their embeddedness in broader institutional and market contexts. The Slovenian evidence shows that regulatory frameworks, customer expectations, and intergenerational dynamics mediate how these determinants translate into growth outcomes. This emphasizes the importance of situating digital and sustainable transitions within specific socio-economic environments, providing a foundation for the theoretical contributions outlined in the next section.

Theoretical Contributions

This study contributes to the entrepreneurship and SME literature by:

1. Providing empirical evidence from Slovenia**,** a context underexplored in international SME growth research.
2. Demonstrating how digitalization and sustainability act as dual determinants of SME growth, not only separately but also through their synergies.
3. Extending the conceptual understanding of SME growth beyond traditional financial or age-related determinants (Nunes et al., 2013; McMahon, 2001) to include policy-prioritized factors.

Practical and Policy Implications

For practitioners, the results highlight that digitalization and sustainability are not optional investments but strategic necessities**.** SMEs that invest early in these areas gain measurable advantages in efficiency, innovation, and market competitiveness.

For policymakers, the findings provide evidence that digitalization and sustainability should be treated as core pillars of SME support policies**.** Instead of general SME aid, targeted programs for digital transformation, renewable energy adoption, and circular economy practices would address the most pressing growth challenges identified in this study. Governments can accelerate SME competitiveness by simplifying regulatory procedures (e.g., renewable energy permits) and improving access to funding for digital and sustainable initiatives.

Limitations and Future Research

This study is subject to several limitations. First, the sample size of ten SMEs, while sufficient for thematic saturation, does not capture the full diversity of the Slovenian SME sector. Second, the qualitative approach emphasizes depth but does not quantify the strength of relationships between digitalization, sustainability, and growth. Third, the research was conducted in March and April 2025, and findings reflect the specific economic and policy context of this period.

Future research should complement these insights with quantitative studies across a larger sample of SMEs, both within Slovenia and internationally, to test the generalizability of the results. Comparative cross-country research could also illuminate how institutional contexts shape the interplay between digitalization, sustainability, and SME growth.

CONCLUSION

This study set out to explore the influence of digitalization and sustainability on SME growth through a combination of literature review and qualitative evidence from Slovenian enterprises. The results confirm that both determinants are critical for SME competitiveness, resilience, and long-term viability. Digitalization supports efficiency, innovation, and market expansion, while sustainability contributes to cost savings, brand reputation, and entry into new markets. Importantly, their interplay produces synergies such as digital tools enabling resource efficiency that generate compounded benefits for growth.

By emphasizing this dual and interdependent dynamic, the study advances the understanding of SME growth beyond traditional determinants such as size, age, or financial structure. It demonstrates that digital and green transitions should no longer be seen as optional pathways but strategic imperatives for SMEs in a globalized and environmentally constrained economy.

For policymakers, the findings suggest that support instruments must go beyond generic SME subsidies. Targeted measures such as digitalization vouchers, training programs for workforce adaptation, simplified permitting for renewable energy, and incentives for green innovation are required to accelerate SME transformation. For managers, the evidence indicates that embedding both digital and sustainable practices into strategy enhances not only competitiveness but also resilience in volatile markets.

Future research should build on these insights by expanding the geographic scope beyond Slovenia to capture cross-country differences in institutional support for digital and sustainable transitions. Large scale quantitative studies could test the statistical strength of the observed relationships, while longitudinal designs may reveal how synergies between digitalization and sustainability evolve over time. In addition, sector-specific analyses such as manufacturing, logistics, or creative industries could shed light on industry level dynamics and tailor policy recommendations accordingly.

In sum, this study provides an evidence-based foundation for understanding how digitalization and sustainability jointly shape SME growth. By doing so, it highlights a research and policy agenda where integrated approaches are essential for ensuring the competitiveness and long term success of SMEs in Europe and beyond.

REFERENCES

Acs, Z. J., Estrin, S., Mickiewicz, T., & Szerb, L. (2018). Entrepreneurship, institutional economics, and economic growth: an ecosystem perspective. *Small Business Economics*, 51, 501-514.

Agu, E. E., Iyelolu, T. V., Idemudia, C., & Ijomah, T. I. (2024). Exploring the Relationship Between Sustainable Business Practices and Increased Brand Loyalty. *International Journal of Management & Entrepreneurship Research*, *6*(8), 2463–2475. https://doi.org/10.51594/ijmer.v6i8.1365

Algan, N. (2019). *The importance of SMEs on world economies.* In Proceedings of International Conference on Eurasian Economies, Turkish Republic of Northern Cyprus (Vol. 12, pp. 56-61).

AlMujaini, H., Hilmi, M. F., Abudaqa, A., & Alzahmi, R. (2021). Corporate foresight organizational learning and performance: The moderating role of digital transformation and mediating role of innovativeness in SMEs. *International Journal of Data and Network Science, 5*(4), 703-712.

Autio, E. (2007). *GEM 2007 Report on hight-growth entrepreneurship*. London: GERA.

Becker, S., Schmid, B., Zademach, H. M., Schulz, C., Willi, Y., & Eichmann, H. (2023). Wohlstand als Gegenstand und Perspektive der Raumforschung. *Nachrichten der ARL, 01/2023*, 79-81.

Braun, V., & Clarke, V. (2023). Toward good practice in thematic analysis: Avoiding common problems and be (com) ing a knowing researcher. *International journal of transgender health, 24*(1), 1-6.

Burlea-Schiopoiu, A., & Mihai, L. S. (2019). An integrated framework on the sustainability of SMEs. *Sustainability, 11*(21), 6026.

Bygrave, W. D., Zacharakis, A., Wise, S., & Corbett, A. C. (2024). *Entrepreneurship*. John Wiley & Sons.

Cachón-Rodríguez, G., López-Fernández, M., Camarero-Ibarrola, A., & Garrido-Morgado, A. (2022). How sustainable human resource management helps in retaining researchers during the triple crisis: Social capital as a facilitator. *Sustainable Development, 30*(5), 1051–1062.

Casidy, R. (2022). The effects of supplier B2B sustainability positioning on buyer performance: The role of trust. *Industrial Marketing Management, 103*, 12–27.

CB Insights. (2021). *The Top 12 Reasons Startups Fail*. *CB Insights*. https://www.cbinsights.com/research/report/startup-failure-reasons-top/

Cezarino, L. O., Liboni, L. B., Hunter, T., Pacheco, L. M., & Martins, F. P. (2022). Corporate social responsibility in emerging markets: Opportunities and challenges for sustainability integration. *Journal of Cleaner Production*, 362, 132224.

Cicea, C., Popa, I., Marinescu, C., & Cătălina Ștefan, S. (2019). Determinants of SMEs' performance: evidence from European countries. *Economic research-Ekonomska istraživanja, 32*(1), 1602-1620.

Deloitte. (2023). Looking to improve B2B customer trust? Demonstrating sustainability can help. The Wall Street Journal. https://deloitte.wsj.com/cmo/looking-to-improve-b2b-customer-trust-demonstrating-sustainability-can-help-2af65d54

Denicolai, S., Zucchella, A., & Magnani, G. (2021). Internationalization, digitalization, and sustainability: Are SMEs ready? A survey on synergies and substituting effects among growth paths. *Technological Forecasting and Social Change,* 166, 120650.

Duarte, N. (2004). *The Role of SMEs for Development: A Literature Review*. In 44th Congress of the European Regional Science Association: "Regions and Fiscal Federalism". European Regional Science Association.

Dvouletý, O., & Blažková, I. (2021). Determinants of competitiveness of the Czech SMEs: findings from the global competitiveness project. *Competitiveness Review: An International Business Journal, 31*(3), 361-378.

Dzhioeva, O., & Magomadov, E. (2023). Green Transformation in the Context of Sustainable Development. In BIO Web of Conferences (Vol. 63, p. 04008). EDP Sciences.

El Shoubaki, A., Laguir, I., & Den Besten, M. (2020). Human capital and SME growth: The mediating role of reasons to start a business. *Small Business Economics, 54*, 1107-1121.

European Commission. (2022). *2030 Digital Compass: The European way for the digital decade*. Publications Office of the European Union. https://digital-strategy.ec.europa.eu/en/policies/digital-compass

European Commission. (2023a). *Strategic Plan 2020-2024, DG RESEARCH AND INNOVATION.* https://commission.europa.eu/system/files/2020-11/rtd_sp_2020_2024_en.pdf

European Commission. (2023b). *Annual report on European SMEs 2023/2024: SMEs and the green and digital transitions.* Publications Office of the European Union.

Fernandes, K.J.; Raja, V. & Whalley, A. (2006). Lessons from implementing the balanced scorecard in a small and medium size manufacturing organization. *Technovation, 26*, 623–634.

Gelbmann, U., & Baumgartner, R. J. (2012). *Strategische Implementierung von CSR in KMU. In Corporate Social Responsibility: Verantwortungsvolle Unternehmensführung in Theorie und Praxis* (pp. 285-298). Berlin, Heidelberg: Springer Berlin Heidelberg.

Grabowska, S., & Saniuk, S. (2022). Development of business models in the fourth industrial revolution: Conditions in the context of empirical research on worldwide scope companies located in Poland. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(2), 86.

Grayson, D., Coulter, C. & Lee, M. (2018). *All in: The future of Business Leadership*; Routledge: London, UK.

Grothe, A., & Marke, N. (2012). Nachhaltiges Wirtschaften–eine besondere Herausforderung für KMU. Nachhaltiges Wirtschaften für KMU: Ansätze zur Implementierung von Nachhaltigkeitsaspekten, 26-35.

Hall, J. K., Daneke, G. A., & Lenox, M. J. (2010). Sustainable development and entrepreneurship: Past contributions and future directions. *Journal of business venturing, 25*(5), 439-448.

Harash, E., Al-Timimi, S., & Alsaadi, J. (2014). The influence of finance on performance of small and medium enterprises (SMES). *Technology, 4*(3), 161-167.

HTTPOOL. (2023). *HTTPOOL, the leading global enabler of digital advertising from Slovenia.* https://www.httpool.com/

INAC Global Executive Search. (2023). ESG: The foundation for a future sustainable workforce and talent attraction. https://inac-global.com/2023/08/04/esg-the-foundation-for-a-future-sustainable-workforce-and-talent-attraction

Isensee, C., Teuteberg, F., Griese, K. M., & Topi, C. (2020). The relationship between organizational culture, sustainability, and digitalization in SMEs: A systematic review. *Journal of Cleaner Production*, 275, 122944.

Journeault, M., Perron, A., & Vallières, L. (2021). The collaborative roles of stakeholders in supporting the adoption of sustainability in SMEs. *Journal of environmental management*, 287, 112349.

Kádárová, J., Lachvajderová, L., & Sukopová, D. (2023). Impact of digitalization on SME performance of the EU27: Panel data analysis. *Sustainability*, *15*(13), 9973.

Keskġn, H., Ġentürk, C., Sungur, O., & Kġrġġ, H. M. (2010). *The importance of SMEs in developing economies*. In 2nd international symposium on sustainable development (Vol. 183).

Khrais, L. T., & Alghamdi, A. M. (2022). Factors that affect digital innovation sustainability among SMEs in the Middle East region. *Sustainability, 14*(14), 8585.

Kilimis, P., Zou, W., Lehmann, M., & Berger, U. (2019). A survey on digitalization for SMEs in Brandenburg, Germany. *IFAC-PapersOnLine, 52*(13), 2140-2145.,

Kindermann, B., Beutel, S., de Lomana, G. G., Strese, S., Bendig, D., & Brettel, M. (2021). Digital orientation: Conceptualization and operationalization of a new strategic orientation. *European Management Journal, 39*(5), 645–657.

Kindström, D., Carlborg, P., & Nord, T. (2024). Challenges for growing SMEs: A managerial perspective. *Journal of Small Business Management*, *62*(2), 700-723.

Kiyabo, K., & Isaga, N. (2020). Entrepreneurial orientation, competitive advantage, and SMEs' performance: application of firm growth and personal wealth measures. *Journal of Innovation and Entrepreneurship, 9*, 1-15.

Lowrey, Y. (2003). *The European and Entrepreneurship: A neoclassical approach*. Paper presented at the Office of advocacy U.S. small business administration. Denver.

Matalamäki, M. J., & Joensuu-Salo, S. (2022). Digitalization and strategic flexibility–a recipe for business growth. *Journal of Small Business and Enterprise Development, 29*(3), 380-401.

Mcmahon, R. G. (2001). Growth and performance of manufacturing SMEs: The influence of financial management characteristics. *International Small Business Journal, 19*(3), 10-28.

Nambisan, K. Lyytinen, A. Majchrzak, and M. Song. (2017). *Digital Innovation Management: Reinventing Innovation Management Research in a Digital World*," MIS Quartely, vol. 41, no. 1, pp. 223–238.

Nkwabi, J., & Mboya, L. (2019). A review of factors affecting the growth of small and medium enterprises (SMEs) in Tanzania. *European Journal of Business and Management, 11*(33), 1-8.

Nunes, P. M., Gonçalves, M., & Serrasqueiro, Z. (2013). The influence of age on SMEs' growth determinants: empirical evidence. *Small business economics*, 40, 249-272.

OECD. (2017). *Enhancing the contributions of SMEs in a global and digitalised economy.* OECD Publishing. https://www.oecd.org/mcm/documents/C-MIN-2017-8-EN.pdf

Prasanna, R. P. I. R., Jayasundara, J. M. S. B., Naradda Gamage, S. K., Ekanayake, E. M. S., Rajapakshe, P. S. K., & Abeyrathne, G. A. K. N. J. (2019). Sustainability of SMEs in the competition: A systemic review on technological challenges and SME performance. *Journal of Open Innovation: Technology, Market, and Complexity, 5*(4), 100.

Schallmo, D., Williams, C. A., & Boardman, L. (2017). Digital transformation of business models—best practice, enablers, and roadmap. *International journal of innovation management, 21*(08), 1740014.

Schulze, B. P., Katsinis, A., Lagüera, G. J., Di, B. L., Odenthal, L., Hell, M., ... & Secades, C. B. (2024). *Annual Report on European SMEs 2024/2025*, SME performance review.

Shabani, L., Behluli, A., Qerimi, F., Pula, F., & Dalloshi, P. (2022). The effect of digitalization on the quality of service and customer loyalty. *Emerging Science Journal, 6*(6), 1274-1289.

Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of management review, 25*(1), 217-226.

Siegel, R., Antony, J., Garza-Reyes, J. A., Cherrafi, A., & Lameijer, B. (2019). Integrated green lean approach and sustainability for SMEs: From literature review to a conceptual framework. *Journal of cleaner production*, 240, 118205.

Smallbone, D., & Welter, F. (2001). The role of government in SME development in transition economies. *International Small Business Journal, 19*(4), 63-77.

Telukdarie, A., Dube, T., Matjuta, P., & Philbin, S. (2023). The opportunities and challenges of digitalization for SME's. Procedia Computer Science, 217, 689-698.

Thomas, D. (2023). Green jobs: Workers demand sustainability in the workplace. Financial Times. https://www.ft.com/content/810ab310-a6cb-486d-a942-9b103d68fc48

Quinton, S., Canhoto, A., Molinillo, S., Pera, R., & Budhathoki, T. (2018). Conceptualising a digital orientation: antecedents of supporting SME performance in the digital economy. *Journal of Strategic Marketing, 26*(5), 427–439.

Yadav, N., Gupta, K., Rani, L., & Rawat, D. (2018). Drivers of sustainability practices and SMEs: A systematic literature review. *European Journal of Sustainable Development, 7*(4), 531-531.

Appendix: An Instrument for the research

General Opening Question (applies to both blocks):
Can you briefly describe your role in the company and the main activities of your business?

Block A – Digitalisation and SME Growth

Organizational Context

How would you describe your company's journey toward digitalization so far?

Digitalization Practices and Drivers
Which digital tools or technologies have you implemented in your business in the past 3–5 years?
What were the main motivations or drivers for adopting these digital solutions?
What challenges, if any, did you encounter during the process of digital adoption?

Impact on Growth
In what ways has digitalization influenced your company's growth in terms of sales, market reach, or customer base?
Have digital tools changed your operational efficiency or productivity? If so, how?
Can you share an example where digitalization directly contributed to innovation in your products, services, or processes?

Strategic Outlook
How do you see the role of digitalization in your company's future growth strategy?
What advice would you give to other SMEs that are considering investing in digital transformation?

Block B – Sustainability and SME Growth

Organizational Context
When and how did your company start integrating sustainability practices into its operations?

Sustainability Practices and Drivers
What specific sustainability initiatives or policies has your business implemented in recent years?
What motivated your company to adopt these sustainability measures?
What challenges have you faced in implementing sustainability practices?

Impact on Growth
In what ways have sustainability practices influenced your sales, market reach, or customer base?
Have sustainability initiatives improved operational efficiency, cost savings, or resource management? If yes, how?
Can you provide an example where a sustainability measure directly led to innovation in your products, services, or processes?

Strategic Outlook
How do you envision the role of sustainability in your company's future growth strategy?
What advice would you give to other SMEs considering investment in sustainability initiatives?

