UNIVERSITATEA BABEŞ-BOLYAI
BABEŞ-BOLYAI TUDOMÁNYEGYETEM
BABEŞ-BOLYAI UNIVERSITÄT
BABEŞ-BOLYAI UNIVERSITY
TRADITIO ET EXCELLENTIA

STUDIA UNIVERSITATIS
BABEŞ-BOLYAI

OECONOMICA

3/2024

STUDIA
UNIVERSITATIS BABEŞ-BOLYAI
OECONOMICA

3/2024

December

EDITORIAL OFFICE OF OECONOMICA: Teodor Mihali str. no. 58-60, s. 251, 418655 Cluj-Napoca,
Phone: 0040-264-41.86.52, oeconomica@econ.ubbcluj.ro, https://studiaoeconomica.reviste.ubbcluj.ro/

YEAR **(Volume 69) 2024**
MONTH **December**
ISSUE **3**

Studia Universitatis Babeş-Bolyai Oeconomica

3

EDITORIAL OFFICE of **Studia Universitatis Babeş-Bolyai Oeconomica**
Teodor Mihali str. no. 58-60, s. 251, 400591 Cluj-Napoca,
Phone: 0040-264-41.86.52, studiaoeconomica@econ.ubbcluj.ro,
https://studia.reviste.ubbcluj.ro/index.php/subboeconomica

SUMAR – SOMMAIRE – CONTENTS – INHALT

STUDIA UNIVERSITATIS BABEȘ-BOLYAI OECONOMICA
VOLUME 69, ISSUE 3, 2024, pp. 1-13
DOI: 10.2478/subboec-2024-0011

HOW IS AI SHAPING THE FUTURE OF WORK? EMPOWERING EMPLOYEES, NOT REPLACING THEM

Anamaria PETRE[*]
Babes-Bolyai University, Romania

Patricia RAȚIU
Babes-Bolyai University, Romania

Codruța OSOIAN
Babes-Bolyai University, Romania

Abstract: In the modern business world, AI is revolutionizing HR departments around the globe and is becoming an essential part of human resource management.

In this paper we explore the role of AI in Human Resource Management and how it can help organizations to remain competitive and efficient, while improving employee empowerment and engagement. We conducted quantitative research involving employees and HR professionals from various sectors in Romania to explore their perceptions of AI implementation in the workplace. The data explores the extent to which AI chatbots can empower employees and improve their efficiency. Additionally, we analyze employees' perceptions regarding the possibility of being replaced by AI, offering insights into their concerns about job displacement alongside the opportunities AI presents for job enhancement.

The research findings reveal a strong positive correlation between favorable perceptions of AI and increased empowerment, while concerns about job displacement negatively affect empowerment. The study's conclusions have significant implications for HR professionals, who can use AI tools to maximize and enhance organizational performance. Moreover, to satisfy the demands of the workforce of the future, our research also emphasizes how important it is for HR experts to integrate technology advancements into their HR strategy.

JEL classification: O33; M12; M15; J24

Keywords: artificial intelligence (AI), empowerment, Human-AI Collaboration, job displacement concerns, workplace transformation

[*] Corresponding author. Address: Faculty of Economics and Business Administration, Babeş-Bolyai University, 58-60, Teodor Mihali Street, 400591, Cluj-Napoca, România, E-mail: anamaria.petre@econ.ubbcluj.ro

1. Introduction

The rapid advancement of technologies, particularly the implementation of AI in companies, is significantly transforming the world of work. As AI becomes more integrated into business operations, it is reshaping various aspects of the workplace, including the role of people in companies, the design of work, the demands on employees, organizational structures, cultures, and leadership. This transformation requires a rethinking of how work is done and must be actively shaped by leaders and organizations.

AI's role in shaping future work environments is significant and wide-ranging. AI has the ability to drastically change how humans work, learn and interact by boosting workplace productivity and creativity. However, realizing AI's full potential in the workplace necessitates careful attention to ethical, societal, and human considerations that will influence how AI is integrated and utilized in these environments.

The intersection of AI and human intelligence is driving the development of a future workplace where collaboration, innovation, and efficiency are key. This convergence is redefining traditional job functions and creating new opportunities for employees and employers to work together in novel ways.

As the opportunities for AI in HR continue to evolve, the focus for HR professionals will move more and more toward strategic functions such as talent management, leadership development, employee wellbeing and positive workplace culture. With AI handling routine tasks, HR teams can now dedicate more time to these high-impact, value-added functions.

The introduction of AI into the workforce presents a dual-edged sword. While AI has the potential to displace many existing jobs, it also creates new opportunities for employment in emerging fields. This shift demands attention to workforce retraining, job creation, and a careful balance between technological progress and human labor.

The rapid advancement of AI has also led to significant changes in work arrangements. Automation and AI technologies have forced many workers to adapt to new work structures and agreements that differ greatly from those of previous generations. These changes are reshaping the traditional employer-employee dynamic and require new approaches to work-life balance, job roles, and collaboration.

Considering all these aspects, we found it useful to explore the use of AI and chatbots in human resource management and its impact on jobs and on human resource management practices.

The purpose of this paper is to explore the role and impact of AI chatbots on HR activities, analyzing how they can contribute to streamlining processes and improving employee empowerment and satisfaction. Additionally, it examines employees' perceptions of AI and their concerns about job displacement, providing insights into how these perceptions impact their acceptance and usage of AI-driven tools.

The interest in this research topic is growing, and it is expected that the potential of AI in the workplace will be better understood and implemented.

The main research questions address in this paper can be formulated as following:

- What is employees' general perception of the integration of AI in HR functions, particularly in terms of their involvement and job enhancement?
- How do employees perceive the potential for AI chatbots to empower them within HR processes?

- How do concerns about job displacement relate to perceptions of AI integration in HR?

To address these questions the paper is organized as follows:

In the first part, we presented a review of the specialized literature that provides the foundational context for understanding the current state of AI adoption.

Next, we described the data used as well as the methodology on which the study is based. We use a quantitative method in order to understand both employees and human resources professionals' perceptions of using AI in HRM.

Afterwards, we presented the results, and finally we concluded with reflections on the future of work and AI's impact on jobs and employment. Possible future directions of study were also proposed.

2. Literature review

Artificial Intelligence involves replicating human intelligence within machines, enabling them to perform tasks such as reasoning, learning, perception, planning, and prediction. A notable advancement in AI is Generative AI, which is capable of producing original content like text, images, and audio by learning from existing data. This breakthrough is transforming industries by offering new possibilities for creating relevant and innovative outputs.

In the field of Human Resources (HR), AI is making significant steps by automating recruitment, refining performance assessments, and customizing employee development. These improvements lead to enhanced efficiency and more data-driven decision-making.

The growing adoption of AI in HRM is driven by the increasing volume of data related to workforce management and organizational processes. According to some authors (Chowdhury et al., 2023), the increasing adoption of AI in HRM is driven by its potential to create value for customers, employees and organizations, concurrently.