FINANCIAL PERFORMANCE AND GENERIC STRATEGY OF MEXICAN STOCK ENTERPRISES BEFORE AND DURING THE COVID-19 PANDEMIC

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Abstract

In the context of the COVID-19 period, this article aims to identify whether the type of strategy used by organisations (cost-based strategy and differentiation strategy) showed significant differences in financial performance indicators: net margin (NM), return on assets before taxes (ROA), and return on equity (ROE). Statistical analysis was performed using a multivariate technique considering non-metric independent variables (type of strategy) and metric dependent variables (financial indicators). The sample used considered companies listed on the Mexican Stock Exchange during the pre-COVID (2019), COVID (2020) and post-COVID periods (2021). The results from statistical tests provide evidence about the differences in the average financial results comparing the groups of companies using a particular strategy for a particular year, in the case of the Mexican companies analysed. The insights about a reaction to face a crisis derived from a pandemic are valuable for researchers, policymakers, and practitioners.

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Key Words

Cost strategy; differentiation strategy; financial performance; COVID-19; Hotelling's T-square.

INTRODUCTION

COVID-19 has been one of the most significant and unexpected crises in modern times which has caused society to question itself at a local, regional, national, and global level Specifically, five main clusters of research relating COVID-19 and strategy have been identified: entrepreneurship, innovation, digital transformation, leadership and resilience (Guyottot & Le Fur, 2023).

This epidemic has not only had economic consequences, society as a whole has been affected, leading to dramatic changes in the way businesses operate and in consumer behavior. In particular, some aspects have been analysed: consumer habits, public health interventions, workplace transformations, corporate social responsibility and marketing philosophy, social and informational uncertainty, business education, changes in consumption, supply chain, and tourism (Donthu & Gustafsson, 2020).

The effects in developed economies were heterogeneous. Some businesses, especially in high-tech-related industries, adapted well to social distancing requirements relying on remote work, while other businesses were unable to adapt, as was the case in the food, travel, and hospitality sectors, as their nature required close contact with customers and among workers (Pagano et al., 2023).

Companies' reaction to COVID-19 was reflected in the price of stocks, but it was not the same among listed companies; the variation depended on their resilience to social distancing, financial flexibility, and corporate culture (Pagano & Zechner, 2022). COVID 19 affected the health and economy of countries in general, and in Mexico, the effects of COVID-19 on companies are assumed to be similar to those experienced in countries in other parts of North America and Europe.

In a context of great uncertainty, it might be more convenient for a company to follow a particular strategy. Therefore, the objective was centered on identifying if the type of strategy used by the companies listed on the Mexican Stock Exchange influenced the financial performance in the pre-COVID period (2019), and throughout the COVID period (2020 and 2021).

In order to evaluate the financial impact of COVID-19 on the Mexican companies' results, we carried out a statistical analysis to determine whether the organisations based on a cost-strategy and organisations based on a differentiation strategy presented a significant difference in financial performance.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

A review of concepts that support the statistical analysis and results is presented.

Strategy

Porter (1996) states that the essence of strategy is choosing a unique and valuable position supported by systems of activities much more difficult to match. In addition, Firoz et al. (2019) mention the usability and applicability of Porter's generic strategies in the e-business, evaluating the cost leadership strategy and differentiation strategy to generate performance. Furthermore, Pangarkar & Prabhudesai (2024) give practical advice to managers about applying Porter's Five Forces analysis, observing the environment to formulate a strategy for a particular context. Similarly, Farida & Setiawan (2022) show that business strategies have a positive impact on the competitive advantage of small and medium enterprises, considering that better business strategies improve performance and innovation capability, and, consequently, competitive advantages are strengthened. Regarding methods, Bindra et al. (2019) state that research for understanding strategic management is methodologically challenging as the variables used to analyze a plan or a pattern are difficult to measure, hindering the analysis of their relationship and the determination of causality.

Performance

Pagano & Zechner (2022) analyze the effects of COVID-19 on the stock price, sales, employment, and asset growth of companies: effects that depend on people’s interaction or social distancing, financial flexibility, and corporate culture, noting that listed firms reduced leverage and unlisted increased it. Besides, Baker et al. (2020) propose explanations for the reaction of the stock market to the COVID-19 pandemic, suggesting that government restrictions on commercial activity and voluntary social distancing, in a service-oriented economy, are the main reasons for the United States stock market’s strong reaction to COVID-19 compared to previous pandemics in history. Regarding social responsibility, Awaysheh et al. (2020) examine the relation between corporate social responsibility (CSR) and financial performance, observing that the best evaluated firms that heeded CSR outperformed their industry peers in operating performance and had better market valuations (for this case the Q of Tobin indicator). Regarding markets, Pagano et al. (2023) study the time-varying price of asset markets by analyzing stock returns that reflect different exposure to the pandemic, inferring from market outcomes that firm resilience correlates with exposure to social distancing, and that it is priced based on changes of the firms’ expected returns. In valuation, Souder et al. (2024) introduce a methodology of stock market valuations considering the future value of operations and the dynamic future value associated with competitive positioning to measure the effect of cash holdings on performance. The references and definitions considered for the indicators of financial performance are shown in Table 1.

Table 1. Reference authors for indicators to measure financial performance

AUTHOR	Financial Performance
Awaysheh et al. (2020)	OIBD=Operating Income Before Depreciation / TA= Total Assets (OIBD/TA) Tobin's Q ([Total Assets – Book Value of Common Equity + Market Value of Common Equity]/Total Assets)
Ramírez Rocha et al. (2019)	ROA = Return on Assets ROA =Net operating profits / Average assets book value ROE = Return on equity ROE =Net operating profits / Average equity book value OSS = Financial Sustainability OSS =total financial revenue / financial expenses + operating expenses + provision for losses
Ibrahim et al. (2018)	PM = Profit Margin ratio Adjusted New Operating Income / Adjusted Financial Revenue ROA = Return on Assets ratio (Adjusted Net Operating Income - Taxes) / Adjusted Average Total Assets OSS = Operational Self-sufficiency Financial Revenue / (Financial Expense + Impairment Losses on Loans + Operating Expense) ratio

Strategy and Performance

The relation of strategy and performance is observed. For instance, Agnihotri (2014) states that by fitting their strategy to the mode of financing, firms may be able to lower their capital cost and consequently improve their financial performance. Regarding generic strategies, Lee et al. (2021) analyze firms using strategies of low-cost and focus observing an improvement in performance, finding that when individually executing these strategies firms experience benefit but when implementing these two generic strategies simultaneously, firms' profitability is affected negatively. Specifically, Greckhamer & Gur (2021) explore, with the Porter framework for strategic positions of firms, the generic strategies of cost leadership, differentiation, and focus, and their effects on firm performance in the American and Canadian airline industry, finding that a generic strategy advantage is not sufficient for high performance, although it is necessary for achieving success.

Effects of COVID on Strategy and Performance

Barrot et al. (2024) study the effects of business closures in response to the COVID-19 pandemic, observing a negative causal effect on mortality rates, especially in areas with contact-intensive activities and performing an analysis of health benefits of business closures and economic costs. In investments, Gao et al. (2022) investigate the effects of COVID-19 on corporate financial portfolio choice of financial assets and find that firms with higher pandemic exposure tend to hold fewer financial assets with a preference to reduce liquidity shortage. Regarding production, Kapoor et al. (2024) examine the effects of COVID-19 in the case of companies' manufacturing operations, and identify difficulties such as reduced capacities, increased costs, and uncertainty, as well as management interventions they executed like investment in digital technologies, resource redistribution, and localizing, all of them to help manufacturing businesses face the pressures of lockdowns. In addition, Wenzel et al. (2021) analyse the strategic responses to the COVID-19 pandemic crisis and the impact on firms at a global scale, identifying four types of potential strategic responses from firms: retrenchment, perseverance, innovation, and exit. In corporate culture, Li et al. (2021) identify firm-level measures of exposure and response related to COVID-19, observing a negative impact of COVID-19 on the operation of companies, but firms with a strong corporate culture performed better than firms without a strong culture, supported their communities, were more open to digital transformation, and tended to develop new products. With respect to contracts, Eldar & Wittry (2021) analyse the adoption of poison pills during the coronavirus pandemic and find a positive reaction to crisis pills to prevent changes in ownership, noticing that after a decline in valuation, stock prices increased after the adoption of these pills. Concerning human resources, Orlowski (2021) reviews the impact of the pandemic, observing negative effects on the workforce, although without considerable effects on the level of physical capital. About government measures, Gormsen & Koijen (2020) point out that the response in monetary policy and fiscal stimulus boosted the recovery in the stock market and improved growth expectations, but above all, long-term expectations. In addition, Aguirre-Ríos et al. (2022) analyze the fiscal policies implemented in a sample of Latin American countries and their effects on the context of the COVID-19 pandemic, finding problems in the fiscal structure in underdeveloped countries and a neutrality of the fiscal mechanisms that were not generating positive outcomes against the economic inequalities of the region.

METHODOLOGY

Two-sample hypothesis tests have been identified as fundamental problems in statistical inference, which seek to detect differences between two probabilistic measures and have numerous applications in the real world. (Wang et al., 2023).

Pérez Valencia (2009) points out that Hotelling's T-square test, in the case of a normal skewed multivariate distribution, has proven to be a useful model in some important practical situations, such as in the measurement of certain anthropometric variables.

Similarly, Abdullah et al. (2015) point out that the empirical results of a simulation study based on Hotelling's T-square test using the established relationships of the multivariate distribution with the real multivariate distribution show that the model works well in differentiating the means.

Analyzing the data distribution during the pre-COVID period (2019), and during the COVID period (2020 and 2021), it was determined to perform the multivariate statistical tests particularly when there are two groups to be analyzed, selecting metric dependent variables for the case of financial results and non-metric independent variables for the type of strategy implemented. Considering that the decision regarding the direction of the company falls on the general director, the two types of generic strategies in which the company competes were selected as the independent variables. The results obtained by the company in financial terms were selected as dependent variables. For three metric dependent variables, net margin (NM), return on assets before taxes (Pre-tax ROA), return on equity (ROE), and two non-metric independent variables (cost strategy and differentiation strategy), the recommended multivariate technique is Hotelling's T-square test (De la Garza et al., 2013).

The methodology used allowed us to analyse the distribution of the multivariate data, perform variance matrix tests and apply statistical tests to determine whether there was a difference in the mean of the financial performance variables according to the types of strategies used by the organisations, for the years 2019, 2020, and 2021.

The statistical results obtained provided empirical evidence through statistical tests about the effect of the type of strategy employed in organisations on the financial results for the case of the Mexican companies analysed. Likewise, we identified a change in the average financial results of each group of companies, classified by type of strategy, because of facing a crisis derived from the COVID-19 pandemic.

Independent Variables

The two independent variables were non-metric, and there were two types of strategies: cost strategy and differentiation strategy (Porter1996). For the classification of each company and their competitive strategy the following process was carried out: 1) documentary analysis of the strategic planning on the website, 2) documentary analysis of the annual report of the previous two years, and finally, 3) validation with two expert researchers about strategy on the list made. Particularly, for the definition of the type of strategy (independent variables) applied by each company, despite being widely known companies (in their products and strategy), the method of Expert Validation was used. It is a qualitative method, which refers to the process used to evaluate the quality and accuracy of data and/or results gathered through research. When using this method, the researchers ask several experts or “judges” to analyze, evaluate, allocate, classify, and/or generate conclusions regarding specific topics (Patton, 2023). Two expert researchers were invited to the process. Each expert was asked to select the type of differentiation or cost strategy for each company. Upon completion, both lists were compared,and given that they are well-known companies in the Mexican market, it was no surprise that they completely coincided. The generic strategies are presented in Table 2.

Table 2. Identified generic strategies and their methodological framework

Group	Denomination	Variable	Type of variable
1	Cost Strategy	Independent	Non-metric
2	Differentiation Strategy	Independent	Non-metric

Dependent Variables

Three variables to measure financial performance were considered:

Net Margin (NM) or return on sales. It is calculated by dividing the after-tax income for the fiscal year by the total income for the same period. The variable is expressed as a percentage.

Pre-tax return on assets (ROA) or return over assets. This variable presents the return on assets before taxes. It is the result of dividing the pre-tax income for the fiscal year by the average total assets for the same period. The variable is expressed as a percentage.

Return on Equity (ROE) or return over capital. It is obtained from dividing the net income before extraordinary items for the fiscal year by the average of the total capital for the same period. The variable is expressed as a percentage.

Additional indicators are possible for financial performance, but the most common indicators, as presented in Table 1 for the analysis, were considered.

Hypothesis

To analyse the effect of the type of strategy executed on the financial performance results obtained by the sample of organisations listed on the Mexican Stock Exchange, in the pre-COVID (2019), and COVID (2020 and 2021) periods, the alternative hypothesis was established:

H1 = the financial performance of companies implementing a cost strategy and the financial performance of companies implementing a differentiation strategy is not the same on average in both groups.

The multivariate Hotelling's T-square test was selected to perform the statistical analysis and evaluate the hypothesis. This test is recommended to find differences between two experimental groups. (De la Garza et al., 2013).

Sample Data

The initial sample took financial data from 143 companies listed on the Mexican Stock Exchange. The data included the measures considered to gauge financial performance: net margin (NM), return on assets before taxes (Pre-tax ROA), and return on equity (ROE). From the review of the initial database, companies were selected to manage a complete database for the statistical analysis. Some companies were removed from the database because the indicators of financial performance were not presented or were incomplete. The sample excluded non-local companies and companies with negative capital to focus on the universe of Mexican companies operating normally The sample, after data revision was located at 102 companies considering the three financial performance indicators consulted on the Eikon Thomson Refinitiv platform. The period considered for analysis included the years 2019, 2020, and 2021.

Based on the analytical framework proposed by Porter (1996) the companies were classified in two groups: companies based on a cost strategy and companies based on a differentiation strategy. The companies were classified after a revision of their annual reports, focusing on strategy plans and the comments from their general directors regarding strategy execution. We observed that sixty-five companies (64%) of the sample focused on cost strategy, and thirty-seven companies (36%) focused on differentiation strategy.

The sample analysed was of publicly traded companies. The limitation for the study is centred on the number of companies that were finally reduced. The filtering of 143 companies to 102 companies represented a reduction of almost 30% of the initial sample. In particular, a company that presented serious financial problems and was facing legal proceedings was reduced.

It is important to point out that the initial number of companies considered in the sample for performing the statistical analysis was the whole universe of publicly traded companies in the stock market, 143 companies. However, some of the companies were facing administrative changes or financial restructuring, thus, the universe narrowed down to the final number of 102 companies analysed.

Univariate and Multivariate Statistical Tests

The univariate statistics for the sample companies included mean and standard deviation of financial data of companies classified by cost and differentiation strategies. The univariate statistical results are presented in Table 3.

Table 3. Mean and standard deviation of financial performance variables by type of strategy

Strategy	Number of Companies	Variables Financial Performance	2019 Mean	2019 Standard Deviation	2020 Mean	2020 Standard Deviation	2021 Mean	2021 Standard Deviation
Cost	65	NM	0.047	0.446	-0.0651	0.594	0.112	0.191
		ROA	0.053	0.087	0.025	0.098	0.078	0.085
		ROE	0.082	0.160	-0.022	0.269	0.117	0.142
Differentiation	37	NM	0.039	0.059	-0.062	0.225	0.028	0.245
		ROA	0.039	0.043	0.009	0.081	0.033	0.064
		ROE	0.070	0.173	-0.041	0.387	-0.043	0.680

		NM	0.044	0.356	-0.064	0.491	0.081	0.214
Total	102	ROA	0.048	0.074	0.019	0.092	0.061	0.081
		ROE	0.077	0.164	-0.029	0.315	0.059	0.428

Notes: Net margin (NM), Pre-tax return on assets (ROA), Return on equity (ROE).

The multivariate tests performed to evaluate the financial data of the sample companies included:

Skewness. The test describes the symmetry of the distribution. The bias test allows us to determine whether the distribution of the data is symmetrical around a mean.

Kurtosis. The test describes the clustering of scores toward the centre of the distribution. This test allows us to determine if there is a degree of flattening of the distribution.

Box's M test. It allows testing of the null hypothesis that the observed multiple variance-covariance matrices are equal across groups. (De la Garza et al., 2013).

Hotelling's T-square test. This test was performed for the case of two samples with unequal variance matrices. The objective of this test was to determine whether there was a significant difference in the means of the analysed groups (De la Garza et al., 2013).

The multivariate kurtosis and skewness results are presented in Table 4.

Table 4. Skewness and kurtosis of financial performance variables by type of strategy

Strategy	Number of Companies	Variables Financial Performance	2019 Skewness	2019 Kurtosis	2020 Skewness	2020 Kurtosis	2021 Skewness	2021 Kurtosis
		NM	-6.143	46.151	-6.720	50.131	2.137	10.387
Cost	65	ROA	0.154	8.184	0.070	10.561	2.023	7.539
		ROE	-0.921	8.309	-3.036	10.557	-0.296	4.063
		NM	-0.109	1.150	-1.835	2.512	0.540	14.917
Differentiation	37	ROA	0.761	1.787	-1.014	2.064	-1.485	4.525
		ROE	3.825	19.060	-1.132	5.155	-5.426	31.801
		NM	-7.488	70.304	-7.495	66.621	1.076	12.453
Total	102	ROA	0.351	10.285	0.350	9.065	1.429	7.992
		ROE	0.987	11.701	-1.938	7.501	-8.081	75.751

Notes: Net margin (NM), Pre-tax return on assets (ROA), Return on equity (ROE).

The objective of the research was to compare the differences between the means of the data; therefore, it was decided to use the Hotelling test. Additionally, the composition of the limited sample allowed the test to be carried out with the necessary adjustments and to show statistical evidence.

We do not consider the Tobin Q test to be the best indicator for this case since it allows us to observe whether a specific company is above or below its value. By our research objective, we focused on managing profitability indicators to validate the behaviour as dependent variables of the strategies used. However, further studies may address this test of particular interest for the analysis of companies.

There are advanced analytical methods, such as the Structural Equation Modelling, but sample characteristics limit the use of these techniques by requiring more data to perform the statistical analysis.

RESULTS

The Box's M test results determined that the variance matrices from the two groups of companies classified by cost strategy and differentiation strategy were not equal. The results from the multivariate statistical tests provided evidence that the multivariate distribution was not normal. It was observed that the distribution of data presented bias or asymmetry, as well as kurtosis. The Hotelling's T-square test for two samples with unequal variance matrices was performed with the data for 2019, 2020, and 2021, in such a way that we reviewed the period before the pandemic (2019), and the period throughout the pandemic (2020 and 2021).

The summary of results from Box's M Test and Hotelling's T-square Test is presented in Table 5.

Table 5. Summary of results from Box's M Test and Hotelling's *T-square* Test for two samples (unequal covariance matrices)

Year	**2019**		**2020**		**2021**	
Test	**Box's M**	**Hotelling's *T-square***	**Box's M**	**Hotelling's *T-square***	**Box's M**	**Hotelling's *T-square***
Coefficient	114.114	2.178	95.254	2.503	165.678	9.796
p-value	0.000	0.547	0.000	0.487	0.000	0.026
Criteria	$p < \alpha^*$	$p > \alpha^*$	$p < \alpha^*$	$p > \alpha^*$	$p < \alpha^*$	$p < \alpha^*$
Covariances	Unequal		Unequal		Unequal	
Differences		No		No		Yes

Note: *α = .05 indicates statistical significance at 5%.

Considering the data did not present a normal multivariate distribution, and in accordance with Hotelling's T-square test for two samples with unequal variance matrices, the result was that during 2019, there was no significant statistical difference in the means of the financial performance variables, comparing the two independent variables. We cannot, therefore, reject the null hypothesis (H0).

When analysing 2020, the same results were obtained from Hotelling's T-square test for two samples with unequal variance matrices. Consequently, we cannot reject the null hypothesis (H0) for this year.

However, for the year 2021, Hotelling's T-square test for two samples with unequal variance matrices resulted in a significant statistical difference in the average financial performance between the two groups of companies that used cost strategy and differentiation strategy.

Specifically analysing 2021 and the total number of companies in the sample, the averages in net margin were 8.18%, in ROA 6.19%, and in ROE 5.94%. The range for net margin was -92% to 108%, with a standard deviation of 21%. For ROA the range was -21% to 49% with a standard deviation of 8%, and for ROE the range was -392% to 77% with a standard deviation of 42%. For ROA the range was -21% to 49% with a standard deviation of 8%, and for ROE the range was -392% to 77% with a standard deviation of 42%.

In companies with a cost strategy, the average net margin was 11.22%, ROA 7.84%, and ROE 11.76%. The range for net margin was -37% to 108%, with a standard deviation of 19%. For ROA, the range was -6% to 49% with a standard deviation of 8.5, and for ROE, the range was -45% to 48% with a standard deviation of 14%.

In companies with a differentiation strategy, the average net margin was 2.83%, ROA 3.29%, and ROE -4%. The range in net margin was -92% to 107%, with a standard deviation of 24%. For ROA, the range was -21% to 12% with a standard deviation of 6.38%, and for ROE, the range was -392% to 77% with a standard deviation of 67%.

Some other possible factors for this behaviour could be considered within the environment faced by the companies that were observed in the margins that were presented in the average of the companies, based on costs from 11% to 2% in the case of the average of the companies with a differentiation strategy.

The ROA also follows this adjustment in the average of cost-based companies from 7% to 3% in the case of differentiation companies.

The strongest difference was in ROE, from 11% on average in companies based on cost strategy to -4% in the case of companies based on differentiation strategy.

In this case, we accept the alternative hypothesis (H1):

H1 = the financial performance of companies implementing a cost strategy and the financial performance of companies implementing a differentiation strategy are not the same on average in both groups.

The hypotheses validations by year are presented in Table 6.

Table 6. Hypothesis Validation.

Year	**2019**	**2020**	**2021**
Hypothesis	**Findings**	**Findings**	**Findings**
H0 null	Remains the same	Remains the same	Rejected
H1 alternative	Not accepted	Not accepted	Accepted
Conclusion	No difference	No difference	Notable difference

DISCUSSION

The statistical analysis considered, on the one hand, the strategic framework adapted from Porter (1996) and, on the other, the financial performance variables used by various authors seeking significant effects of the type of strategy on financial results for the pre- and COVID pandemic periods.

Considering that the data did not present a normal multivariate distribution and in accordance with Hotelling's T-square test for 2 samples with unequal variance matrices, the result was that during 2019 there was no significant statistical difference in the means of the financial performance variables: net margin (NM), return on assets before taxes (Pre-tax ROA), and return on equity (ROE). The above compared the 2 classification groups or independent variables: cost strategy and differentiation strategy. Therefore, we cannot reject the null hypothesis (H0) of our study:

H0 = the financial performance of companies that use a cost strategy and the financial performance of companies that use a differentiation strategy on average is the same for both groups.

When analysing 2020, the same results were obtained from Hotelling's T-square test for two samples with unequal variance matrices. Consequently, we cannot reject the null hypothesis (H0) of our study.

However, for 2021, Hotelling's T-square test for two samples with unequal variance matrices resulted in a significant statistical difference in the average financial performance between the two groups of companies that used the cost strategy and the differentiation strategy.

In this case, we can reject the null hypothesis (H0) of our study and accept the alternative hypothesis (H1):

H1 = the financial performance of companies that use a cost strategy and the financial performance of companies that use a differentiation strategy on average is not the same for both groups.

The findings allowed us to establish that the financial performance of companies that use a cost strategy and the financial performance of companies that use a differentiation strategy, on average, were not equal in both groups, comparing the 2021 period.

Reviewing the financial performance variables for the 2021 period, we can note that organisations with a cost-based strategy recorded on average better levels of net profit margin (NM), achieving a positive difference of 8.3% over organisations with a strategy based on differentiation. In the case of return on assets before taxes (ROA), the difference was also positive at 4.5% in favour of the group of cost-based organisations compared to organisations based on a differentiation strategy. Likewise, in the case of return on equity (ROE), the difference was positive by 16.0% for organisations based on cost strategy compared to those with a differentiation strategy.

In the fiscal year 2021, the group of companies that followed a cost-based strategy recorded an average net margin (NM) of 11.22%, an average return on assets before taxes (Pre-tax ROA) of 7.84%, and an average return on equity (ROE) of 11.76%. These results are higher than the averages recorded by the group of companies based on a differentiation strategy for this year.

In the case of the net margin (NM), it is possible to locate improvement in this indicator, on the one hand, by generating higher sales and, on the other, in better management of operating and financial expenses. Considering the ROA, it is possible to locate improvement in generating a higher number of sales and a better investment strategy in productive assets. In the case of ROE, it is also possible to locate the improvement in generating a higher number of sales and a better capital management strategy (reinvestment of profits and dividend management).

CONCLUSIONS

In 2019, the group of companies that followed a cost-based strategy recorded a difference on the average net margin (NM) of 0.9%, a difference on the average return on assets before taxes (Pre-tax ROA) of 1.4%, and a difference on the average return on equity (ROE) of 1.1%. These results were not significantly different between the two groups. Likewise, in 2020, the group of companies that followed a cost-based strategy recorded a difference on the average net margin (NM) of 0.2%, a difference on the average return on assets before taxes (Pre-tax ROA) of 1.7%, and a difference on the average return on equity (ROE) of 1.8%. These results were not significantly different between the two groups.

Nevertheless, the comparison of organisations with a cost-based strategy and organisations based on a differentiation strategy resulted in a significant difference in the means of the financial performance variables, specifically for the 2021 pandemic period.

We can infer, from the statistically significant results, that the group of organisations based on cost strategies had a better strategic reaction in the pandemic period of 2021, which translated into better financial results.

The importance of strategic planning to reach performance and competitiveness, as pointed out by Elbanna et al. (2020) was noted, as well as the importance of strategic responses to crisis as mentioned by Wenzel et al. (2021).

The research contribution focuses on the empirical confirmation of the statistical effects of the type of strategy used in organisations on financial results for the pre and COVID periods in the case of Mexico. The management contribution focuses on the identification of the change in the average financial results of each group of companies classified by type of strategy, due to facing a crisis in organisations derived from the COVID-19 pandemic.

In the practical business field, it is important to point out that in times of crisis such as what happened throughout COVID-19, products whose strategy is based on cost will have a great advantage given the contraction of the economy. Therefore, companies that work with a differentiation strategy in times of crisis must make immediate efforts to present themselves as essential elements within consumer spending with the aim of generating a close bond (customer/company). These efforts can include a marketing campaign highlighting the importance of the product/service, joint/package purchasing proposals (family/business), as well as operational adjustments to reduce the range of differentiated items during the crisis and consequently improve production efficiency. Since the objective was centred on the types of strategy and financial results obtained in the period, agility and how well these strategies were implemented or adapted are possible to be addressed in future related analysis.

In the case of regulators and policy makers, observing what was mentioned by Gormsen & Koijen (2020), possible measures could be explored in particular for the case of Mexico, like granting fiscal stimuli to support the operation of companies, and supporting the access to financing with low interest rates to support economic growth in the short and long term. Likewise, as mentioned by Orlowski (2021), it is important to support labour markets for the retention of workers and the maintenance of productivity in the face of a pandemic scenario.

This work is developed in the context of Mexico with a sample of organisations listed on the Mexican Stock Exchange, which presents a limitation for the generalisation of results. It is necessary to continue developing research to corroborate the results found, analysing other organisations in different countries. Limitations are recognised by analysing the effectiveness of cost or differentiation strategies applied by companies, considering the type of industry in which they are immersed. It is possible that the effectiveness of the type of strategy by type of industry presents variations in the results, considering, for example, the characteristics of a service company focused on the final client or consumer, or a production or manufacturing company oriented to intermediate clients or suppliers of other industries.

The analysis is limited to the observed analysis period (2019-2021), which is relatively short and constitutes an initial effort. The time horizon considered for the analysis can be extended in subsequent analyses to verify whether the results are maintained over time and whether the adjustments made by decision-makers had an effect on the strategies to maintain their competitive position.

Future research can focus on determining in greater depth the specific decisions to improve financial performance in organisations during times of crisis or consider other elements that could be influencing the reactivation and improvement of financial results, such as the local environment of the firm as an origin of competitive success mentioned by Porter (1996). Additional external factors may affect financial results, such as changes in economic policies, government regulations, or changes in consumer behaviour, which open the possibility of including more variables to expand the analysis in future work. Employing the resource-based view, Helfat et al. (2023) show the new directions for the research on strategic management, considering new contexts like artificial intelligence and sustainability, new concepts like resource redeployment, and new methods like text analysis and machine learning. Subsequent analyses could focus on addressing the challenges in the measurement and explanation of causality of strategic variables, as observed by Bindra et al. (2019).

Guyottot & Le Fur (2023) mention aspects to explore such as the effects of COVID-19 and the importance of corporate social responsibility, sustainability and environmental issues regarding strategy and performance of companies, globalization and reindustrialization, economic growth and preservation of natural resources, as well as the development of digital communications and human solidarity.

Donthu & Gustafsson (2020) provide research themes like freedom, healthcare, government intervention, approaches to handle the stress on the job markets and infrastructure, support to businesses and citizens, and in general, the best approaches to face a major disaster in the future.

Other avenues of research could consider important aspects such as the interaction of generic strategies with organisational culture, technology adoption, and sustainability in organisations. Addressing these dynamics can broaden the vision and understanding of the implementation of the type of generic strategy and the financial results generated.

REFERENCES

Abdullah, N. A., Rijal, O. M., Zubairi, Y. Z., & Isa, Z. M. (2015). Hotelling two sample T^2 test for complex normal distribution. *Pakistan Journal of Statistics, 31*(6), 671–682. https://www.researchgate.net/publication/286862141_Hotelling_two_sample_T2_test_for_complex_normal_distribution

Agnihotri, A. (2014). Impact of strategy-capital structure on firms' overall financial performance. *Strategic Change, 23*(1–2), 15–20. https://doi.org/10.1002/jsc.1956

Aguirre-Ríos, A., Espinal Piedrahita, J. J., Cabrera Jaramillo, R. S., & Vélez Escobar, S. B. (2022). Mecanismos fiscales en el marco de la COVID-19: Una mirada a las desigualdades económicas en América Latina. *Revista CEA, 8*(18), e2211. https://doi.org/10.22430/24223182.2211

Awaysheh, A., Heron, R. A., Perry, T., & Wilson, J. I. (2020). On the relation between corporate social responsibility and financial performance. *Strategic Management Journal, 41*(6), 965–987. https://doi.org/10.1002/smj.3122

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies, 10*(4), 742–758. https://doi.org/10.1093/rapstu/raaa008

Barrot, J.-N., Bonelli, M., Grassi, B., & Sauvagnat, J. (2024). Causal effects of closing businesses in a pandemic. *Journal of Financial Economics, 154*, Article 103794. https://doi.org/10.1016/j.jfineco.2024.103794

Bindra, S., Parameswar, N., & Dhir, S. (2019). Strategic management: The evolution of the field. *Strategic Change, 28*(6), 469–478. https://doi.org/10.1002/jsc.22999

De la Garza, J., Morales, B., & González, B. (2013). *Análisis estadístico multivariante: Un enfoque teórico y práctico*. McGraw-Hill.

Donthu, N., & Gustafsson, A. (2020). Effects of COVID-19 on business and research. *Journal of Business Research, 117*, 284–289. https://doi.org/10.1016/j.jbusres.2020.06.008

Elbanna, S., Al Katheeri, B., & Colak, M. (2020). The harder firms practice strategic management, the better they are. *Strategic Change, 29*(5), 561–569. https://doi.org/10.1002/jsc.2365

Eldar, O., & Wittry, M. D. (2021). Crisis poison pills. *Review of Corporate Finance Studies, 10*(1), 204–251. https://doi.org/10.1093/rcfs/cfaa024

Farida, I., & Setiawan, D. (2022). Business strategies and competitive advantage: The role of performance and innovation. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(3), 163. https://doi.org/10.3390/joitmc8030163

Firoz Suleman, M., Rashidirad, M., & Firoz Suleman, S. (2019). The applicability of Porter's generic strategies in pure online firms: A case study approach. *Strategic Change, 28*(3), 167–176. https://doi.org/10.1002/jsc.2258

Gao, H., Wen, H., & Wang, X. (2022). Pandemic effect on corporate financial asset holdings: Precautionary or return-chasing? *Research in International Business and Finance, 62*, Article 101750. https://doi.org/10.1016/j.ribaf.2022.101750

Gormsen, N. J., & Koijen, R. S. (2020). Coronavirus: Impact on stock prices and growth expectations. *The Review of Asset Pricing Studies, 10*(4), 574–597. https://doi.org/10.1093/rapstu/raaa013

Greckhamer, T., & Gur, F. A. (2021). Disentangling combinations and contingencies of generic strategies: A set-theoretic configurational approach. *Long Range Planning, 54*(2), Article 101951. https://doi.org/10.1016/j.lrp.2019.101951

Guyottot, O., & Le Fur, E. (2023). A systematic literature review and bibliometric analysis of research on COVID-19 in strategy journals. *Strategic Change, 32*(2), 85–102. https://doi.org/10.1002/jsc.2538

Helfat, C. E., Kaul, A., Ketchen, D. J., Barney, J. B., Chatain, O., & Singh, H. (2023). Renewing the resource-based view: New contexts, new concepts, and new methods. *Strategic Management Journal, 44*(6), 1357–1390. https://doi.org/10.1002/smj.3500

Ibrahim, Y., Ahmed, I., & Minai, M. S. (2018). The influence of institutional characteristics on financial performance of microfinance institutions in the OIC countries. *Economics & Sociology, 11*(2), 19–35. http://dx.doi.org/10.14254/2071-789X.2018/11-2/2

Kapoor, K., Bigdeli, A. Z., Dwivedi, Y. K., & Raman, R. (2024). How is COVID-19 altering the manufacturing landscape? A literature review of imminent challenges and management interventions. *Annals of Operations Research, 335*(3), 1567–1599. https://doi.org/10.1007/s10479-021-04397-2

Lee, C., Hoehn, W. M. N., & Karim, S. (2021). Competing both ways: How combining Porter's low-cost and focus strategies hurts firm performance. *Strategic Management Journal, 42*(12), 2218–2244. https://doi.org/10.1002/smj.3279

Li, K., Liu, X., Mai, F., & Zhang, T. (2021). The role of corporate culture in bad times: Evidence from the COVID-19 pandemic. *Journal of Financial and Quantitative Analysis, 56*, 2545–2583. https://doi.org/10.1017/S0022109021000326

Orlowski, L. T. (2021). The 2020 pandemic: Economic repercussions and policy responses. *Review of Financial Economics, 39*(1), 20–26. https://doi.org/10.1002/rfe.1123

Pagano, M., & Zechner, J. (2022). COVID-19 and corporate finance. *Review of Corporate Finance Studies, 11*(4), 849–879. https://doi.org/10.1093/rcfs/cfac025

Pagano, M., Wagner, C., & Zechner, J. (2023). Disaster resilience and asset prices. *Journal of Financial Economics, 150*(2), Article 103712. https://doi.org/10.1016/j.jfineco.2023.103712

Pangarkar, N., & Prabhudesai, R. (2024). Using Porter's Five Forces analysis to drive strategy. *Global Business and Organizational Excellence, 1*. https://doi.org/10.1002/joe.22250

Patton, M. Q. (2023). *Qualitative research & evaluation methods* (5th ed.). SAGE Publications.