Impact of AI-powered HRM applications on organizational and employee outcomes

The opportunities and constraints of AI and other automated technologies for HRM were discussed by Budhwar et al. (2022) in their systematic review of the literature. They also looked at how the automated HRM functions can affect organisational and employee results.

AI-enabled HRM adoption gives organisations tha chance to achieve the best possible strategic business results, including improved overall business performance (Li et al., 2019), cost-effective service excellence (Wirtz, 2019), operational efficiency, customer engagement and loyalty (Prentice and Nguyen, 2020; Botha, 2019; Tarafdar et al., 2019).

Most importantly is the fact that AI-focused HRM creates favourable employee outcomes such as job satisfaction (Nguyen and Malik, 2022), commitment, employee engagement, and participation, thereby increasing their performance (Castellacci and Viñas-Bardolet, 2019). Employee retention and satisfaction have increased as a result of the deployment of chatbots and virtual assistants driven by AI (Khan et al., 2020).

The AI-HRM literature, however, still lacks a thorough understanding of how AI and related technologies can provide solutions for efficient HRM and sub-functional areas, as well as how AI-enabled HRM functions connect to other operational tasks to improve organisational outcomes (Agrawal et al., 2017).

Makridis and Han Hun (2021) found that employees typically feel more empowered to exploit their abilities at work and have greater levels of well-being, as a reaction to technological change. However, this effect is stronger when employees receive task direction and guidance from their manager and when their organization fosters a culture of trust.

According to research, employees are more likely to be proactive and creative when given the freedom to use their specific and unique competences and abilities, which helps companies innovate (Seibert et al., 2011; Zhang and Bartol, 2010).

Concerns over job displacement for HR roles

Although the positive consequences of advanced technologies are emphasized in the literature, several negative issues have also been identified. There have been significant concerns expressed about AI's potential to eliminate jobs (Malik, 2020). The American Psychological Association's (APA) 2024 Work in America survey reveals that 41% of U.S. workers are worried that AI will eventually make some or all of their job duties obsolete in the future. According to researchers (Brougham and Haar, 2020), AI may eventually replace 57% of OECD employment, and most businesses are under pressure to develop AI data analytics capabilities.

Job displacement due to AI may vary across sectors, with industries like manufacturing and transportation, which involve more routine tasks, experiencing more significant job displacement compared to sectors like healthcare and education.

In their theory of job replacement through AI, Huang and Rust (2018) significantly contributed to the literature concerning this double-edged effect of AI in services. The authors discuss how AI can reshape services, potentially replacing service workers entirely, but also emphasize the need for employees to focus on developing their intuitive and empathetic skills that AI cannot replicate. Only cognitive and analytical jobs requiring little emotional or social complexity can be completed by service robots. In people-intensive services, we still believe that employees are the most important resource.

System level challenges

According to Brougham and Hair (2020), a major obstacle to effectively embracing and integrating cutting-edge technologies in the workplace is employees' unfavourable views towards technological advancements. Therefore, the question of how to reduce employee anxiety around the integration of new technologies into HRM operations must be addressed. In this regard, experts argue that appropriate and significant training is crucial for minimising workers' disapproval of new technological implementations (Brougham and Haar, 2020). Businesses will be better equipped to handle the future of work if they can successfully combine AI technologies with the knowledge and abilities of their employees. According to other writers (Bititci et al., 2016), a suitable organisational culture is necessary for the long-term, successful deployment of automation technology.

Fostering Human-AI collaboration

Finding a balance between automation and human interaction in the workplace is crucial as AI develops. Increased productivity and creativity may result from the mutually beneficial link between AI and human labour.

Nawaz and Gomes (2019) acknowledge that chatbots should not replace human recruiters. They advocate for a collaborative approach, where chatbots enhance the capabilities of HR teams by automating tasks and providing 24/7 assistance, ultimately improving overall efficiency and the candidate experience in the recruitment process.

The future of work is not about AI replacing humans but about fostering effective human-AI collaboration. For instance, AI can help design more efficient work processes, while humans can provide creativity and emotional intelligence.

Companies have to provide training and development initiatives that give staff members the know-how to collaborate with AI in order to optimise the advantages of human-AI cooperation. This covers both soft skills like flexibility, problem-solving and moral decision-making as well as technical abilities like AI and data analysis. Also, HR managers should take into consideration that tasks that individuals will most likely perform in the future will call for advanced emotional and cognitive abilities. When properly implemented, with the correct people employed, HR staff retrained and a culture of internal transparency to avoid AI from being used as a tool of control, using AI to improve organisational performance can be successful (Sakka et al., 2022).

Additionally, given the changing nature of the workplace with its hybrid model and increased emphasis on diversity and inclusion, HR's strategic component - which must make use of AI's capabilities in HR, becomes even more crucial (Kaur and Gandolfi, 2023).

A study conducted by Pan et al., (2022) explored the factors influencing the adoption of artificial intelligence (AI) in employee recruitment. They found that perceived usefulness, organizational culture, and job requirements significantly affect AI adoption. The study also emphasized the importance of considering organizational and job-related factors when implementing AI in recruitment.

According to Arslan et al. (2022), evaluating performance in teams that include both people and robots is one of the major problems for HRM. They have highlighted the possibilities of drawing on insights from the literature on computer gaming, where performance evaluation models have been built to analyse human performance in the same environment as AI, and have noted to the scarcity of existing frameworks to guide HRM function in this regard.

AI should be leveraged not only for improving economic efficiency, but also for cultivating a more inclusive, dynamic and rewarding work environment that values human contributions. By addressing challenges and fostering collaboration between humans and AI, businesses can stimulate innovation and growth, leading to a future in which both organizations and employees can achieve sustained development.

Therefore, this study proposes three hypotheses:

Hypothesis 1: Employees who perceive AI as a tool for empowerment will have higher satisfaction levels with HR processes.

Hypothesis 2: Concerns about job displacement will negatively affect employees' perception of AI's role in HR.

Hypothesis 3: HR professionals will have a more positive view of AI's potential than employees.

3. Methodology

The use of chatbots driven by generative AI in HR represents a dramatic change towards increased productivity, responsiveness and general employee satisfaction. These chatbots demonstrate their diverse influence on changing HR relations by automating intricate HR processes and streamlining the employee journey.

This paper adopts a mixed-methods design, encompassing both primary and secondary data. This study employs a quantitative research design to investigate employees' and HR professionals' perceptions of AI implementation in HR functions. Data were collected through a structured survey with two distinct respondent groups: HR professionals and employees.

The survey included questions assessing: general perceptions of AI in HR (5 items), job enhancement through AI integration (8 items), employee empowerment through AI (7 items), concerns about job displacement due to AI (7 items), general questions to identify respondents (gender, age, years of experience, company size and job position). Except for demographic data, all the mentioned variables were assessed using a Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5).