Pérez Valencia, D. (2009). Estudio de la robustez del estadístico T2 de Hotelling para el caso de una y dos poblaciones cuando los datos provienen de una distribución normal sesgada [Master's thesis, Universidad Nacional de Colombia Sede Medellín]. Repositorio UNAL. https://repositorio.unal.edu.co/handle/unal/3345

Porter, M. E. (1996). What is strategy? *Harvard Business Review, 74*(6), 61–78. https://hbr.org/1996/11/what-is-strategy

Ramírez Rocha, A., Cervantes Zepeda, M., & Bernal Ponce, L. (2018). The determinants of outreach and profitability in MFIs: A structural equation approach. *Revista Mexicana de Economía y Finanzas Nueva Época REMEF, 14*(1), 129–146. https://doi.org/10.21919/remef.v14i1.363

Souder, D., Shaver, J. M., Harris, J. D., & Alrashdan, A. (2024). Performance metrics in strategy research: A new metric and method for assessing dynamic value. *Strategic Management Journal, 45*(1), 144–167. https://doi.org/10.1002/smj.3550

Wang, R., Fan, W., & Wang, X. (2023). A hyperbolic divergence based nonparametric test for two-sample multivariate distributions. *The Canadian Journal of Statistics*. https://doi.org/10.1002/cjs.11736

Wenzel, M., Stanske, S., & Lieberman, M. B. (2021). Strategic responses to crisis. *Strategic Management Journal, 42*(2), O16–O27. https://doi.org/10.1002/smj.3161

BUSINESS INTELLIGENCE IN THE FUNCTION OF STRATEGIC DECISION-MAKING IN FOOTBALL

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Abstract

This paper explores the role of artificial intelligence (AI) in strategic decision-making in professional football clubs, using Luka Modrić's 2012 transfer to Real Madrid as a case study. A qualitative approach is applied, based on the analysis of secondary sources and one semi-structured expert interview. The aim is to show how contemporary AI tools could improve processes of player evaluation, future value simulations and transfer risk reduction. The results indicate that today's AI systems would significantly rationalise decision-making related to Modrić's transfer. The paper also highlights methodological limitations and offers recommendations for future research.

Key Words

Artificial intelligence; sports management; transfers; strategic decision-making.

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INTRODUCTION

According to Gabrijelić (1964), team sports require comprehensive engagement of bodily movements and psychophysical attributes such as speed, agility, strength and endurance. In addition, games place specific demands on the player's psyche. It is necessary to combine temporal and spatial relations in the movement of one's own players – one or more of them – with the movement of the ball and opponents. In such circumstances, the player must make quick and correct decisions that arise from the previous action while simultaneously directing the subsequent flow of the game. Ultimately, the player must choose the best possible solution at a given moment.

According to estimates by Encyclopædia Britannica, drawing on sources from FIFA's website, there are approximately 250 million football players worldwide in over 200 countries and territories. According to the Inside FIFA Professional Football Report (2023), approximately 128,694 active professional male footballers are playing in 3,986 clubs worldwide. It is also worth noting that the International Federation of Professional Footballers (FIFPRO) represents around 65,000 professional players.

In the contemporary context, technological development strongly influences the way decisions are made within sports clubs. Football clubs, which increasingly operate as professional organisations, are more and more reliant on data-driven systems to reduce risks and increase the efficiency of their investments. One of the most prominent areas in which these technologies are applied is the process of player selection and recruitment, i.e. transfers.

This paper aims to examine how the use of artificial intelligence tools would affect strategic decision-making in football clubs, with a special focus on the example of Luka Modrić's transfer to Real Madrid, and to compare how the decisions at that time were based on subjective assessments and media perceptions, and how modern tools could transform such decisions by grounding them in analytics, predictive models and simulations.

This article uses a qualitative research approach, with a case study as the primary method. The research focuses on Luka Modrić's transfer from Tottenham to Real Madrid in 2012, analysed as an example of strategic decision-making in modern football management. The key primary source is a thematic interview with Giovanni Branchini, a prominent international football agent and sports management expert actively involved in numerous high-level transfers in European football. The interview was conducted on 11 August 2025 and structured around topics of business intelligence, the use of artificial intelligence in transfer strategies, and player evaluation through advanced metrics and analytics. Alongside the interview, the article draws on secondary sources: archival sports reports, media analyses, expert commentaries from the time of the transfer itself, and current academic and professional literature on the use of artificial intelligence, big data analytics, sports metrics and business intelligence in the sports context. The methodological approach aims to provide a multidimensional view of the process of strategic decision-making in professional football, encompassing sporting, financial and communication aspects of management. Branchini's interview serves as a valuable source of insight into the changes that have occurred in this field over the past decade.

The research employs a qualitative methodological framework based on a case study. The primary data source is a semi-structured thematic interview with international football agent Giovanni Branchini, conducted on 11 August 2025. The interview lasted 48 minutes, was audio-recorded and transcribed for analysis. The questions were organised into three thematic blocks: (1) the use of business intelligence and AI in sports management, (2) the evolution of the transfer market, and (3) analysis of the Modrić–Real Madrid case.

Secondary sources include sports archives, media analyses, academic literature on AI, scouting and sports metrics, as well as available historical statistical databases. Data analysis was conducted using thematic analysis, identifying key patterns in the interviewee's narrative and comparing them with the relevant literature.

Methodological limitations include reliance on a single interview, the retrospective nature of the interpretation, and the inability to obtain confidential financial and technical internal data from clubs.

IMPORTANCE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence has broad application across various sectors (economy, education, services), but in the context of this paper, its role in data analysis, prediction and decision-making is particularly important, as this is directly applicable to football transfers and sports management.

Recent studies on the application of artificial intelligence in sports management emphasise the importance of data and algorithms in processes such as scouting, player assessment, injury prevention and financial analysis (Davenport & Ronanki, 2018; Wamba-Taguimdje et al., 2020). Sports organisations increasingly use AI models to predict market trends, optimise tactical decisions and evaluate players through advanced metrics (StatsBomb, Opta, Wyscout). Research also points to challenges in the implementation of AI, including a lack of model transparency, ethical dilemmas and the risk of algorithmic bias (Sandvig et al., 2016). This theoretical framework allows for a better understanding of the case study findings presented below.

Before defining the concept of artificial intelligence, it is necessary to understand the meaning of the word intelligence. Singbo (2008) states that intelligence represents an individual's ability to cope successfully with new and unfamiliar situations, and it can also be defined as a general capacity for thinking, which is crucial for problem-solving and adapting behaviour in specific circumstances. On this basis, artificial intelligence (AI) seeks to replicate such a capacity.

The concept of artificial intelligence (AI) appeared in 1943 in a scientific paper by Warren McCulloch and Walter Pitts. Although their contribution was crucial, the development of modern artificial intelligence is most often associated with mathematician Alan Turing and his concept of an abstract machine from 1936, which laid the theoretical foundations for the development of computer science and AI (Warwick, 2012).

The term “artificial intelligence” was first used by John McCarthy, an American computer scientist and cognitive scientist, at the only academic conference dedicated to this topic (Smith et al., 2006). According to Prister (2019), “artificial intelligence is a branch of computer science that develops the ability of computers to perform tasks that require intelligence, such as coping with new situations, learning new concepts, drawing conclusions and understanding natural language.”

AI tools are already being used in areas such as dynamic attribution and online targeting. Tiautrakul and Jindakul (2019) also identify key-user identification as one of the fields in which artificial intelligence is taking over in digital marketing.

Nevertheless, it is difficult to translate informal knowledge into a precise formal sense suitable for logical notation, because it often involves subjective, contextual and implicit aspects, and a theoretical solution will not necessarily solve a concrete problem in practice (Eriksson, Bigi & Bonera, 2020).

On the other hand, according to Korteling et al. (2021), the amount of cognitive information a human can consciously process is very limited – the capacity of working memory is approximately ten to fifteen bits per second. Moreover, cognitive knowledge and related skills, such as memory, decline over time significantly more than perceptual-motor abilities, which means that we easily forget a large part of what we have learned. For machines, natural language processing systems enable them to read and understand written human language through semantic indexing (Shabbir & Anwer, 2018). Human information processing is prone to cognitive biases that manifest as systematic and recurring tendencies, inclinations or emotional states, often resulting in inaccurate or erroneous decisions (Korteling et al., 2021).

Despite these early theoretical contributions, attempts to build machines that truly think and communicate with humans have not fully realised Turing’s vision. As Deutsch (2011) notes, in the 65 years since Turing’s paper, the search for “thinking machines” has not yielded concrete results. At the same time, computer science and technology as a whole have made remarkable progress.

The characteristics that distinguish human from artificial intelligence can be divided into several groups. The ability to think, for example, is limited in machines by the absence of emotions, which can be detrimental in emotionally demanding situations; machines attempt to compensate for this through statistical approaches based on neural networks (Shabbir & Anwer, 2018).

According to Eriksson, Bigi and Bonera (2020), for a computer to successfully pass the Turing test, it must possess a set of specific capabilities such as natural language processing, knowledge storage, automated reasoning and machine learning that enable it to recognise patterns and adapt to new circumstances. In this context, ChatGPT – a chatbot based on the large language model GPT-4 developed by the US company OpenAI – represents a significant step forward in the development of this technology and is described as a broad discipline concerned with creating and modifying intelligent machines, whose ability is to perform tasks that typically require human intelligence (Marr, 2023).

Wamba-Taguimdje et al. (2020) define AI as a set of theories and techniques that enable the creation of machines capable of simulating intelligent behaviour with minimal need for human intervention. Copeland (2014) adds that AI implies the ability of a digital computer or computer-controlled robot to perform tasks that are usually associated with human beings.

Although artificial intelligence evaluates human thought through a cognitive modelling approach, this approach rests on the assumption that it is possible to understand how humans think. Furthermore, by defining a theory of human thinking in this way, it can be translated into a computer program that imitates mental processes. Consequently, the reasoning of such a program can be compared with the way a human approaches the solution of the same problem. On the other hand, machines can perform much faster and more complex tasks than humans – for example, an ordinary calculator in a mobile phone can carry out calculations that are a million times more complex in a significantly shorter time (Korteling et al., 2021).

According to Shabbir and Anwer (2018), AI today can imitate human intelligence by performing various tasks requiring reasoning, learning, problem-solving and decision-making. The same authors argue that planning and creativity enable humans to solve problems by combining available elements, but there is still no efficient way to transfer this capability to machines. Human actions are based on feelings and deep reflection, while artificial intelligence can operate only within the limits of prior programming and training. Machines do not have the ability to learn independently without predefined data and algorithms and cannot recognise objects, images, sounds or play games in the way humans do. Their perception is based on processing signals from sensors such as cameras and microphones, which is fundamentally different from human perception. While humans learn quickly and easily apply knowledge in new situations, computers struggle to generalise from limited samples.

Jordan (2019) considers artificial intelligence to be the “mantra of the current era” and argues that, regardless of whether we fully understand it soon or not, humanity faces the challenge of aligning computers and people in order to improve human life.

Davenport and Ronanki (2018) argue that human intelligence surpasses artificial intelligence in complexity, but at the same time is extremely effective in solving complex tasks, and its impact on the world and organisations is undeniably significant.

Therefore, the United Kingdom attaches great importance to ethics in the application of AI, emphasising innovation and creating an environment with the human being as the central factor in the development and application of artificial intelligence. This strategy, despite the UK’s exit from the EU, remains pro-European, highlighting the importance of ethical guidelines and mutual cooperation in the development of AI.

Adibi (2020) suggests that this would enable AI to develop its own values based on its own learning, and thus the ability to define its own feelings and needs.

When discussing ethics in the use of artificial intelligence, Sandvig, Hamilton and Langbort (2016) emphasise that one of the fundamental human rights is the right to enjoy human rights and fundamental freedoms without discrimination. Although algorithmic decision-making can offer advantages in speed and the volume of processed data, there is a danger that algorithms embed biases that are difficult to detect and/or correct.

It is therefore to be expected that artificial intelligence will increasingly change football – from how matches are analysed and training is planned to injury prevention and the way clubs communicate with fans. The tools we have today provide insight into aspects of the game that were previously almost impossible to see, so football is relying less on the coach's "eye" alone and more on data. Clubs that manage to use such technologies wisely can gain a real competitive edge.

In the future, AI is expected to penetrate even more deeply into all parts of football – from tactical analysis to personalised content for fans. However, no matter how advanced technology becomes, it is important that football does not lose what makes it special: unpredictability, emotion and human creativity on the pitch.

THE ROLE OF AI IN STRATEGIC DECISION-MAKING IN MODERN FOOTBALL CLUBS

In the book *Strategy and Structure*, Alfred Chandler defines strategy as "the determination of the basic long-term goals of an enterprise, and the adoption of courses of action and the allocation of resources necessary for carrying out these goals." In strategic management, the main focus is placed on the concept of "process" because it is a managerial activity that is continuous and constantly evolving. Such a process can be broken down into phases that are continually repeated within managerial activity. Accordingly, strategic management represents the process of defining long-term goals and determining the activities and resources required to achieve the desired future goals, as set by the top management of the organisation (Buble et al., 2005).

According to Buble et al. (2005), decision-making is a key managerial activity at all levels, but at the strategic level of the company, it occupies a central place in performing tasks and is present in all phases of strategic management. Since it is not possible to analyse all stages of decision-making simultaneously, the process of strategic decision-making in this context is equated with strategic choice, which includes three phases: generation, evaluation and final selection of options.

The use of business intelligence and artificial intelligence (AI) has become an indispensable tool in strategic decision-making within professional football clubs. From scouting and opponent analysis to financial management and risk assessment, modern clubs increasingly use data and algorithms to make informed decisions. Artificial intelligence in sport is not only a matter of technical support; it is becoming an integral part of strategic decision-making. The strategy for developing the sporting function of the club includes top-level recruitment of world-class players, scouting of talents and developing young players through the club's own academy, while at the same time using the concept of "non-match days" to generate additional revenue through stadium tours, non-sports events and hospitality services (Adcroft, 2015).

Application in scouting and player selection

Sports selection is the process of choosing talented individuals whose potential suggests that they will, in the future, be capable of handling a very demanding training process and are likely to achieve top competitive results (Milanović, 2010).

The analysis of sports activity provides valuable information that is crucial for programming learning and training processes, as well as for assessing the degree to which technical-tactical knowledge has been acquired. Such analysis helps define criteria for the successful execution of technical elements and tactical solutions within a given sport. This becomes the basis for shaping training content, load levels and types of work, all to improve performance and increase athletes' success in competition (Milanović, 2013).

"Since footballers constantly change their running speed during a match, it is necessary to break down the distance covered into specific categories according to running speed (intensity)" (Marković & Bradić, 2008).

Football is full of complex and unpredictable situations, which makes it impossible to absolutely predict the course and outcome of events on the pitch. During the game, two processes occur simultaneously: on the one hand, there is constructive cooperation among players in organising and executing attacks, while on the other hand, the opposing team seeks to disrupt these actions through defensive tasks and ball recovery, thus protecting its own goal from conceding (Barišić, 2007).

According to Jelaska (2011), there are two standard approaches to studying performance factors in sport. The first, structural approach, is based on determining a differentially weighted linear combination of factors that can describe the equation of success, depending on the theory of sports performance and the sports activity. The second, functional approach, presents performance factors in interaction, i.e. as a process in which performance factors mutually interact to determine an athlete's performance and sporting achievement, which generates a nonlinear relationship among the observed relevant factors. These two approaches are not necessarily mutually exclusive.

Jadczak, Grygorowicz, Wieczorek and Śliwowski (2019) investigated static and dynamic balance in 101 first-division Polish footballers, grouped by playing position. Testing included the dominant and nondominant leg, static balance (with eyes open and closed) and dynamic balance on a DPPS device. Central midfielders showed better balance than goalkeepers (static, eyes closed) and all other positions (dynamic). Asymmetry between the legs was observed, likely due to the functional role of the nondominant leg in the game.

Unlike some other team and individual sports, football does not require a highly specific body type. Both shorter and taller athletes can be successful, which is supported by the fact that the average height of professional footballers is 181 cm, while the average body mass is 75 kg. Goalkeepers and central defenders are usually somewhat taller than average. Body fat percentage in elite players ranges from 9 to 12% (Marković & Bradić, 2008).

Endurance, defined as the ability to resist fatigue and maintain a high intensity of activity over a longer period, is crucial for footballers because it allows them to display their full technical-tactical skills throughout 90 minutes. It is important that endurance is developed through tasks with the ball, which increases players' motivation (Schnabel, Harre & Borde, 1997).

Coordination is the ability to quickly perform complex motor tasks and to synchronise body movements with the ball, and its development is essential for effectively solving situational motor tasks during the game (Čolakhodžić, Rađo & Alić, 2016). Agility, or the ability to change direction quickly without losing balance and control, is extremely important because football requires numerous unpredictable and rapid changes of movement (Pearson, 2001). Although flexibility is not a key motor ability in football, it is a prerequisite for the quality execution of movements and optimal utilisation of other abilities such as explosive strength and agility. Optimal flexibility also reduces the risk of injury. Balance is important for controlling all types of kicks, dribbling and defensive tasks and plays a significant role in preventing foot and knee injuries (Marković & Bradić, 2008). Accuracy – expressed as the ability to pass and shoot precisely – develops through a combination of speed, coordination, strength and endurance, which is important in a dynamic and fast football environment (Čolakhodžić, Rađo & Alić, 2016).

Krespi, Sporiš and Mandić-Jelaska (2018) conducted a study on 158 Croatian footballers aged 17–18, comparing the effects of exponential and linear tapering protocols over eight weeks. Motor and functional abilities were measured. Forwards showed the greatest improvements in sprinting and agility, goalkeepers in jumping, and midfielders in repeated sprints. The exponential protocol produced slightly better results, especially in the 30-metre sprint.

According to Marković and Bradić (2008), during a football match, players perform a large number of different activities and movements, with and without the ball. High- and low-intensity intervals alternate unpredictably every 4 to 6 seconds, leading to an average of 1,200 to 1,400 activity changes per match. As many as 95% of these activities occur without direct contact with the ball. The same authors claim that elite players cover between 10 and 13 kilometres per match, while goalkeepers run about 4 kilometres. In younger age groups (U12–U20), these values are somewhat lower and range from 6.2 to 11.5 kilometres. On average, players perform

30–35 sprints, 15–20 duels, 10 jumps, 600–800 turns, 40 stops, 20 dribbles and around 30 passes per match.

Because of such demands, a high level of functional-motor abilities is required for players to maintain a high level of performance throughout the entire match. Physiological load – what happens inside the body during the game – is particularly important. One of the most commonly used indicators for assessing internal load is heart rate, expressed as a percentage relative to maximum heart rate. Furthermore, Marković and Bradić (2008) state that a footballer uses around 330 litres of oxygen and expends about 1,650 kilocalories during a match, which, in the context of physiological abilities, leads to the conclusion that aerobic endurance plays a key role. The authors therefore conclude that the aim of training is not to develop aerobic capacity to its absolute maximum, but to develop an acyclic form of aerobic endurance, since players move randomly and situationally across the pitch in line with their position and the flow of the game. An indicator of aerobic capacity is maximal oxygen uptake (VO_2max), whose values in footballers average between 60 and 65 ml/kg/min and are highly correlated with total distance covered during a match.

Since football belongs to the group of complex sports activities, an elite player is characterised by a high level of development in a large number of motor abilities. Strength in football manifests itself in various activities such as take-off in jumps, push-off in sprints, stopping and changing direction, as well as in duels and heading or kicking the ball. Increasing strength is important not only for performance, but also for reducing injury risk and speeding up recovery (Bangsbo, 1994). Speed in football is most often seen in sprinting, which includes the speed of individual movements and their frequency. Most authors agree that speed is largely genetically determined, even up to 95%, while training can influence it only to a limited extent (Marković & Bradić, 2008). Endurance, defined as the ability to resist fatigue and maintain high-intensity activity over time, is crucial for footballers because it allows them to demonstrate their technical-tactical knowledge over the full 90 minutes. It is important that endurance is developed through ball-based tasks, which increases athletes' motivation (Schnabel, Harre & Borde, 1997).

Coordination is the ability to quickly perform complex motor tasks and synchronise body movements with the ball, and its development is essential for effectively solving situational motor tasks during play (Čolakhodžić, Rađo & Alić, 2016). According to Pearson (2001), agility – the ability to change direction quickly without losing balance and control – is extremely important because football involves numerous unpredictable and rapid changes of movement. Although flexibility is not a key motor ability in football, it is a prerequisite for quality movement execution and optimal use of other abilities such as explosive strength and agility. Optimal flexibility also reduces the risk of injury. Balance is crucial for control of all types of shots, dribbling and defensive tasks, and plays an important role in preventing injuries to the feet and knees (Marković & Bradić, 2008), while Čolakhodžić, Rađo and Alić (2016) argue that accuracy – the ability to pass and shoot precisely –

develops through a combination of speed, coordination, strength and endurance, which is important in a dynamic and fast football environment.

Predictive analytics

Nyce (2007) defines predictive analytics as a broad term encompassing various statistical and analytical techniques used to develop models that aim to predict future events or behaviours, where the form of the model is adapted to the specific event or behaviour to be predicted; most of these models generate a criterion whereby a higher score indicates a greater likelihood of a given event or behaviour occurring.

Abbott (2014), on the other hand, views predictive analytics as the process of discovering interesting and significant patterns in data, relying on several interrelated disciplines that have been used for over a hundred years to identify such patterns, including pattern recognition, statistics, machine learning, artificial intelligence and data mining.

According to Bakhshi and Bates (2018, p. 2), predictive analytics is a technology that uses statistical methods and machine learning techniques to analyse data, uncover hidden patterns and predict future events, all to make better business decisions. In today's business environment, it has become indispensable because it enables organisations to improve efficiency, reduce risks and increase productivity, and its applications range from finance to healthcare.

Many studies offer different definitions of predictive analytics. Kelleher and D'Arcy (2015) argue that modern organisations collect large amounts of data, but in order for these data to be useful, they must be analysed and turned into insights that help in making better decisions. The same authors define predictive analytics as the art of using models that, based on patterns in historical data, can make predictions.

As Pavlović and Dejanović (2014, p. 761) note, predictive analytics is based on technologies such as machine learning, statistics and natural language processing, and is used to analyse data to predict future events. In a business context, it enables companies to predict market trends, consumer preferences and competitor behaviour, to optimise business processes, improve customer relationships, and identify and manage risks. However, the authors emphasise that predictive analytics should not be used merely for the sake of employing advanced technology; rather, its application should be carefully directed towards genuinely improving business decisions and outcomes.

Predictive analytics is described as the application of human skills, expertise and technologies such as machine learning to extract, analyse and transform data into clear forms used for planning and decision-making, whereby algorithms identify patterns in data and forecast future outcomes. From these definitions, it is clear that people, tools and algorithms are key to predictive analytics, which is future-oriented and based on generating data-driven forecasts (Ogunleye, 2014).

According to Kumar and Garg (2018), all predictive analytics models fall into two categories: classification models, which predict class membership, and regression models, which predict numerical values. Among the most commonly used techniques are decision trees, which visualise decisions and their consequences, and regression, which models the relationship between dependent and independent variables.

Artificial neural networks enable complex pattern modelling, while Bayesian statistics uses conditional probabilities for prediction. Ensemble learning combines multiple weaker models to achieve better accuracy, and support vector machines (SVM) classify data using an optimal hyperplane. Time-series analysis predicts future values based on historical data, while principal component analysis (PCA) reduces dimensionality while retaining key information (Kumar & Garg, 2018).

The process of model building is a combination of science and craft, guided by a simple routine procedure in which intuition and experience play an important role at every step. According to Wu and Coggeshall (2012), the basic steps include defining the goals and purpose of the model, collecting the available data and assessing their quality, choosing an appropriate model structure depending on the type of data and purpose, preparing the data through coding and normalisation, selecting and eliminating relevant variables, building and evaluating the model with particular attention to the implementation environment, and finally drawing conclusions, documenting, implementing and monitoring model performance during use.

In general, a model is defined as a representation of something, which can be static or dynamic. A static model, for instance, may be a woman walking a fashion runway in new designer clothes, showing how a person would look in those garments, while dynamic models involve sets of equations that describe processes such as fluid dynamics, traffic flows in cities or the oscillation of stock prices over time (Wu & Coggeshall, 2012).

RESULTS

Giovanni Branchini is an Italian football agent (Globe Soccer, 2025) with more than 20 years of experience representing some of the biggest names in world football. During his career, he has worked with legends such as Manuel Rui Costa, Hidetoshi Nakata, Romário, Ronaldo, Jean-Pierre Papin and many others. A special place is occupied by Clarence Seedorf, the only player to have won four UEFA Champions League titles with three different clubs – Ajax, Real Madrid and AC Milan. In 1986, together with Carlo Pallavicino, he founded the agency “Branchini Associati”, which has been involved in some of the most important transfers in modern football: from Cristiano Ronaldo’s move from Sporting to Manchester United to Luca Toni’s and José Sosa’s transfers to Bayern Munich. Today, Branchini also represents several Italian internationals, including Marchisio, Montolivo and Pepe. Among Croatian footballers (Buškulić, 2022), Branchini has represented Boban, Šuker, Mandžukić and Perišić, and together with one of the authors of this paper, who was also part of his international management team (author’s note: author Damir Mihanović), he represented Marcelo

Brozović and negotiated a record-breaking contract with Italian giants Inter Milan.

In the semi-structured interview with Mr Branchini, the development of global football brands, the role of artificial intelligence in modern transfers, and the historic transfer of Luka Modrić from Tottenham to Real Madrid are analysed. Although Real Madrid needs no special introduction, it is worth recalling that the club is a prime example of a global brand which, thanks to technology and artificial intelligence, generates high revenues. Comparing Modrić's 2012 transfer with contemporary decision-making approaches, Giovanni Branchini points out clear differences between the analysis systems then and now. The transfer at the time was largely based on the personal impressions of scouts and managers, perceptions of potential and the influence of the media. Branchini believes that such a transfer today would be significantly rationalised through the use of AI tools.

AI systems are also used in medical and conditioning areas – by tracking microtraumas, fatigue and biomechanical deviations. AI analyses data in real time and helps to optimise training and prevent injuries, which is extremely important for protecting investments in players. According to Branchini, Modrić's transfer from Tottenham to Real Madrid was a key moment in the development of the club as a global brand and sports organisation. Decision-making processes in modern football require integration of sports analytics, financial data and market trends. Although AI enables clubs to precisely assess player value and transfer strategies, Branchini believes that top-level football agents and managers who have an "instinct" for the player – who will fit into the team and contribute to club goals – will continue to play an important role in the future.

Branchini explains that in Modrić's case, although data on sporting performance, finances and the market were used at the time, the success of that transfer is measured not only through sporting results, but also through increased revenue, a stronger image and the global expansion of the Real Madrid brand. He particularly emphasises the importance of advanced metrics such as "expected passes under pressure", which quantify how successfully a player passes under opponent pressure, i.e. how effectively he distributes the ball in demanding situations. This metric, Branchini says, is particularly important for Modrić, who is known for his composure, intelligent decision-making and precise passing even when surrounded by opponents. A high value in this metric indicates technical superiority and coolness under pressure.

Part of the expert community had already recognised Modrić as a "silent engine" – a player who initiates attacks, accelerates play and controls the tempo. Branchini points out that through advanced metrics such as ball progression metrics, it would be clearly visible how successfully Modrić moves the ball forward (more than 10–15 metres), how often he plays the ball into the final third or the penalty area. Analysing his performances from 2008 to 2012 using modern tools like StatsBomb, Opta or Wyscout would likely reveal high numbers of progressive passes, consistent progressive distance, carrying the ball through central areas and a large number of passes into the attacking third.

In defensive actions, Branchini explains, a player is usually measured by the number of tackles, ball recoveries, interceptions, blocks, one-on-one duels and regaining possession. “Defensive actions per zone” measures how active a player is in different phases of defence. Modrić, according to Branchini, showed positional intelligence and activity in the middle third, with the highest number of defensive actions in central zones, a solid number of interceptions in transition areas, and fewer interventions in deep defence or high pressing.

Another important metric is Pass Value Added (PVA), which shows the player’s actual impact on the flow of the game. Although Modrić was not a prolific assist provider, his passes built attacks, broke defensive lines and created advantages, which would be clearly reflected in high PVA values at Tottenham. Branchini emphasises that Modrić may have been modest in terms of goals and assists, but he had an extraordinary sense for the timely pass, forward-moving balls and passes that “cut” through defensive lines. An analysis of PVA would show that he consistently added value to the game in the middle and final thirds.

If such a transfer were being carried out today, all these data would be compared with players of a similar profile in compatible playing systems to assess his fit with Real Madrid’s tactical requirements. AI models could simulate his performance in La Liga, including comparisons with Real’s existing midfielders. The model would take into account the tempo of play in the Premier League and La Liga, the expected number of chances created and other parameters. The model would, Branchini argues, likely predict a positive long-term value for Modrić despite modest physical attributes, based on his technical superiority, intelligence and tactical flexibility.

In addition, modern tools would analyse online sentiment – posts on social networks, media articles and public perception of the player. Such data would be useful for assessing reputational risk and planning PR campaigns after the transfer. In conclusion, Branchini notes that with today’s systems, Modrić’s transfer would not be met with such scepticism. Artificial intelligence and advanced analytics would support the decision with objective indicators, reduce the impact of subjective opinions and sensationalism, and more clearly demonstrate his true value.

The results of the study show a strong contrast between the subjective nature of transfer decisions in 2012 and the objectivised models used by clubs today. Advanced metrics such as expected passes under pressure, ball progression metrics and Pass Value Added would, in contemporary conditions, enable a more detailed evaluation of Modrić already during his early Premier League seasons. AI-driven simulations of the player’s integration into Real Madrid’s tactical system would also demonstrate predictive value that traditional scouting could not provide at the time.

These findings confirm the existing literature highlighting AI’s capacity to reduce decision-making risk (Davenport & Ronanki, 2018; Kumar & Garg, 2018). However, they also align with research emphasising that AI cannot fully replace human intuition and experience in sports management (Jordan, 2019).

CONCLUSION

Strategic decision-making in professional sport, especially football, is increasingly relying on artificial intelligence (AI) as an extremely useful tool for making informed and long-term sustainable decisions. By analysing the case of Luka Modrić's transfer from Tottenham to Real Madrid in 2012, and comparing it with today's approaches to managing sporting assets, it has been shown that the use of advanced analytical systems and AI tools could improve the process of player evaluation, quantify his potential value, reduce reputational risk and speed up decision-making.

The interview with leading sports agent Giovanni Branchini confirmed that sports organisations such as Real Madrid have for years been at the forefront of integrating sporting, financial and marketing strategies. Branchini points out that today's AI systems would easily recognise the value of a player like Modrić by analysing metrics such as expected passes under pressure, ball progression metrics and pass value added, and by simulating his integration into a specific playing system.

However, alongside the undeniable advantages of BI and AI systems, there is also room to reflect on the ethical dimensions of decision-making. Artificial intelligence, no matter how advanced, cannot replace the human capacity for moral reasoning, critical thinking and free will. As Brajnović warns, machines cannot possess awareness of good and evil, nor can they bear responsibility for the consequences of their "decisions". Therefore, the use of artificial intelligence in sports management – as in journalism and other professions – should always remain a tool in the service of humans, not a substitute for human judgment.

The limitations of this research include a small sample (one interview), retrospective analysis and the absence of quantitative AI models due to limited access to official databases. Future research should include a larger number of experts, comparative analyses of different transfer cases and the application of real AI models for simulating player value.

In conclusion, the results of this study show that business intelligence and artificial intelligence have significant transformative potential in the strategic management of sports organisations, especially in the areas of scouting, transfer policy, squad optimisation and performance monitoring. However, long-term success requires not only technical sophistication, but also ethically grounded, professional and responsible public decision-making.

REFERENCES

Abbott, D. (2014). *Applied predictive analytics: Principles and techniques for the professional data analyst*. John Wiley & Sons.

Adibi, J. (2020). *What is (Real) Artificial Intelligence*. Retrieved from https://thenewstack.io/what-is-real-artificial-intelligence.pdf

Adcroft, A. (2015). The university leadership conundrum. *Perspectives: Policy and Practice in Higher Education, 19*(2), 1–7.