For the variables "General perceptions of AI in HR" and "Employee empowerment through AI", the items were carefully designed based on existing research in the field to capture respondents' perceptions. For "General perceptions of AI in HR", one of the items was: "How likely are you to trust AI-driven HR decisions compared to human-made decisions?". In the case of employee empowerment through AI, one of the items used was: "AI enables employees to make more informed decisions in their roles."

For the other two variables ("Job enhancement through AI Integration" and "Concerns about job displacement due to AI") validated scales were used: the adapted Job Characteristics Model (Hackman and Oldham, 1976) and an adapted version of the Fear of Job Loss Scale (Brynjolfsson and McAfee, 2014).

Data was gathered via online Google forms, and between January 2024 and May 2024, links to the questionnaire were shared via personal contacts and social networking sites such as LinkedIn. Out of all the responses received, only 197 were filled completely and correctly (108 employees and 89 HR professionals).

4. Data Analysis and Results

The first part of analysis focuses on demographic data in terms of gender, age, years of experience, company size, and job position. The study involved 108 employee respondents and 89 HR professionals. Among the employee respondents, a majority were female (51%), with a significant portion (49%) aged 26-35 years. The majority worked in IT, followed by commerce and finance roles. Most had 2-4 years of experience and worked in medium-sized companies (100-500 employees). For the HR professionals, the majority were female (70%) and aged between 36-45 years. A significant proportion (53%) held HR specialist roles, with 4 years of experience and worked in medium-sized companies.

Next, we will analyze the data collected from both HR professionals and employees to understand their perceptions and attitudes of AI implementation in the workplace.

The *first part of the analysis focuses on respondents' perceptions of AI-driven chatbots* used in HR related activities (not general workplace tasks). Below is a comparison of the views expressed by the two respondent groupings.

The data shows that among HR professionals, 77% agreed or strongly agreed that AI chatbots would positively impact HR departments, with a mean score of 4.03. Employees, in contrast, were slightly less enthusiastic, with 60% expressing openness to AI in HR functions. However, a notable 30% were neutral, suggesting that while many employees see the potential of AI, there is still uncertainty or lack of familiarity with how it would impact their daily work lives.

Regarding the effectiveness of AI chatbots in addressing frequent HR-related inquiries, HR professionals gave a positive assessment (mean score of 3.73), with 60% believing chatbots could handle employee questions as effectively as a human HR representative. However, among employees, 50% felt uncertain about whether AI would meet their needs as effectively as human professionals, with only 30% expressing confidence in its capabilities. This discrepancy highlights a possible gap in the perception of AI's abilities between HR and general employees.

By automating repetitive work and increasing overall efficiency, AI integration in HR aims to *empower HR professionals and employees* alike. Our research indicates that although employee perceptions differ, HR experts view AI as a tool for empowerment.

HR professionals overwhelmingly agreed (93%) that AI chatbots would save time by automating routine tasks, with a mean score of 4.26. This would empower HR teams to focus on HR strategic activities. Among employees, 70% agreed that AI could help streamline HR-related tasks, though some (20%) were concerned that this might reduce human interaction in key HR processes. Despite this, 60% of employees indicated that they would welcome AI assistance for administrative tasks, as long as it doesn't replace the personal touch for more complex issues.

Both HR professionals and employees agreed that AI could enhance autonomy in HR tasks. For instance, 86% of HR professionals believed AI would allow employees to manage HR-related requests independently, with a mean score of 4.20. Among employees, 55% expressed a strong preference for having the ability to handle HR inquiries themselves. This indicates a shared belief that AI can contribute to a more self-sufficient workforce, empowering employees to resolve issues without having to contact HR for every request.

AI's integration in HR aims not only to empower HR professionals but also to *improve the overall employee experience*. The ability of employees to access HR services quickly and efficiently through AI is seen as a major advantage.

HR professionals and employees recognize the potential of AI in improving satisfaction with HR services. HR professionals (83%) agreed that AI would enhance employee satisfaction by providing quicker access to HR services (mean score of 4.03). Similarly, 60% of employees felt that AI would lead to a better overall HR experience. However, 20% of employees expressed concerns about AI potentially reducing personal engagement with HR staff. A percent of 80% of employees believed AI would increase their ability to manage their own HR-related tasks, such as updating personal information or checking leave balances. This aligns with HR professionals' views that AI could contribute to a more empowered workforce.

Despite the fact that AI is widely acknowledged to have the potential to enhance HR practices, concerns over job displacement remain prevalent, particularly among employees. Opinions varied more among employees than among HR specialists.

According to our survey, 40% of HR professionals saw AI as a chance to concentrate on higher-level responsibilities, while only 20% believed it will replace their current roles. Employees were more worried about losing their jobs, though. While 50% of workers thought that AI may merely alter the nature of HR work without resulting in a mass loss of jobs, 40% of workers said it might endanger certain HR job functions.

To understand the relationship between key variables and provide deeper insights into the data, we conducted several statistical analyses, including the calculation of means and correlation coefficients.

Table 1. Means of the studied variable

Variable	HR Professionals Mean	Employees Mean
General perception of AI in HR	4.03	3.96
Job enhancement through AI integration	4.26	4.10
Employee empowerment through AI	4.05	4.03
Concerns about job displacement	3.73	3.87

Both employees and HR professionals view AI in HR-related activities favourably, as shown in Table 1, with HR professionals exhibiting somewhat greater optimism overall. Although both groups agree that AI has the ability to improve jobs and give workers more authority, HR experts give job enhancement a higher rating. However, compared to HR professionals, employees are a little more concerned about the possibility that AI may replace jobs.

Correlations for the studied variables are presented in Table 2:

Table 2. Correlations among variables

Variable	General perception of AI in HR	Job enhancement through AI integration	Employee empowerment through AI	Concerns about job displacement
General perception of AI in HR	1.00			
Job enhancement through AI integration	0.682	1.00		
Employee empowerment through AI	0.756	0.835	1.00	
Concerns about job displacement	-0.475	-0.563	-0.452	1.00

$p<0.05$

The correlation analysis reveals significant relationships among the variables related to AI in HR, employee empowerment and job displacement concerns. A positive correlation was found between the general perception of AI in HR and empowerment (r = 0.756), indicating that employees who view AI favorably are more likely to feel empowered in their roles. This finding aligns with research suggesting that perceived organizational support positively influences employee empowerment and performance (Kumar, Liu & Jin, 2022). Additionally, employee empowerment through AI was positively correlated with job enhancement (r = 0.835), suggesting that AI can improve job performance and satisfaction, enhancing autonomy.

On the other hand, concerns about job displacement showed a negative correlation with empowerment (r = -0.452), supporting the literature that highlights how job insecurity can diminish morale and engagement (Jung et al., 2021). The negative association between displacement concerns and empowerment suggests that while AI can enhance employees' abilities, fears of job loss may mitigate these benefits.

Based on positive correlation between AI perception and empowerment, hypothesis 1 is supported. Employees who view AI favorably are more likely to believe it can enhance their autonomy, thus increasing satisfaction. Also, negative correlation between displacement concerns and empowerment supports hypothesis 2. Employees who worry about job displacement tend to have lower perceptions of AI's empowerment potential. Also, the data supports hypothesis 3, as HR professionals showed a slightly more favorable view of AI in HR functions, with a higher mean score for empowerment and job enhancement.

These findings highlight how critical it is to handle both the advantages and disadvantages of integrating AI in the workplace. To fully realise AI's potential, it is imperative to reduce workers' concerns about job displacement, even while AI offers chances for employment enhancement and increased empowerment.

5. Discussions

The findings of this study highlight several key areas where HR managers can optimize their approach to integrating AI technologies, specifically chatbots, into HR practices. Based on the analysis, the following recommendations are proposed:

1. The results from our study indicate that while HR professionals generally hold a positive view of AI technologies (mean score of 4.03 for general perceptions), employees exhibit a more cautious stance (with 30% remaining neutral). Given this variance in perspectives, it is advisable for HR managers to implement AI technologies in stages, allowing employees time to familiarize themselves with the tools and gradually integrate them into daily practices. This gradual adoption helps mitigate resistance to change and facilitates smoother transitions. Previous research supports this approach, emphasizing the importance of providing employees with adequate time and training to adjust to new technologies (Huang and Rust, 2021).
2. While HR professionals are confident in AI's potential to automate routine tasks, employees show more hesitation regarding the efficiency of AI-driven tools (50% expressed uncertainty about AI's effectiveness). This discrepancy underscores the importance of training programs. HR managers should invest in educating both HR staff and employees on the capabilities and limitations of AI technologies, ensuring they understand how these tools enhance efficiency without replacing the personal

touch necessary for complex HR matters. Some researchers (Rane, Choudhary & Rane, 2024; Molino, Cortese & Ghislieri, 2020) suggest that comprehensive training not only enhances technology adoption but also increases trust in AI systems. Also the literature highlights that if employees lack any skills, these AI systems help them identify their training needs and complete the required courses (Budhwar, 2022).

3. To bridge the gap in perceptions between HR professionals and employees, it is crucial for HR managers to maintain transparent communication. Many employees are still uncertain about how AI will impact their roles, especially concerning job displacement (mean score of 3.87 for concerns about job displacement). HR managers should proactively communicate the benefits of AI, addressing concerns and clarifying that AI will serve as a tool to enhance, rather than replace human roles. Such transparency has been shown to improve employee engagement and reduce fear of technology-driven job loss (Biswas & Bhatnagar, 2013).

4. The study reveals that both HR professionals and employees believe AI can enhance autonomy in HR-related tasks, such as managing leave requests and benefits (86% of HR professionals and 55% of employees). To capitalize on this, HR managers should leverage AI tools that empower employees to handle routine HR tasks independently. This not only increases efficiency but also fosters a sense of empowerment among employees, aligning with findings from existing studies that AI-driven autonomy leads to higher job satisfaction and employee engagement (Davenport & Kirby, 2016).

We consider that by putting these suggestions into practice, HR managers may minimise the difficulties and unknowns that come with integrating new technology while successfully utilising AI's potential to improve organisational effectiveness, employee engagement, and general satisfaction.

6. Conclusions

This paper highlights that AI is significantly reshaping HR practices, particularly in areas such as job empowerment, employee engagement and job enhancement. These transformations are expected to accelerate, urging HR professionals to adapt their strategies to leverage AI effectively.

In light of the research findings, it is crucial for HR managers to focus on inclusivity, ensuring that employees feel empowered and supported in their interaction with AI technologies. Engaging employees in discussions about AI's role in enhancing their work, rather than replacing it, is key to fostering trust. Managers should involve employees in shaping AI-driven processes, which could increase trust. This approach not only promotes a positive organizational culture but also aligns with market trends toward transparency and collaboration (Huang and Rust, 2021).

Despite the benefits, concerns regarding job displacement and reduced human interaction remain significant barriers. These concerns must be addressed to ensure that AI adoption adds sustained value to organizations and aligns with workforce expectations. Therefore it is crucial for policymakers and businesses to proactively address this issue to ensure a just transition and minimize the negative effects on employees, and also to understand the broader effects of AI on HRM.

However, as long as businesses adopt this technology, the partnership of artificial intelligence and human knowledge will become a powerful force that not only meets demands but also actively shapes the nature of work in the future. The combination of artificial and human intelligence holds the potential to revolutionise the workplace by boosting output, innovation and general well-being.

Although the path to an AI-enabled workplace is complicated, it offers a future in which companies and workers benefit with careful strategic planning and ethical considerations (Budhwar, 2022). AI supports sustainable business models and improves HR procedures as it is incorporated more and more into HR operations.

Understanding these dynamics is crucial for creating effective strategies to manage workforce transitions and ensure that employees have the skills needed to succeed in an AI-driven environment.

Regarding future perspectives, human resource management should prepare for the rise of new roles and job functions in HR, such as AI ethics officers, who will ensure that AI algorithms are applied ethically and fairly. As AI becomes more integrated into HR processes, these roles will become increasingly important, and HR professionals must ensure that AI is used efficiently and fairly.

In conclusion, AI plays an essential role in strengthening HRM functions and activities, providing opportunities for significant advancement in employee management and organizational efficiency.

References

Agrawal, A., Gans, J., & Goldfarb, A. (2017). What to expect from artificial intelligence. MIT Sloan Management Review, 58(3), 23-26

Arslan, A., Cooper, C., Khan, Z., Golgeci, I., Ali, I. (2022). Artificial intelligence and human workers interaction at team level: a conceptual assessment of the challenges and potential HRM strategies*, International Journal of Manpower*, 43 (1), 75-88

Bititci, U., Cocca, P., Ates, A. (2016). Impact of visual performance management systems on the performance management practices of organisations*. International Journal of Production Research*, 54(6), 1571–1593

Biswas, S., Bhatnagar, J. (2013), Mediator analysis of employee engagement: role of perceived organizational support, p-o fit, organizational commitment and job satisfaction. *Vikalpa: The Journal for Decision Makers*, 38(1), 27-40

Brougham, D., Haar, J. (2020). Technological disruption and employment: The influence on job insecurity and turnover intentions: A multi-country study. *Technological Forecasting and Social Change*, 161, 120276

Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company

Budhwar, P., Malik, A., De Silva, M. T. T., Thevisuthan, P. (2022). Artificial intelligence – challenges and opportunities for international HRM: a review and research agenda*. The International Journal of Human Resource Management,* 33(6), 1065–1097

Castellacci, F., & Viñas-Bardolet, C. (2019). Internet use and job satisfaction. *Computers in Human Behavior*, 90, 141–152

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review,* 33(1)

Davenport, T.H., Kirby, J. (2016), Winners and Losers in the Age of Smart Machines, MIT Sloan Management Review; *Cambridge*, 57(3), 21-25