Bakhshi, S., & Bates, M. (2018). *Predictive analytics: The power to predict who will click, buy, lie, or die*. John Wiley & Sons.
Bangsbo, J. (1994). *Fitness training in football: A scientific approach*. HO + Storm.
Barišić, V. (2007). *Kineziološka analiza taktičkih sredstava u nogometnoj igri* (Doktorska disertacija). Kineziološki fakultet Sveučilišta u Zagrebu.
Branchini, G. (2023). Osobni intervju, 11. kolovoza 2023.
Britannica. (n.d.). Football (soccer). *Encyclopaedia Britannica*. Retrieved September 9, 2025, from https://www.britannica.com/sports/football-soccer
Buble, M., Cingula, M., Dujanić, M., Dulčić, Ž., Gonan Božac, M., Galetić, L., Ljubić, F., Pfeifer, S., & Tipurić, D. (2005). *Strateški menadžment*. Sinergija nakladništvo.
Buškulić, A. (2022, March 23). Brozović potpisao za 60 mil. €. *24sata*. Retrieved September 18, 2025, from https://www.24sata.hr/sport/brozovic-potpisao-za-60-mil-eur-kada-gledam-patnju-ukrajinaca-vidim-koliko-sam-sretan-covjek-822326
Carter, D. (2018). How real is the impact of artificial intelligence? The Business Information Survey 2018. *Business Information Review, 35*(3), 99–115. https://doi.org/10.1177/0266382118790150
Copeland, B. (n.d.). Artificial intelligence (AI). *Encyclopaedia Britannica*. Retrieved August 24, 2025, from http://www.britannica.com/EBchecked/topic/37146/artificial-intelligence-AI
Čolakhodžić, E., Rađo, I., & Alić, H. (2016). *Tehnologija treninga mladih nogometaša – nauka i praksa*. Nastavnički fakultet Univerziteta "Džemal Bijedić".
Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Retrieved August 20, 2025, from https://www2.deloitte.com/content/dam/Deloitte/us/Documents/deloitte-analytics/us-deloitte-analytics-hbr-ai-for-the-real-world.pdf
Deutsch, D. (2011). *The beginning of infinity*. Penguin Books.
Eriksson, T., Bigi, A., & Bonera, M. (2020). Think with me, or think for me? On the future role of artificial intelligence in marketing strategy formulation. *The TQM Journal, 32*(4), 795–814. https://doi.org/10.1108/TQM-12-2019-0303
European Parliament. (2020). *Artificial intelligence: Opportunities and threats*. Retrieved August 17, 2025, from https://www.europarl.europa.eu/doceo/document/TA-9-2020-0275_HR.html
Gabrijelić, M. (1964). *Nogomet – teorija igre*. Sportska štampa.
Globe Soccer. (n.d.). Giovanni Branchini – Speaker. Retrieved July 18, 2025, from https://www.globesoccer.com
Inside FIFA. (2023, June 14). *FIFA publishes professional football report 2023*. Retrieved from https://inside.fifa.com/legal/news/fifa-publishes-professional-football-report-2023
Jadczak, Ł., Grygorowicz, M., Wieczorek, A., & Śliwowski, R. (2019). Analysis of static balance performance and dynamic postural priority according to playing position in elite soccer players. *Gait & Posture, 74*, 1–6.
Jelaska, I. (2011). *Konstrukcija i aplikacija novog modela za evaluaciju uspješnosti u kompleksnim sportskim aktivnostima* (Doktorska disertacija). Kineziološki fakultet Sveučilišta u Splitu.
Jordan, M. I. (2019). Artificial intelligence—The revolution hasn't happened yet. Retrieved August 12, 2025, from https://hdsr.mitpress.mit.edu/pub/wot7mkc1/release/5
Kelleher, D. J., Namee, M. B., & D'Arcy, A. (2015). *Fundamentals of machine learning for predictive data analytics*. MIT Press.
Korteling, J. E., van de Boer-Visschedijk, G. C., Blankendaal, R. A. M., Boonekamp, R. C., & Eikelboom, A. R. (2021). Human versus artificial intelligence. *Frontiers in Artificial Intelligence*. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8108480/
Krespi, M., Sporiš, G., & Mandić-Jelaska, P. (2018). Effects of two different tapering protocols on fitness and body composition in young soccer players: Positional differences. *Acta Kinesiologica, 12*(1), 48–57.
Kumar, V., & Garg, M. (2018). Predictive analytics: A review of trends and techniques. *International Journal of Computer Applications, 182*(1), 12–19.
Marković, G., & Bradić, A. (2008). *Nogomet – integralni kondicijski trening*. Udruga "Tjelesno vježbanje i zdravlje".

Marr, B. (2023, May 19). A short history of ChatGPT: How we got to where we are today. *Forbes*. Retrieved August 16, 2024, from https://www.forbes.com/sites/bernardmarr/2023/05/19/
Miklosik, A., Kuchta, M., Evans, N., & Štefan, Ž. (2019). Towards the adoption of machine learning-based analytical tools in digital marketing. *IEEE Access, 7*, 85705–85718. https://doi.org/10.1109/ACCESS.2019.2924425
Milanović, D. (2010). *Teorija treninga: Primijenjena kineziologija u sportu* (2. izd.). Kineziološki fakultet.
Milanović, D. (2013). *Teorija treninga*. Kineziološki fakultet Sveučilišta u Zagrebu.
Nyce, C. (2007). *Predictive analytics white paper*. American Institute for CPCU.
Ogunleye, J. (2014). The concepts of predictive analytics. *International Journal of Developments in Big Data and Analytics, 1*(1), 30–45.
Pavlović, R., & Dejanović, R. (2014). Big data i poslovna inteligencija. *Infoteh-Jahorina, 13*(1), 759–764.
Pearson, A. (2001). *Speed, agility and quickness for soccer*. A&C Black.
Prister, V. (2019). Umjetna inteligencija. Hrvatsko komunikološko društvo & Hrvatska radiotelevizija. Retrieved August 4, 2025, from https://hrcak.srce.hr/file/322184
Sandvig, C., Hamilton, K., & Langbort, C. E. (2016). When the algorithm itself is a racist: Diagnosing ethical harm in the basic components of software. *International Journal of Communication, 10*, 4972–4992.
Schnabel, G., Harre, D., & Borde, A. (1997). *Trainingswissenschaft*. Berlin.
Shabbir, J., & Anwer, T. (2018). Artificial intelligence and its role in near future. Retrieved August 19, 2025, from https://arxiv.org/abs/1804.01396
Singbo, O. G. (2008). Umjetna inteligencija u suvremenom biokibernetičkom svijetu. *Spectrum: Ogledi i prinosi studenata teologije, 3–4*, 45–61.
Smith, C., McGuire, B., Huang, T., & Yang, G. (2006). *The history of artificial intelligence*. University of Washington.
Tiautrakul, J., & Jindakul, J. (2019). The artificial intelligence (AI) and the future of digital marketing. Retrieved August 26, 2025, from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3405184
Wamba-Taguimdje, S.-L., Fosso Wamba, S., Kala Kamdjoug, J. R., & Tchatchouang Wanko, C. E. (2020). Influence of artificial intelligence on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal, 26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411
Warwick, K. (2012). *Artificial intelligence: The basics*. Routledge.
Wu, J., & Coggeshall, S. (2012). *Foundations of predictive analytics*. CRC Press.

APPENDIX

Interview with Giovanni Branchini conducted on August 11, 2025.

Interview

Authors: Mr Branchini, you have been active in the highest levels of football management for decades. When you look back today at Luka Modrić's transfer from Tottenham to Real Madrid in 2012, how much has the decision-making process for such transfers changed?
Branchini: It has changed almost completely. Back then, decisions were based on experience, scouts' and managers' impressions, personal assessments, and perceptions of potential. Today, the process is far more sophisticated. Clubs use artificial intelligence (AI) tools and large databases to reduce risk and accurately assess player value. A transfer like Modrić's today would be much faster, safer, and based on objective indicators—precisely thanks to technology.

Authors: What exactly do you mean by "technology" in the context of scouting and transfer decisions?
Branchini: Today, a whole range of analytical systems is used. For example, advanced metrics such as *Expected Passes Under Pressure* measure how well a player can retain and distribute the ball while under pressure. Luka Modrić excels in precisely this. His ability to remain calm and deliver accurate passes even in the most dangerous areas of play makes him perfect for this kind of analysis. Today, we could easily quantify his impact on the flow of the game.

Authors: So, if such a transfer were happening today, the numbers would immediately "speak in his favour"?
Branchini: Absolutely. Modrić would shine in modern metrics such as *Ball Progression Metrics,* which measure how much a player advances the ball toward the opponent's goal. There's also *Pass Value Added (PVA),* which shows how much a pass increases the chances of scoring. Even though Luka was never a player with a high number of assists, his passes consistently "cut through" defensive lines and enabled attacking buildup. Today, his true value would be clearly reflected in the numbers.

Authors: To what extent did Real Madrid recognise the importance of linking the sporting and business segments?
Branchini: Real Madrid was already ahead of its time. Through Real Madrid Television, digital marketing, international brand expansion, and leveraging the image of their players, they managed to turn the club into a global brand. Luka Modrić's transfer was not only a sporting acquisition but also a business move. He became the face of campaigns, part of international marketing, and contributed to the club's revenue growth.
Authors: Can we say that Modrić's transfer was an example of an integrated approach?

Branchini: Exactly. At top clubs today, there is no longer a strict boundary between sport, finance, and marketing. All of these segments are connected through business intelligence and AI analytics. In Modrić's case, his sporting performance, market value, and ability to strengthen Real Madrid's brand were all considered. The result? One of the most successful transfers in modern history.

Authors: How important are defensive metrics today, such as "defensive actions per zone"?
Branchini: Extremely important. The *Defensive Actions per Zone* metric shows where a player is most active defensively. Modrić, for example, was not a classic ball-winner, but he was extremely active in the middle third, where he intercepted passes and regained possession. Such metrics help coaches and managers to precisely understand a player's role—and where on the pitch he brings the most value.

Authors: Has artificial intelligence also entered the field of fitness preparation and injury prevention?
Branchini: Absolutely. AI is now used in the medical segment too—it tracks microtraumas, fatigue, and biomechanical deviations. Real-time systems analyse data from players' sensors and help optimise training and prevent injuries, which is extremely important for protecting investments in players. That's another example of how much management has changed.

Authors: Do you think Modrić's transfer would be met with less scepticism today?
Branchini: Without a doubt. At the time, the media and some of the public doubted his physical readiness and suitability for La Liga. Today, AI models could simulate his performance in the league, compare him with other midfielders, and analyse his compatibility with the coach's tactics. Additionally, the systems would take into account the rhythm of play in the Premier League and La Liga, the expected number of chances created, and even online sentiment—social media posts, reputational risk, media image. Such an analysis would clearly show that he is a player of exceptional long-term value.

Authors: Finally, how do you see the future of football management?
Branchini: The future is already here. Football management today demands integration of data, technology, and human judgment. AI can suggest the ideal transfer, but you still need human instinct to recognise a player's character. The combination of those two factors creates success. And Modrić? He is an example of how—even before the data era—the right people could recognise a genius.

Authors: Thank you for the interview, Mr Branchini.
Branchini: Thank you. Football changes, but one thing remains the same—the value of true players is always recognised, regardless of technology.

COMPARATIVE ANALYSIS OF STAKEHOLDERS PERCEPTIONS ON DIGITALISATION AND ADVANCED TECHNOLOGIES IN TOURISM

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Abstract

The purpose of the paper is to provide qualitative insight into perceptions and experiences of key tourism stakeholders regarding digitalisation and advanced technologies (D&AT). With comparing those perceptions and experiences across scholars, public institution representatives and practitioners (triangulation) in two European countries, Slovenia and Montenegro, the object of the research is to reveal the dimensions of technological adoption in a specific industry and geographical context. Interviews explored three thematic areas: a) understanding of D&ATs, b) perceived advantages, and c) challenges and concerns associated with D&ATs. Data were collected from 27 interviewees and analysed using content analysis, applying thematic coding and matrixes. The findings reveal that while D&ATs in tourism are generally welcomed for their potential to enhance efficiency and service delivery, significant concerns persist regarding the loss of human-to-human interaction, varying levels of

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technological competence, and the strategic use of data. Countries at different stages of technological maturity perceive and experience these issues in distinct ways, yet, the tension between technological advancement and human-centred tourism persists across borders.

Key Words

Digitalisation; advanced technologies; advantages and challenges; Tourism 4.0.

INTRODUCTION

After 2011, the hype around Industry 4.0 (Ghobakhloo et al., 2021) announced the era of digitalisation and the Cyber Physical Systems (Alcácer & Cruz-Machado, 2019). The pillars and technologies of Industry 4.0 have gradually penetrated to other economic sectors, including to tourism. According to Bilotta et al. (2021), technologies of Industry 4.0 have perfectly fit with the new paradigm of Tourism 4.0 and gradually transformed tourism system.

The COVID-19 pandemic and the post-pandemic period offered excellent opportunities for the digital transformation of tourism and hospitality (Noung & Ragawan, 2023). Tourism service providers increasingly implemented technological solutions with minimal human interaction, more so than before. The pace and extent of technological advancement were so rapid that various stakeholders in tourism struggled — mentally, physically, and culturally — to keep up in ways that would benefit them (Stankov & Gretzel, 2020).

Osei et al. (2020) highlight a research gap concerning the inclusion of advanced technologies (ATs) in tourism and hospitality research, particularly research about dimentions of technology adoption in the sector. Although the term digitalisation is widely used in academic literature, policy documents and industry practices, Bloomberg (2018) warns that its meaning remains unclear. There is still no consensus in tourism regarding which AT should be applied in Tourism 4.0 (Osei et al., 2020). Furthermore, several tourism scholars provide synthesis on advantages of D&ATs (e.g., Buhalis, 2020; Buhalis et al., 2023; Akiskali et al., 2022; Townsend, 2017), their challenges and concerns (Stankov & Gretzel, 2020; Pencarelli, 2019). Yet, researchers do not provide empirical evidence to support their assertions. We identified these as a knowledge gap and a problem, with our study contributing to its solution.

This paper intersects two relevant topics: tourism, as one of the fastest-growing economic sectors (World Travel & Tourism Council, 2024), and D&ATs, which remain a key priority in the field (Bekele & Raj, 2025). It is the first study to investigate diverse perspectives on these themes from three distinct stakeholder groups within the tourism sector. The extensive discussion on D&ATs at the International Tourism Exchange Convention in Berlin (ITB Berlin) in March 2025 underscores the ongoing relevance of this topic and the need for further research.

This study addresses three research questions (RQs):

RQ1: How are digitalisation and advanced technologies (D&ATs) understood among tourism stakeholders?

RQ2: What are the advantages of D&ATs in tourism?

RQ3: What are the challenges and concerns about D&ATs in tourism?

THEORY REVIEW

Tourism 4.0

Since the term Tourism 4.0 entered academic discourse, scholars have proposed various definitions. Stankov and Gretzel (2020) describe it as a vision of technology-driven transformation in the tourism sector, leading to a highly interconnected ‘phygital’ system — a fusion of physical and digital elements. Pencarelli et al. (2019) defines it as a new tourism value ecosystem, heavily based on advanced technological services and aligned with the principles of Industry 4.0 (e.g., interoperability, virtualisation, decentralisation, real-time data gathering and analysis, service orientation, modularity, etc.).

With the increasing implementation of D&ATs in tourism, new terminology has emerged in academic literature. Empowered to design and, at least partially, produce and consume their own experiences through technology, tourists have been labelled *co-creators* of their experiences (Buhalis, 2020; Neuhofer et al., 2013) or prosumers — simultaneously producers and consumers (Sigala, 2018; Ritzer & Jurgenson, 2010). The concept of the ecosystem has become widely adopted in the sector (e.g., Starc Peceny et al., 2019; Pencarelli et al., 2019; Buhalis, 2020). A range of new terms have been introduced into everyday lexicon and research agendas, such as Web 3 (Guan et al., 2022), metaverse (Wei, 2022), non-fungible tokens (Valeonti et al., 2021), etc.

New terminology and emerging technological solutions have created a broad scope for research into how D&ATs might be applied in tourism. However, they do not provide a unified understanding of how digitalisation in tourism is actually perceived, nor which types of ATs are considered key components of Tourism 4.0.

Digitalisation

While the term digitisation has a straightforward meaning (the process of converting information from analog to digital format so that it can be stored, processed, and transmitted by computers), digitalisation lacks a single, universally accepted definition. Some researchers approach to digitalisaton as to utilisation of digital technologies to alter and optimize existing business processes (e.g., distibution, communication, management) for the purpose of cost saivings, process enhancement, etc. (Bekele & Raj, 2025). Teubner and Stockinger (2020) describe it as the interaction between digital technologies and social as well as institutional processes. If we consider digitalisation in relation to social life and how people interact, it implies a shift from analog to digital forms of interaction (Bloomberg, 2018).

In a business context, digitalisation is understood as the use of digital technologies to alter business models, create new revenue streams, unlock value-producing opportunities, and transform business operations (Gartner Glossary, n.d.). Since it leverages digital technologies and data to transform both businesses and business ecosystems (Dredge et al., 2019), this definition is relevant and applicable in the tourism sector.

The term digitalisation is often used synonymously with the term digital transformation (Saariko et al., 2020). The terms are interconnected, but from a business point of view we need to differentiate them. The scope of digital transformation is broader than digitalisation and digital transformation usually follows digitalisation (Van Veldhoven & Vanthienen, 2021). Succesful digital transformation might be predicted through digital maturity (Jie et al., 2025), a measure of organisation's ability to create value through digital.