Hackman, J. R., & Oldham, G. R. (1976). *Motivation through the design of work: Test of a theory*. Organizational Behavior and Human Performance, 16(2), 250–279

Huang, M.-H., Rust, R., T. (2021), A Framework for Collaborative Artificial Intelligence in Marketing, *Journal of Retailing,* 98(2), 209-223

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155–172

Jung, H., S., Jung, Y., S., Yoon, H., H. (2021), COVID-19: The effects of job insecurity on the job engagement and turnover intent of deluxe hotel employees and the moderating role of generational characteristics, *International Journal of Hospitality Management,* Volume 92

Kaur, M. and Gandolfi, F. (2023), Artificial Intelligence in Human Resource Management - Challenges and Future Research Recommendations, *Review of International Comparative Management*, Volume 24, Issue 3

Khan, A. I., Shahzad, F., & Afzal, M. K. (2020). Role of AI and big data analytics in human resource management. *Journal of Open Innovation: Technology, Market, and Complexity*, 6(2)

Kumar, N., Liu, Z., Jin, Y. (2022), Evaluation of Employee Empowerment on Taking Charge Behaviour: An Application of Perceived Organizational Support as a Moderator, *Psychology Research and Behavior Management*, 15, 1055-1066

Li, J. J., Bonn, M. A., & Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organisational support and competitive psychological climate. Tourism Management, 73, 172–181

Makridis, and Han Hun, (2021), Future of work and employee empowerment and satisfaction: Evidence from a decade of technological change, *Technological Forecasting & Social Change,* 173

Malik, A., Srikanth, N. R., Budhwar, P. (2020). Digitisation, artificial intelligence (AI) and HRM. In J. Crawshaw, P. Budhwar, & A Davis (Eds.), *Human resource management: Strategic and international perspectives* (pp. 88–111), Sage

Molino, M., Cortese, C. G., & Ghislieri, C. (2020). The promotion of technology acceptance and work engagement in industry 4.0: from personal resources to information and training, International *Journal of Environmental Research and Public Health*, 17(7), 2438

Nawaz, N., & Gomes, A. M. (2019). Artificial Intelligence Chatbots are New Recruiters, *International Journal of Advanced Computer Science and Applications,* Vol. 10, No. 9

Nguyen, T. M., & Malik, A. (2022). 'Impact of knowledge sharing on employees' service quality: The moderating role of artificial intelligence. *International Marketing Review*, ahead-of-print

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *The International Journal of Human Resource Management*, 33(6), 1125-1147

Prentice, C., & Nguyen, M. (2020). Engaging and retaining customers with AI and employee service. *Journal of Retailing and Consumer Services*, 56, 102186

Rane, N., Choudhary, S. P., Rane, J. (2024). Acceptance of artificial intelligence: key factors, challenges, and implementation strategies. *Journal of Applied Artificial Intelligence*, 5(2), pp. 50–70

Sakka, F., El Maknouzi, M. E. H., & Sadok, H. (2022). Human Resource Management in The Era of Artificial Intelligence: Future HR Work Practices, Anticipated Skill Set, Financial and Legal Implications. *Academy of Strategic Management Journal*, 21, 1-14

Seibert, S.E., Wang, G., Courtright, S.H, 2011. Antecedents and consequences of psychological and team empowerment in organizations: a meta-analytic review. *J. Appl. Psychol*. 96 (5), 981–1003

Tarafdar, M., Beath, C. M., & Ross, J. W. (2019). Using AI to enhance business operations. *MIT Sloan Management Review,* 60(4), 37–44

Zhang, X., Bartol, K.M, 2010. Linking empowering leadership and employee creativity: the influence of psychological empowerment, intrinsic motivation, and creative process engagement. *Acad. Manag. J*. 53 (1), 107–128

Wirtz, J. (2019). Organisational ambidexterity: Cost-effective service excellence, servrobots, and artificial intelligence. Organizational Dynamics, 49(3), 1–9

STUDIA UNIVERSITATIS BABEŞ-BOLYAI OECONOMICA
VOLUME 69, ISSUE 3, 2024, pp. 14-23
DOI: 10.2478/subboec-2024-0012

HRM ALGORITHMS AND VALUE CREATION THROUGH AI IN TRAINING AND DEVELOPMENT

Diana IVANA*
Babes-Bolyai University, Romania

Abstract: The purpose of this research study is to investigate the effect of HRM algorithms thorough Artificial Intelligence (AI) on small and medium-sized enterprises, with a specific focus on Learning and Development processes. Based on insights shared by technical and HR managers, this study shows that AI-driven HRM algorithms provide effective mechanisms for improving the efficiency of training sessions to cater learning interests while synchronizing it with business requirements. The results also suggest that although there is concern about AI replacing human teachers and the strategy of virtual classes, the potential benefits in changing the learning and development process makes it generally positive on deploying AI. In other words, AI could bring great hope of improving education/training and yet there are some limitations.

JEL Classification: M12, M15, M54

Keywords: HRM algorithms, Recruitment and Selection, HR procedure, software solutions

1. Introduction

Using the right HRM algorithms is essential for making insightful decisions (George, Haas, and Pentland, 2014). Remarkable digital enterprises such as Google, Microsoft, IBM, and Linkedin provide platforms or tools that facilitate the investigation of human resource management (HRM) activities, including recruiting, remuneration, employee engagement, and turnover control (Walter, 2018).

Nowadays, HRM procedures are increasingly performed using software algorithms—a group of computer-programmed instructions designed to automatically finish a task that transforms data into output (Meijerink and Bondarouk, 2023).

* Corresponding author. Address: Faculty of Economics and Business Administration, Babeş-Bolyai University, 58-60, Teodor Mihali Street, 400591, Cluj-Napoca, România, E-mail: diana.ivana@econ.ubbcluj.ro

Researchers looked at how workers are affected by algorithmic management because HRM algorithms automate decision-making about workers. The available evidence points in two important directions: first, researchers have shown that algorithms limit workers' job autonomy and value (Gandini, 2019); second, workers have attempted to regain autonomy and value by attempting to offset algorithm-enabled control (Meijerink and Bondarouk, 2023).

HRM academics have questioned the usefulness of algorithms in decision-making (Angrave et al., 2016) and have come to the conclusion that the tools' strategic worth is not well supported by data. Thus, the purpose of this study is to explain the significance of HRM in businesses and how it differs from the conventional statistical approach in its application.

2. Review of the scientific literature

It can be suggested to utilize the term "Algorithmic Human Resource Management" in order to gather information on actual topics to set the scene for this research. Actually, software algorithms are being utilized in the workplace to handle digital data and therefore HR decision-making procedures are becoming fully or partially automated. Nevertheless, the usage of digital data to support HR decision-making is growing. When everything is taken into account, these advancements are significantly changing the way labor is managed and HR procedures are carried out. The use of software algorithms that function on digital data to improve HR-related choices and/or automate HRM tasks is known as "algorithmic HRM" (Strohmeier, 2018; Veen et al., 2019).