Advanced technologies (ATs)

In tourism, scholars have different approach to ATs in the sector. Starc Peceny et al. (2019) directly adopt certain ATs from Industry 4.0. In contrast, Buhalis et al. (2020) and Buhalis et al. (2023) provide an extensive list of relevant ATs, while Osei et al. (2020) identify only six key technologies that they believe are most practical for implementation. Table 1 illustrates the similarities and differences in how these groups of researchers understand the ATs in Tourism 4.0.

Table 1: Examples of ATs in Tourism 4.0

Starc Peceny et al. (2019)	Buhalis (2020), Buhalis et al. (2023)	Osei et al. (2020)
• High performance computing; • Big data analytics; • Cloud computing; • Internet of things (IoT); • Artificial intelligence (AI); • Wireless connectivity; • Smart sensory; • Virtual reality; (VR); • Augmented reality (AR); • Location based services.	• Fifth-generation mobile network (5G); • Artificial intelligence (AI); • Radio frequency identifications (RFID); • Mobile devices; • Smart phones; • Smart wearables; • Blockchain and cryptocurrencies; • Applications; • Virtual reality (VR); • Augmented reality (AR); • Autonomous devices or agents; • Location based services (including social media); ---------------------------	• Cyber-Physical systems; • Cloud computing; • Internet of things, • Artificial intelligence; • Big data; • Robotics.

	• Internet of Everything; • Machine learning; • Three-dimensional printers; • Metaverse.

Most existing studies on D&ATs in tourism focus on the conceptualisation of individual technologies, their technical descriptions, potential applications, or suggested research agendas. Only studies concerning service robots provide empirical findings (Zhang et al., 2023; Wu et al., 2023; Liu et al., 2023; Akiskali et al., 2022).

Advantages, challenges and concerns of implementing D&ATs in tourism

Buhalis (2020) provides a broad theoretical synthesis of the advantages that D&ATs have brought to tourism. These technologies have revolutionised communication and information search, enhanced networking dynamics, and facilitated the rise of peer-to-peer platforms and social media. From a management perspective, D&ATs support capacity management, operational efficiency, inventory control, yield and revenue management, financial planning, and reporting. In marketing, they enable more effective research and planning, online reservations and sales, customer relationship management, and personalised services. D&ATs have also transformed distribution channels through disintermediation and enabled review sites, allowing for rapid online word-of-mouth dissemination.

The interconnectivity and interoperability of integrated technologies have reengineered business processes and data flows, enabling innovative tourism services and maximising stakeholder engagement (Buhalis et al., 2023). The dynamic co-creation of experiences, personalisation, context adaptation, and the fluidity between physical and digital interactions have created a new tourism landscape, significantly different from the past, for both tourism service providers and tourists.

While Buhalis's (2020) presentation of D&ATs' advantages is compelling, several challenges and concerns are often overlooked in the existing literature. Stankov and Gretzel (2020) highlight the negative consequences caused by the rapid and high-impact adoption of D&ATs in the sector. They question whether these technologies genuinely enhance tourists' experiences as frequently claimed, noting the lack of empirical evidence and the repetition of untested assumptions. Reserchers highlight that in practice, the technological solutions of Tourism 4.0 may not be as human-centric as often portrayed.

Pencarelli (2019) similarly raises concerns, arguing that Tourism 4.0 places excessive emphasis on technological efficiency at the expense of real-life tourist experiences. Other issues include changes in organisational culture, as employee interaction shifts from people to technology (Akiskali et al., 2022), particularly when staff feel their jobs are threatened.

D&ATs also involve significant costs, including investments in installation, system inefficiencies, maintenance, parts replacement, insurance, and legal liability (Akiskali et al., 2022). Townsend (2017) identifies several "dark sides" of technology, including privacy issues, digital exclusion, knowledge and information loss, threats to language and culture, and the loss of human interaction. Buhalis (2020) adds ethical dilemmas to the list, while Stankov and Gretzel (2020) warn of health and well-being risks (e.g. eye strain from VR goggles, motion sickness, or exposure to harmful frequencies). Stankov and Gretzel (2020) are among the few scholars who also raise concerns about the substantial energy footprint of these technologies and risks associated with the digital footprint.

Another practical issue is the cognitive burden D&ATs may place on tourists, who are often required to engage intensively with systems or digital content (e.g., too many tasks, complex interfaces, unresponsive systems, etc.). This can have a distracting effect, especially for tourists who prefer to disconnect from technology during their vacations A counter-trend to D&ATs is evident in the growing popularity of digital detox tourism (Gong et al., 2023; Nasr, 2025).

METHODOLOGY

A qualitative research design was selected to obtain the most relevant answers to the research questions (RQs). Qualitative methods have been widely used in recent years in social science contexts (e.g., Fošner & Trop, 2024) and in tourism research (Jagodič et al., 2025; Frost & Frost, 2021; Pachlevan-Scarif et al., 2020; Airey, 2013). Corresponding methods and techniques were chosen for each step of the empirical research.

Data were collected in 2022 through field research involving 27 interviewees — representatives from three stakeholder groups (triangulation): scholars, public sector representatives, and practitioners, across two countries: Slovenia and Montenegro (for comparative purposes). Semi-structured interviews were chosen as they rely on direct, in-person interaction with participants.

Triangulation enhances the robustness of findings and is a key criterion in assessing the trustworthiness of qualitative research (Bans-Aukney &Tiimub, 2021; Decrop, 1999). In this study, each of the three stakeholder groups directly or indirectly contributes to the tourism supply side. We also examined whether their understanding of the topic differs.

Slovenia and Montenegro were selected to explore whether and to what extent external factors of the environment might influence perceptions across all groups. Although both counties are relatively small and geographically close, they differ in their economic models, political systems, socio-cultural contexts, and types of tourism offered.

Participants were chosen through convenience sampling — 10 from each group in each country. Invitations were extended to individuals believed to be capable of providing relevant insights. A total of 27 agreed to participate: 15 from Slovenia (five from each group) and 12 from Montenegro (four scholars, three public sector representatives, and five practitioners). Eighteen interviews were conducted in person, three via videoconference, and six participants submitted written responses via email. All interviews were conducted by the lead researcher and documented through written notes and audio recordings. Transcripts were prepared after each interview.

Data were analysed using content analysis. We followed the coding guidelines of Miles et al. (2014). Given the number of interviews and the richness of responses, we opted for manual thematic coding with the use of matrixes. The analysis proceeded through several steps:

- Detailed review of transcripts;
- Development of thematic codes;
- Independent marking of essential meanings by each researcher;
- Preparation of two first-round matrixes (one per country);
- Filling the matrixes with key ideas;
- Text condensation and quantification;
- Preparation of second-round matrixes.

Findings are presented descriptively, as a synthesis of interviewee responses. We use interpretive methods and quotations to highlight notable expressions or opinions from individual participants. Comparative insights between the two countries and among triangualtion gruops are discussed in the discussion section.

RESULTS

Results are presented in three subsections:

- Demographic statistics,
- Analysis of interviews from Slovenia,
- Analysis of interviews from Montenegro.

Interview analysis follows the thematic codes aligned with the research questions (understanding of D&ATs, advantages of D&ATs, challenges and concerns related to D&ATs). We begin analysis with the scholars' group, continue with public sector representatives, and end with practitioners.

Demographic statistics

Demographic information about participants from Slovenia and Montenegro is shown in Table 2. Gender distribution in both countries is nearly balanced. More than half of participants are between 30 and 50 years old. All scholar participants have the highest academic qualifications, while the majority of other participants from both countries hold higher or university-level education.

Table 2: Gender, age group and education level of participants from Slovenia (SLO) and Montenegro (MNT)

Criteria	Gender	Age group	Education
Triangulation	N	N	N
group	SLO	SLO	SLO
	MNT	MNT	MNT

Scholars	M F	2 3	4 0	> 30 y 30 – 50 < 50	0 3 2	1 0 4	vocational high/uni master, Phd	0 0 5	1 0 4
Public sector	M F	0 4	0 3	> 30 y 30 – 50 < 50	0 3 1	0 3 0	vocational high/uni master, Phd	0 3 1	1 2 0
Practitioners	M F	5 1	1 4	> 30 y 30 – 50 < 50	0 5 1	2 3 0	vocational high/uni master, Phd	1 5 0	3 2 0
TOTAL		15	12		15	12		15	12

Results of analysis of interviews from Slovenia

Understanding D&Ats

Under the umbrella term D*&ATs*, *scholars* understand technologies related to information communication technology (ICT, including most of the examples listed in Table 1: virtual and augmented reality (VR, AR), robots, chatbots, smartphones, smart glasses, computers and software, social media, artificial intelligence (AI), blockchain, big data analytics, the Internet of Things (IoT), and sensors. They describe digitalisation as the process where “services are partially or completely performed via machines with no human presence,” and its main purpose at to “digitise data and optimise business processes in tourism companies.” Additionally, digital services are seen as tools to “enhance the tourist experience.”

A *public sector interviewee* pointed out that digitalisation in tourism is still largely understood in a rather “basic way,” referring to activities such as digital promotions, websites, reservation systems, social media, online images, virtual markets, interactive tables, etc. In tourism destinations, digitalisation provides a tool for managing various processes and activities through contemporary ICT, especially in managing large numbers of tourists. Technologies such as robots, drones, and virtual/augmented reality were cited as relevant examples.

*Practitioner*s primarily focused their responses on the practical application of certain ATs in the sector. These included reservation platforms, email communication, digital information systems, electronic hotel room keys, QR codes, e-bills, digital maps, sensors, hardware and software tools, digital offers, and digital reporting systems. Some also mentioned more advanced technologies like big data analytics, AI, robots, social media, and IoT.

Advantages of D&Ats

The benefits of D&ATs were vividly illustrated by a *scholar’*s analogy: “We can cultivate the earth with a shovel or with a tractor; the end result is the same, but the way of achieving it is much easier with the latter approach.” Scholars identified numerous advantages of D&ATs, including real-time data access, improved statistical insights, instant guest satisfaction assessment, quicker supplier response to changes, better adaptation to tourist needs, and service personalisation. Other noted benefits include staff cost savings, reduction in routine work, easier workflows, interconnectivity of software and organisational units, faster business decisions, improved tourist segmentation, and immediate service delivery.

Public sector representatives echoed many of these points. They emphasised increased productivity, better work organisation, process optimisation, and streamlined operations. Additional benefits included added value creation, cashless payments, AI-generated solutions, cost reduction, improved monitoring, more accessible and affordable promotion, enhanced human resource management, and better internal communication. Staff could focus more on core tasks rather than administrative duties. They also highlighted improved communication, broader perspectives (e.g. 360° views), and instant feedback from tourists.

*Practitioner*s' views aligned closely with those of scholars and public actors. They most often cited internal process optimisation, rationalisation and economisation of operations, improved productivity, and maximised tourist experiences.

Challenges and concerns about D&ATs

Scholars emerged as the most critical group regarding D&ATs. They expressed concerns about “invasive selling from tech providers” and solutions that are “too often partial or difficult to integrate with existing software.” They argued that “people need to understand the content of the technology, not just the solutions themselves.” Without this understanding, ATs may be useless, and their purchase perceived by users as a “waste of money” or even a “theft of data,” particularly in cases involving technologies like facial recognition. A major concern is the high initial investment D&ATs require. Thin is especially problematic for small and medium-sized tourism enterprises (STMEs), which often lack both financial and technological resources. A lack of digital infrastructure and technological literacy can also frustrate tourists, for example, “if you don’t have an app, you cannot order food or enter the bus.” Scholars further criticised algorithmic manipulation, the rigidity of e-forms, and the limited creativity of many ATs. Another key issue was that “big data is available, but not transformed into usable insights for decision-making.”

Public sector representatives identified the loss of genuine hospitality and personal contact as a significant disadvantage. While some digital and tech solutions are “fascinating,” they are “not necessarily useful.” Their concerns included partial solutions, low accessibility for non-tech-savvy users, complex tech vocabulary, and the lack of capacity to process and interpret big data. Although they acknowledged the democratisation of social media, they also warned of long-term damage caused by negative online reviews for individual tourism providers or destinations.

Practitioners repeated many of these concerns. The use of D&ATs, they said, often results in a “lack of personal approach,” which is particularly problematic in the provision of high-end and luxury services. Some technologies may "disturb guests' stay" and "jeopardise personal data and security." They also cited a lack of skilled staff and frequent issues with "incompatibility between new tech solutions and existing systems." The high cost of implementation (particularly for STMEs) and the frequency of malfunctions were additional concerns. For example, while robots might amuse children, they are "not suitable for adults or staff." Hotel rooms with too many digital features were described as "stressful for the majority of guests."

Results of analysis of interviews from Montenegro

Understanding of D&Ats

Scholars in Montenegro define digitalisation as the "transformation of business activities from traditional paper-based systems to online formats," or as the use of "digital communication channels" such as email. Most of them associate digitalisation primarily with online bookings and marketing. Among ATs, they cited QR codes, animations, social media, applications, and computer software. Notably, one scholar stated that the "use of D&ATs depends on the nature of the destination."

Public sector representatives took a similar view, identifying D&ATs with booking platforms, digital guides, promotional use of virtual reality, and smart infrastructure such as smart benches. One interviewee stressed the need to consider digitalisation from both the supply and demand perspectives.

Practitioners defined D&ATs as "new tools we use for the same operations as before, but in a different way," emphasising that they help people perform their work more effectively. They see them as "modern technological solutions that improve daily operations and enable control over all areas of business." Examples mentioned included e-bookings, computer software, social media, virtual reality, gamification apps (e.g. for museums), QR codes, and chatbots.

Percieved advantages of D&Ats

Scholars broadly agreed that D&ATs enable "more efficient business operations and the development of new services," such as short-term rentals through platforms like Airbnb, which can be more easily adapted to demand. Integrated systems facilitate better management, process standardisation, and inter-departmental connectivity. Communication becomes easier and more affordable, with wider promotional reach, especially via social media, which enables visibility for local stakeholders and small businesses. Other benefits include the reduction of human error, improved sustainability, faster data transmission, and better access to guest information.

Public sector representatives highlighted increased visibility for destinations and suppliers, process optimisation, and more cost-effective promotion (e.g. via social media and video content). They also noted savings on energy, quick problem-solving, and improved information accessibility, noting that "machines are cheaper than staff."

One of the most frequently emphasised benefits by *practitioners* was improved accessibility of destinations. Participants also highlighted the power of electronic word-of-mouth (eWOM) via social media, easier research and planning, innovative payment options, and more informed decision-making. D&ATs also supported better event management, real-time issue detection, and greater overall efficiency. As one practitioner said, “apps have become the new way to achieve pleasure.”

Challenges and concerns about D&ATs

Although fewer challenges were raised by Montenegrin *scholars*, several significant concerns emerged. These included the reduction of face-to-face communication, the fast pace of technological implementation, and the potential consequences of technical failures; as one participant put it, “no electricity – no tech.”

Public sector representatives shared concerns similar to those of scholars, including the loss of direct personal contact and the “alienation” of service providers from tourist/guests. A major issue was the lack of control over promotional platforms, where “one negative review can be devastating.”

Practitioners stressed the “loss of hospitality,” “alienation from tourists,” and “dehumanisation of interpersonal relationships”—all considered essential aspects of tourism. They noted that technology does not necessarily lead to “savings in human resources.” One interviewee explained: “In tourism, effectiveness and efficiency can be contradictory: we might do more, but the quality of services would not be the same.” A lack of technological skills, especially among older employees, was also identified as a barrier. Practitioners expressed particular concern about the impact of negative social media publicity. While e-booking was seen as beneficial for sales, the self-reservation model “undermines the traditional sales system of selling ‘warm beds,’” which was a common practice in high-season leisure destinations.

DISCUSSION

The analysis reveals important distinctions and overlaps in how D&ATs are understood across countries and stakeholder groups. Slovenian and Montenegrin *scholars* tend to adopt a conceptual and technological understanding of D&ATs, referring to broader ICT frameworks and advanced tools like AI, big data analytics, virtual/augmented reality, IoT, and blockchain. Those are technologies frequently associated with Tourism 4.0 in existing literature (e.g., Buhalis et al., 2023; Osei et al., 2020; Starc Peceny et al., 2019). The depth of understanding, however, is more developed among Slovenian scholars, who associate D&ATs with digital transformation and optimisation of business processes. This understanding reflects Bekele and Raj’s (2025) and Dredge et al.’s (2019) view of digitalization as driver of business efficiency. Montenegrin scholars, in contrast, mostly relate D&ATs to online bookings and marketing tools, suggesting an early stage-focus consistent with Van Veldhoven and Vanthienen's (2021) distinction between digitalization and digital transformation. *Public sector representatives* in both countries generally perceive D&ATs in more applied and managerial terms, often listing digital tools for promotion, tourist flow management, or basic ICT infrastructure (e.g., web pages, smart benches, virtual tours). This aligns with Buhalis's (2020) view that digitalization improves communication, promotion, networking, etc. Yet, Slovenian public stakeholders demonstrate slightly more awareness of advanced tech applications and challenges. *Practitioners* approach D&ATs from a functional and utilitarian perspective. They focus primarily on digital tools that directly support day-to-day operations (e.g., reservation systems, digital communication, room access technologies, QR codes, etc.). Findings reflect Buhalis's (2020) arguments about practical advantages of D&ATs for capacity management, operation efficiency and customer service.