Intelligent decision-making cannot be supported by the volume, velocity, and variety of big data (Laney, 2001) unless suitable algorithms are developed and applied. In today's digitalized workforce, the rapid increase in data is becoming more prominent, as noted by George, Haas, and Pentland (2014). To make sense of this data, it has become crucial to leverage algorithms for analysis. As a result of the increasing data-driven nature of HRM operations, there is a growing focus on developing and incorporating advanced HRM algorithms, particularly within the HRM domain.

Big Data is becoming more and more difficult to handle manually due to its immense volume and accelerating collection rate. In this case, data can be automatically and successfully altered using software approaches. Software algorithms are sets of computer-programmed instructions that automatically translate input into output to accomplish a task. (Meijerink et.al, 2021). Algorithms have been utilized in training and performance management to balance HR capacities versus developmental expectations (Lin & Hsu, 2010) and to anticipate competency gaps in software engineering management (Colomo-Palacios, et. al, 2014).

In today's workplace, HR processes such as coaching, mentoring, reskilling, onboarding, and upskilling have been seamlessly integrated with digital tools, modern innovations, and technology, thus creating a more hybrid work environment (Cheng and Hackett, 2021). Moreover, through an analysis of the practice-oriented literature, it was revealed that the implementation of bottom-up training algorithms empowers employees to identify their training needs and communicate them to their employer, leading to a more proactive approach to professional development (Cheng and Hackett, 2021).

According to Walker (2012), managers can learn about potential training needs at different stages of an employee's career by utilizing data collected from both current and former employees. Vencat (2006) discusses a platform that Cisco employees utilized to share movies, including ones from YouTube channels, in order to foster team learning. Engineers at Whirlpool have created an interactive webcast tutorial platform that enables them to share the training with other staff members across 70 countries and promptly resolve product concerns (Vencat, 2006). The academic community has not yet looked at the effects of self-driven, bottom-up on-the-job training methods that are partially made possible by algorithmic platforms. The research on this topic shows that automation and artificial intelligence (AI) have a significant impact on learning and development (L&D). For example, Bhatt and Muduli (2022) found that advances in artificial intelligence (AI) including robots, artificial neural networks, and natural language processing can improve the effectiveness of learning and development (L&D) processes, evaluate learners' aptitudes, and track learners' progress. In a similar way, Huang et al. (2021) highlight the benefits of AI for education and training, particularly for virtual classrooms and adaptive learning.

According to Roschelle et al. (2020), artificial intelligence (AI) can act as a toolbox, allowing us to study, imagine, and debate as-yet-unrealized future learning scenarios thus impacting the nature of labor in the future.

Even though there has been a considerable amount of discussion about the use of automation and artificial intelligence (AI) in learning and development (L&D) process, there are still unanswered questions. Focusing on the specific tools and algorithms utilized by businesses to automate their L&D processes and identifying industry best practices, this study aims to address these gaps. Additionally, it seeks to recognize and assess the impact of widespread AI adoption on the effectiveness of L&D within the IT&C industry in Romania.

3. Research methodology

We are conducting a study to explore the impact of AI on learning and development in the professional IT&C sector. Our primary goal is to investigate the following secondary objectives:

- Evaluate how AI influences training and development effectiveness in the accounting sector.
- Explore the potential of using AI in the accounting sector to improve learning and development outcomes.

Quantitative data was collected through a questionnaire (Milind Sathe, 2022) distributed among 20 technical and HR managers in Cluj-Napoca from small and medium-sized enterprises. The questionnaire, structured in a Google Form, was emailed to all managers to gather their feedback. The questionnaire consists of six parts:

Part A: Respondents' personal information;
Part B: Customizing the learning paths;
Part C: Strengthening Training and Development;
Part D: Including training criteria;
Part E: Emphasizing Virtual Learning;
Part F: Effectiveness in Learning and Development

There is much flexibility in the data analysis since all questions except those in section A are in the Likert scale format whereby responses range between strongly disagree (1) and strongly agree (5). The participants were engaged in answering a questionnaire which was then analyzed using MS Excel and SPSS software.
To adhere to research norms such as ethical considerations, all participants are provided with clear information about the study's objectives and their data will be used for academic purposes only.

With regard to respondents demographics, 31.3% are female and 68.8.% male (Figure 1); this data bringing to the fore the fact that in the IT&C industry the most managerial roles are dominated by males. Also, the most respondents have between 10 and 15 years experience (Figure 2), result that indicates that a managerial role comes with a lot of work and years of experience in the technological field.

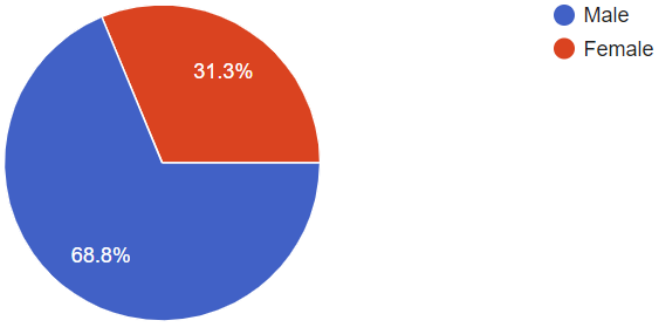

Figure 1: Respondents' gender

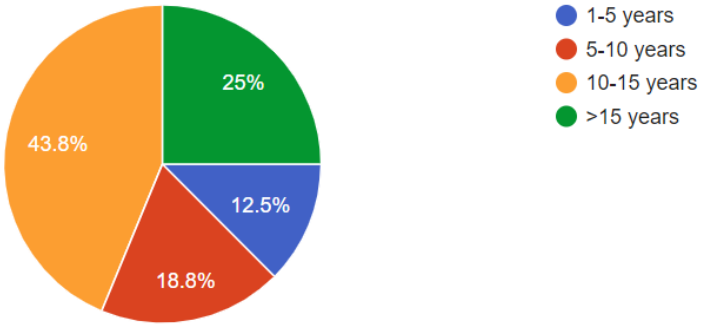

Figure 2: Respondents' experience

4. Results and discussion

The representation of the results was done following the model developed by Milind Sath (2022) in the thesis regarding the implementation of AI tools in the learning and development process in accounting. Each section from A to F will be analysed by using frequency analysis.

The survey results in Table 1 show that managers mostly think AI is pretty suitable for making training more personalized. Most of them agreed or strongly agreed that AI can figure out what each employees' needs and set up the right training for them. AI-powered personal learning plans can also help employees hit their learning targets better. All the same, AI-based assessments done by learning platforms seem to agree that they can make sensible predictions as long an employee set up some goals and give it a few specifics from their records. From this research perspective, it could be mentioned that this is clear validation that the use of AI to enhance training and personalized learning paths is a coherent goal. The results are also sustained by the literature evidence, which shows that HR professionals can customize solutions to meet the specific needs of each employee with the help of AI-driven tools that offer personalization and adaptability (Huang & Rust, 2021). This is evident in the fields of development and learning, where adaptive learning technologies offer individualized training opportunities that support employees in realizing their greatest potential (Brynjolfsson, Wang and Zhang, 2021).

Table 1: Personalizing the Learning Pathways by AI Adoption

Variables	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI is provided support to identify personalized learning requirements.	0%	0%	18.8%	43.8%	37.5%
AI makes it possible for training programmes to be tailored to the specific requirements of each individual worker.	0%	0%	18.8%	50%	31.3 %
Employees achieve their learning objectives more quickly because the learning pathways are designed as per personal preferences and objectives	0%	0%	12.5%	62.5%	25 %
AI-powered learning systems analyse each learner and recommend a learning programme based on his or her previous performance and objectives.	0%	6.3%	6.3%	56.3%	31.3%

Various viewpoints on the impact of automation and personalization in learning and development are summarized in Table 2. Although the majority of participants had varying opinions on automation being primarily a time saving tool, some were ambivalent and others disagreed entirely. A sizeable minority also believed that more representative input would help deliver a better, tailored learning and support experience overall; many were still undecided. In addition, many respondents indicated that they would support a targeted approach to higher completion rates as the best response (though several took no position on this question).

Most were in agreement that automating analysis to assess if learning is effective enough was something worth striving for, but a few others strongly disagreed or at least did not agree. These results show, that automation and personal performance feedback have a significant positive correlation on learning outcomes; however with some variability in the results. Nevertheless, the research results is supported by literature studies that mentioned that AI-driven technologies can also help with internal talent development by pointing out high-potential workers and recommending customized training programs (Saling & Do, 2020). To sum up, artificial intelligence (AI) and automation are vital to the recruitment and development of talent, revolutionizing the process and improving focused talent development.

Table 2: Reinforcing Training and Development by Adoption of AI

Variables	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Automation of learning and development processes save time			25%	12.5%	62.5%
Employee engagement is increased by personalizing the learning and reinforcement processes.		6.3 %	25 %	37.5 %	31.3 %
Increasing completion rates by personalizing the learning and reinforcement processes.			12.5 %	62.5 %	25 %
Automation of analytics measure learning effectiveness of employees		6.3 %	18.8 %	25 %	50 %

Table 3 refers to how AI-powered learning systems is being perceived and the impact it has had on training and development process. Further, credit for believing AI helps learning get smoother and more structured. Most were in favour of this view however a few disagreed or had a neutral opinion. Regarding changing business environment, mostly has mixed opinion about automation in training and development requirements; some agreed with it when others disagreed or showed neutral feelings.

About reducing manual work (shortening the process of defining training needs) - most respondents thought it was useful, a few had no opinion on this or disagreed with it. Some only partially agreed or reported being neutral but the vast majority said that training was easiest to measure by its impact on employee performance. Moreover, the findings reveal that AI technologies have the potential to advance learning and education in many respects yet are also lacking on several issues. Through AI and automatization, organizations can increase overall productivity, decrease human error, streamline HR processes, and automate repetitive tasks (Bennett, 2022). These upgrades have the potential to save a large amount of money and free up funds for more important HR projects (Harrison et al., 2020).

Table 3: Integrating Training Requirements by Adoption of AI

Variables	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
A learning system, powered with AI simplifies the learning and development process		12.5 %	12.5 %	25%	50%
Training and development requirements are automatically integrated with the changes of the business environment		12.5 %	25 %	25 %	37.5 %
Time can be saved as minimization of manual works on identifying training requirements			26.7 %	26.7 %	46.7 %
The outcome of training can be easily measured with the performance of employees		6.3 %	25 %	6.3%	62.5 %

Table 4 provides perspectives on the impact of AI and virtual learning platforms on the training and development process. Whether AI tutors will take on the traditional roles of educators such as lecturers, trainers, or teachers is a different type of question with more diverse opinions.

While some respondents strongly opposed the concept, others were either neutral or believed that AI tutors could help with such tasks. Most respondents believed that virtual learning is a cost-effective solution, but a small number were opposed. There was no consensus on how employers should balance work pressures with virtual learning for their employees. For some, scheduling was a challenge, but for others, it was manageable. AI-Powered Virtual Learning AI-based virtual learning platforms were almost unanimously viewed as a valuable source of ongoing support for improving knowledge, skills, and abilities.

Table 4: Integrating Training Requirements by Adoption of AI

Variables	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI tutors can take the place of teachers, lecturers, speakers, and coaches.	18.8 %	25%	18.8 %	12.5%	25 %
Virtual learning flatforms are cost effective.			6.3 %	31.3 %	62.5 %
Employees can easily find time for virtual learning while performing in their jobs.		13.3 %	20 %	33.3%	33.3%
AI based virtual learning platforms provide continuous support to improve knowledge as well as skills.			18.8 %	37.5 %	43.8 %

These technologies, as shown in the literature, use adaptive learning platforms and intelligent tutoring systems to give workers individualized and enriching experiences (Huang, Saleh and Liu., 2021). Through the application of AI-driven

analytics, organizations can effectively identify skill gaps and anticipate future training needs upfront. In the end, this promotes strategic growth and advancement by enabling businesses to make more intelligent investments in learning and development initiatives (Saling & Do, 2020).

Table 5 provides some estimates of how much the introduction of AI might affect the effectiveness of learning and advancement. Many respondents believed that personalization of learning paths could be made more effective through AI. However, some respondents were neutral on this. Most recognized some benefits of AI but supported its use in training and development to varying degrees. While some respondents found it helpful to facilitate necessary preparation through AI, others remained meutral. Conversely, most respondents questioned the effectiveness of AI-powered instruction by either disagreeing or remaining neutral, reflecting uncertainty about virtual learning. Although AI is increasingly praised as an engine for learning and development, attitudes vary widely as to what value it can actually provide.

The main point made here is that automation and artificial intelligence (AI) can improve human resource development by using customization and adaptability as essential mechanisms. Customization can result in more interesting and productive learning opportunities, which can improve skill development and boost employee satisfaction (Kim, 2022).

Table 5: Effectiveness of Learning and Development

Variables	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Personalizing the Learning Pathways by AI adoption improves the effectiveness of learning and development.			12.5 %	50%	37.5 %
Reinforcing training and development by AI adoption improves the effectiveness of learning and development.		6.7 %	20 %	40 %	33.3 %
Integrating training requirements by AI adoption improves the effectiveness of learning and development		6.3 %	25 %	43.8%	25 %
Focusing on virtual learning by AI adoption improves the effectiveness of learning and development			25 %	43.8 %	31.2 %

5. Conclusions

Research based on small and medium companies conducted among HR managers as well technical managers characterizes the impact of artificial intelligence (AI) in learning and development (L&D), intrinsic tendency is reframed. Most workers believe the use of AI can help tailor training programs to individuals' learning path,

better equip them with what they need in order for their learnings and experience lead to increased organizational success. That said, views on how effective and impactful the implementation of AI is can differ. Many believe that AI-powered learning platforms are beneficial in terms of ease of learning and provide personalized assistance suitable to their needs, with an individual approach for each employee. Nevertheless, the efficiency of AI to ultimately replace conventional educators altogether and maintain a balance between work commitments with distance learning remains unanswered.