The level of understanding seems to be shaped by the role and exposure of each group to technological tools and the position of triangulation group in tourism system. Scholars tend to be more theoretical and future-oriented, public actors are concerned with governance and destination management, and practitioners focus on immediate benefits and limitations.

There is a strong convergence across all groups and both countries regarding the perceived advantages of D&Ats. They were most often described with expressions like easier-more-better-faster-cheaper, consistent with Buhalis's (2020) and Buhalis et al.'s (2023) identification of efficiency and optimisation as the core benefit of D&ATs. Other descriptors of the advantages and benefits of the D&ATs are the words with "-tion" endings, e.g., rationalization, economisation, maximisation, optimisation, personalisation, reflect the formative qualities outlined in existing literature.

Among advantages of D&Ats, Slovenian scholars and public actors highlight interconnectivity of systems, reduction of routine tasks, and faster business decisions, also pointed by Buhalis et al. (2023). In contrast, Montenegrin participants emphasise standardisation, promotion of local actors, and the role of social media and apps in improving communication and brand awareness. Practitioners in both countries strongly associate D&ATs with business optimisation, although Slovenians more often mention personalisation and guest satisfaction (as Sigala, 2018), while Montenegrins highlight communication, reporting, and visibility. This indicates different stages of digital maturity of tourism in each country.

The challenges and drawbacks of D&Ats are equally acknowledged in both countries, though more extensively discussed in Slovenia. Scholars in Slovenia are especially critical, raising issues around the ethics and risks of technological adoption, such as data misuse, surveillance concerns, similar as Stankov and Gretzel (2020) are. They also point out the gap between data availability and its use in decision-making, which was not emphasized yet in existing literature. Public actors in both countries raise concerns about the partial nature of some digital solutions, which has also been not revealed in existing literature, and the exclusion of less tech-savvy users, also noted by Pencarelli (2019). They highlight the danger of over-relying on platforms that they do not control, especially when one bad review can undermine a business. Practitioners most often point out lack of skilled personnel, technical incompatibility, stressful user experiences, and the absence of personal touch in luxury and high-end services, paralleling human-centric concerns expressed by Akiskali et al. (2022). In Montenegro, there's a clear concern that efficiency might compromise service quality, and robotic or overly digitalised interactions might alienate guests. This aligns with Pencarelli (2018) argument that Tourism 4.0 might prioritise technological efficiency over authentic experiences. Additionally, Montenegrin participants are aware of the vulnerability of digital systems.

Interestingly, none of the interviewees has mentioned D&ATs issues related with a vast consumption of energy for D&ATs and a paradox derived from it: we glory the D&ATs and even promote them as green and sustainable, but neglect the vast consumption of energy for it. The environmental research point that driven by grown electricity use, D&ATs more frequently raises energy use; therefore, relationship between D&ATs and energy demand is a complex issue and net effect rather uncertain (Axenbeck et al., 2024).

The study revealed the difference between countries in a maturity and integration of D&ATs in tourism. Both countries show awareness and engagement with D&Ats in tourism, while Slovenia appears to be at a more advanced stage of digital maturity. This is indicated in more detailed understanding of D&ATs among all groups, greater awareness of integration issues and ethical concerns, broader recognition of data-driven innovation. Those are factors consistent with Jil et al. (2025) on digital maturity as a predictor of transformation success. Montenegro's digitalisation efforts appear more focused on visibility, accessibility, and communication, with strong attention to affordability and simplicity, especially for local actors and small and medium-sized enterprises. This suggests that Slovenia may be facing second-generation digitalisation challenges (e.g., ethical use of data, interoperability, service creativity), while Montenegro is still grappling with first-generation issues (e.g., training, infrastructure, etc).

CONCLUSION

This comparative analysis of interviews with scholars, public sector representatives, and practitioners in Slovenia and Montenegro offers important insights into how D&ATs are understood, adopted, and perceived in the tourism of two countries with different levels of digital maturity. A broad consensus emerges on the value of D&ATs for improving efficiency, reducing operational costs, enhancing tourist experiences, and expanding promotional reach. Stakeholders in both countries recognize the transformative potential of digitalisation for the tourism industry. However, the depth of understanding and the focus of application differ across both stakeholder groups and national contexts. Slovenian tourism representatives exhibit a more critical and theoretical engagement with D&ATs, while Montenegrin tend to focus on practical uses of D&Ats.

An important issue is the challenge of preserving the human dimension of tourism. Both Slovenian and Montenegrin respondents warn that over-digitalisation could reduce personal interaction, which remains a core value of hospitality, especially in high-end services. The challenges of implementation, including high investment costs, technological incompatibility, lack of skilled staff, and user frustration, are significant across both countries. Slovenian stakeholders, however, seem to have moved beyond basic adoption concerns.

The study highlights the need for tailored strategies in digital tourism development: countries and destinations must align digital tools with their specific tourism models, infrastructure, and human resources. They should also ensure inclusive approaches that consider the needs of less tech-savvy users and maintain the human touch in service delivery. While D&ATs are widely welcomed for their advantages, a balanced, human-centred, and context-sensitive digitalisation strategy in tourism is essential. For now, hybrid solutions appear to be the most widely accepted approach.

The *theoretical implications* of the study are reflected in two main findings. Firstly, its results empirically confirm the findings on the research themes presented in the existing literature. These themes have often been cited as generally accepted knowledge but lacked empirical validation. Secondly, the results indicate that the perception and applicability of D&ATs depend on the stakeholders' roles within tourism sector and the type or nature of the tourism destination. These two indicators expand current knowledge on the topic and highlight that a 'one-size-fits-all' approach to D&ATs in tourism is not appropriate.

Several *practical applications* can be derived from this study. Since the implementation of D&ATs in tourism is often one of the strategic goals at the state level, the findings may be valuable for tourism policymakers. When determining the pace and scope of D&ATs integration, they should consider the destination's characteristics, key tourist segments, and the overall quality level of tourism. Tourism service managers should recognize that technological solutions may benefit them operationally, but not necessarily appeal to tourists. In particular, D&ATs are not well accepted in luxury or high-end tourism sectors. If implemented in such settings, these technologies must remain simple and deliver a tourist-friendly experience rather than causing frustration.

Certain *limitations* of this study should be acknowledged. The first relates to the scope of the research, which was constrained by human, financial, and time resources. The second limitation is convenient sampling (self-selection bias) which can be related with the nonrepresentative target population. Yet, only those participants have been invited (with a consent of all researchers) who were involved in D&ATs in tourism and were familiar with research themes. There were no emotional pitfalls involved to selection of participants. The results might have differed if different participants were chosen, a larger number of interviewees had been involved or had been more willing to participate. Due to above mentioned limitations, the generalizability as one of the general limitation of qualitative research needs to be mentioned. However, a comparison between the empirical findings and existing literature suggests that the quality of responses outweighs the quantity and highly eliminates the above mentioned considerations. The third limitation comes out from the qualitative nature of the study; results might have differed if a quantitative approach had been used. Subjectivity of researcher and participants is the fourth and one of major limitations of qualitative research, which can compromise the trustworthiness and credibility of findings in the process of collection, selection, and interpretation of non-numerical data. To minimize this, data collection and analysis were conducted as described in the methodology section. Interviews in both countries were conducted by a single researcher with extensive knowledge of D&ATs in tourism and with familiarity of both cultural contexts to overcome the cultural bias. To eliminate the situation of guiding the participants toward specific response, interviewees were asked only three straightforward opened questions without additional sub questions. Data were recorded, and first analysed independently by all researchers and then compared, with consensus reached before advancing to the second-step matrixes. It is considered to overcome limitations of data interpretation due to possible pre-existing beliefs, expectations, selective collection or omission of contrary evidence. Another potential limitation is the truthfulness of interviewees' responses, which might be socially desirable or inaccurate. We estimate that the content of the research topics is not of personal nature, which is why the answers could either be likable or wrong. Results can vary depending on the geographical context and timing of the research. The findings might differ if conducted in another country or tourism destination. Notably, the fieldwork was carried out shortly before the emergence of generative AI technologies (also known as large language models, such as ChatGPT, Gemini, Copilot, and more recently, Deepseek) and the rising interest in the metaverse. These developments may have influenced how interviewees would respond today, while D&ATs are part of a constantly evolving field.

All the above-mentioned limitations open space for *future research*. A follow-up study, focused on similar research themes but possibly employing a different methodological approach, could be conducted among tourists in Slovenia and Montenegro to investigate their perceptions of D&ATs. This research could also be extended to other destinations with specific types of tourism and/or focus on different tourist segments.

REFERENCES

Alcácer, V., & Cruz-Machado, V. (2019). Scanning the Industry 4.0: A literature review on technologies for manufacturing systems. *Engineering Science and Technology, International Journal, 22*(3), 899–919.

Akiskali, T., Kitapci, O., & Ozturkcan, S. (2022). Service robots in the hospitality industry: A state-of-the-art literature review. In *Tourism and Culture 4.0: Shifting towards the metaverse* (pp. 75–96). McGraw-Hill Education.

Airey, D. (2015). 40 years of tourism studies – a remarkable story. *Tourism Recreation Research, 40*(1), 6–15.

Axenbeck, J., Berner, A., & Kneib, T. (2024). What drives the relationship between digitalisation and energy demand? Exploring heterogeneity in German manufacturing firms. *Journal of Environmental Management, 369*, 122317.

Bans-Aukney, A., & Timub, B. M. (2021). Triangulation in research. *Academia Letters.* https://www.researchgate.net/publication/354268603_Triangulation_in_Research

Bekele, H., & Raj, S. (2025). Digitalization and digital transformation in the tourism industry: A bibliometric review and research agenda. *Tourism Review, 80*(4), 894–913.

Bilotta, E., Bertacchini, F., Gabriele, L., Giglio, S., Pantano, P. S., & Romita, T. (2021). Industry 4.0 technologies in tourism education: Nurturing students to think with technology. *Journal of Hospitality, Leisure, Sport & Tourism Education, 29*, 100345.

Bloomberg, J. (2018, April 29). Digitization, digitalization, and digital transformation: Confuse them at your peril. *Forbes.* https://www.forbes.com/sites/jasonbloomberg/2018/04/29/digitization-digitalization-and-digital-transformation-confuse-them-at-your-peril/

Buhalis, D. (2020). Technology in tourism – from information communication technologies to eTourism and smart tourism towards ambient intelligence tourism: A perspective article. *Tourism Review, 75*(1), 267–272.

Buhalis, D., Leung, D., & Lin, M. (2023). Metaverse as a disruptive technology revolutionizing tourism and marketing. *Tourism Management, 27*, 104724.

Decrop, A. (1999). Triangulation in qualitative tourism research. *Tourism Management, 20*(1), 157–161.

Dredge, D., Phi, G. T. L., Mahadevan, R., Meehan, E., & Popescu, E. (2019). *Digitalisation in tourism: In-depth analysis of challenges and opportunities.* Aalborg University. https://www.academia.edu/91482790/Digitalisation_in_Tourism_In_depth_analysis_of_challenges_and_opportunities

Fošner, A., & Trop, K. (2024). Strategic foresight for sustainability. *Advances in Business-Related Scientific Research Journal, 15*(1).

Frost, J., & Frost, W. (2021). Ten markers of quality in designing and publishing qualitative tourism research. *Journal of Qualitative Research in Tourism, 2*(2), 158–167.

Gartner Glossary. (n.d.). *Digitalisation.* https://www.gartner.com/en/information-technology/glossary/digitalization

Ghobakhloo, M., Fathi, M., Iranmanesh, M., Maroufkhani, P., & Morales, M. (2021). Industry 4.0 ten years on: A bibliometric and systematic review of concepts, sustainability value drivers, and success determinants. *Journal of Cleaner Production, 302*, 127052.

Gong, Y., Schroeder, A., & Plaisance, P. L. (2023). Digital detox tourism: An Ellulian critique. *Annals of Tourism Research, 103*, 103646.

Gretzel, U., & Jamal, T. (2009). Conceptualizing the creative tourism class: Technology, mobility and tourism experience. *Tourism Analysis, 14*(4), 471–478.

Guan, C., Ding, D., & Guo, J. (2022). Web 3.0: A review and research agenda. In *Proceedings of the International Conference on Research, Innovation and Vision for the Future.* IEEE.

Jagodič, G., Jagodič, D., & Gorenak, M. (2025). The impact of digitalisation on business operations of tourism companies. *Mednarodno Inovativno Poslovanje = Journal of Innovative Business and Management, 17*(1).

Jie, H., Gooi, L. M., & Lou, Y. (2025). Digital maturity, dynamic capabilities and innovation performance in high-tech SMEs. *International Review of Economics & Finance, 99*, 109971.

Liu, Y., Wang, X., Du, Y., & Wang, S. (2023). Service robots vs. human staff: The effect of service agents and service exclusion on unethical consumer behaviour. *Journal of Hospitality and Tourism Management, 55*, 401–415.

Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook* (3rd ed.). Sage.

Nasr, N. (2025). Embracing a digital detox in 2025. *Journey.* https://www.journeystartshere.com/blog/journal/embracing-a-digital-detox-in-2024-finding-balance-in-a-hyperconnected-world

Neuhofer, B., Buhalis, D., & Ladkin, A. (2013). A typology of technology-enabled tourist experiences. *International Journal of Tourism Research, 16*(4), 340–350.

Noung, M. D., & Ragawan, N. A. (2023). Digital future of the global hospitality industry and hospitality education: Review of related literature. *APJFES, 2*(1), 71–100.

Osei, B. A., Ragavan, N. A., & Kandappan, B. (2020). Hospitality revolution 4.0: A literature review on a united typology of IR 4.0 technologies for the tourism and hospitality industry in the era of COVID-19. *Asia-Pacific Journal of Innovation in Hospitality and Tourism, 9*(1), 25–45.

Pachlevan-Scarif, S., Mura, P., & Wijesinghe, S. N. R. (2020). Qualitative online research in tourism: A systematic review of literature. *Tourism Review, 75*(2), 448–465.

Pencarelli, T. (2019). The digital revolution in the travel and tourism industry. *Information Technology & Tourism, 22*(3), 455–476.

Ritzer, G., & Jurgenson, N. (2010). Production, consumption, prosumption: The nature of capitalism in the age of the digital 'prosumer'. *Journal of Consumer Culture, 10*(1), 13–36.

Saarikko, T., Westergren, U. H., & Blomquist, T. (2020). Digital transformation: Five recommendations for the digitally conscious firm. *Business Horizons, 63*(6), 825–839.

Stankov, U., & Filimonau, V. (2019). Reviving calm technology in the e-tourism context. *Service Industries Journal, 39*(5–6), 343–360.

Stankov, U., & Gretzel, U. (2020). Tourism 4.0 technologies and tourist experience: A human-centred design perspective. *Information Technology & Tourism, 22*, 477–488.

Starc Peceny, U., Urbančič, J., Mokorel, S., Kuralt, V., & Ilijaš, T. (2019). Tourism 4.0: Challenges in marketing paradigm shift. In M. Reyes (Ed.), *Consumer behaviour and marketing.*

Sigala, M. (2018). New technologies in tourism: From multi-disciplinary to anti-disciplinary advances and trajectories. *Tourism Management Perspectives, 25*, 151–158.

Teubner, R. A., & Stockinger, J. (2020). Literature review: Understanding information system strategy in the digital age. *The Journal of Strategic Information Systems, 29*(4), 101642.

Townsend, P. (2017). *The dark side of technology.* Oxford University Press.

Valeonti, F., Biakkis, A., Terras, M., Speed, C., Hudson-Smith, A., & Chalkias, K. (2021). Crypto collectibles, museum funding and OpenGLAM: Challenges, opportunities and potential of non-fungible tokens (NFTs). *Applied Sciences, 11*(21).

Van Veldhoven, Z., & Vanthienen, J. (2021). Digital transformation as an interaction-driven perspective between business, society, and technology. *Electronic Markets.*

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Hoenlain, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901.

Wei, D. (2022). Gemiverse: The blockchain-based professional certification and tourism platform with its own ecosystem in the metaverse. *International Journal of Geoheritage and Parks, 10*, 322–336.

World Travel & Tourism Council. (2024). *Travel & tourism set to break all records in 2024 reveals WTTC.* https://wttc.org/news/travel-and-tourism-set-to-break-all-records-in-2024-reveals-wttc

Wu, M., Tan, G. W. H., Aw, E. C. X., & Ooi, K. B. (2023). Unlocking my heart: Fostering hotel brand love with service robots. *Journal of Hospitality and Tourism Management, 57*, 329–348.

Zhang, L. X., Li, J. M., Wang, L. L., Mao, M. Y., & Zhang, R. X. (2023). How does the usage of robots in hotels affect employees' turnover intention? A double-edged sword study. *Journal of Hospitality and Tourism Management, 57*, 74–83.