The results show the necessity of more studies into implementation plans to AI-based learning and development solutions in practice. The use of artificial intelligence (AI) in training could therefore have a remarkable impact on the trainers' outcomes and customized learning experiences. So as to deal with such issues at an organizational level, it is important that there be continuous research and development as also echoed by other participants. Notwithstanding the fact that AI can revolutionize HR practices and instructional environments overnight, further investigations are still needed on this ground.

References

Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and analytics: Why HR is set to fail the big data challenge. *Human Resource Management Journal*, 26(1), 1–11, https://doi.org/10.1111/1748-8583.12090.

Bennett, E. E. (2022). Leveraging technology to design and deliver human resource development. In In the emerald handbook of work, workplaces and disruptive issues in HRM (pp. 261–276). Emerald Publishing Limited. https://doi.org/10.1108/978-1-80071-779- 420221026.

Bhatt, P. K., Muduli, A. (2022). Artificial intelligence in learning and development: A systematic literature review. *European Journal of Training and Development,* 47(7/8), 677–694. https://doi.org/10.1108/EJTD-09-2021-0143, DOI: 10.1108/EJTD-09-2021-0143.

Brynjolfsson, E., Wang, C., & Zhang, X. (2021). The economics of IT and digitization: Eight questions for research. *MIS Quarterly*, 45(1), 473–477.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science,* 49(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9.

Cheng, M. M., & Hackett, R. D. (2021). A critical review of algorithms in HRM: Definition, theory, and practice. *Human Resource Management Review,* 31(1), 100698. https://doi.org/10.1016/j.hrmr.2019.100698.

Colomo-Palacios, R., González-Carrasco, I., López-Cuadrado, J.L. et al. (2014). I-Competere: Using applied intelligence in search of competency gaps in software project managers. *Inf Syst Front* 16, 607–625. https://doi.org/10.1007/s10796-012-9369-6.

Gandini, A. (2019). Labour process theory and the gig economy. *Human Relations,* 72(6), 1039–1056. https://doi.org/10.1177/0018726718790002.

George, G., Haas, M. R., & Pentland, A. (2014). Big Data and management. *Academy of Management Journal*, 57(2), 321–326, https://doi.org/10.5465/amj.2014.4002.

Harrison, P., Nichol, L., Gold, J. (2020). Redefining HRD roles and practice in the machine learning revolution. In The Future of HRD, Volume I: Innovation and Technology (pp. 143–166). Springer Nature. https://doi.org/10.1007/978-3-030-52410-4_6.

Huang, J., Saleh, S., Liu, Y. (2021). A review on artificial intelligence in education. *Academic Journal of Interdisciplinary Studies*, 10(3), 206–206. https://doi.org/10.36941/ajis-2021-0077.

Kim, S. (2022). Working with robots: Human resource development considerations in human robot interaction. *Human Resource Development Review*, 21(1), 48–74. https://doi.org/10. 1177/15344843211068810.

Laney, D. (2001). 3D data management: Controlling data volume, velocity and variety. META Group Research Note (February 2001).

Lin, C., Hsu, M. (2010). Holistic decision system for human resource capability identification. *Industrial Management & Data Systems*, Vol. 110 No. 2, pp. 230-248. https://doi.org/10.1108/02635571011020322.

Meijerink, J., Bondarouk, T. (2023). The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. *Human Resource Management Review,* 100876. https://doi.org/10.1016/j.hrmr.2021.100876.

Meijerink, J., Boons, M., Keegan, A., & Marler, J. (2021). Algorithmic human resource management: Synthesizing developments and cross-disciplinary insights on digital HRM. *The International Journal of Human Resource Management,* 32(12), 2545–2562. https://doi.org/10.1080/09585192.2021.1925326.

Roschelle, J., Lester, J. E., & Fusco, J. L. (2020). AI and the future of learning: Expert panel report. *Digital Promise.* https://doi.org/10.51388/20.500.12265/106.

Saling, K. C., Do, M. D. (2020). Leveraging people analytics for an adaptive complex talent management system. *Procedia Computer Science*, 168(January), 105–111. https://doi.org/0.1016/j.procs.2020.02.269.

Sathe, T. M. (2020). Artificial Intelligence Influenced Learning and Development in the Accounting Sector. (Master's thesis, National College of Ireland). Under the supervision of Dr. K. M. Ebenade. https://norma.ncirl.ie/5913/.

Strohmeier, S. (2018). Smart HRM–a Delphi study on the application and consequences of the internet of things in human resource management. *The International Journal of Human Resource Management,* 1–30, https://doi.org/10.1080/09585192.2018.1443963.

Veen, A., Barratt, T., & Goods, C. (2019). Platform-capital's 'app-etite' for control: A labour process analysis of food-delivery work in Australia. Work, *Employment and Society,* 34(3), 388–406, https://doi.org/10.1177/09500170198369.

Vencat, E. F. (2006). The Power of We; Companies are using YouTube-like technology to tap the ideas and energy of employees. Newsweek (International ed.). Retrieved from ProQuest Canadian Business & Current Affairs Database (November 20).

Walker, J. (2012). Meet the new boss: Big data. *Wall Street Journal.* https://doi.org/10.1016/j.ssresearch.2010.05.001.

Walter, D. (2018). Microsoft workplace analytics: How your business can benefit. *Business News Daily*. https://www.businessnewsdaily.com/11092-microsoft-workplace-analytics-business.html

STUDIA UNIVERSITATIS BABEȘ-BOLYAI OECONOMICA
VOLUME 69, ISSUE 3, 2024, pp. 24-42
DOI: 10.2478/subboec-2024-0013

EXPLORING THE INTERPLAY BETWEEN DIGITALIZATION, CORPORATE GOVERNANCE, AND SDG REPORTING: A PATHWAY TO SUSTAINABLE DEVELOPMENT

Cristina Alexandrina ȘTEFĂNESCU*
Babes-Bolyai University, Romania

Abstract: This study explores the role of digitalization in advancing sustainable development and its potential to improve SDG reporting. It investigates how digital technologies, along with other macroeconomic factors such as governance, economic, environmental, and social factors, can enhance the quality and effectiveness of sustainability reporting across different countries. Grounded in stakeholder and resilience theory, the research employs OLS regression along with robustness and heterogeneity tests to ensure the reliability and validity of the findings. The study contributes to the literature by highlighting the interconnections between digitalization, corporate governance, and SDG reporting. It also reveals that corporate governance does moderate the relationship between digitalization and SDG reporting. The findings show that countries with higher adoption of digital technologies tend to demonstrate improved sustainability reporting, along with strong performance in environmental health, ecosystem vitality, and economic progress. However, digitalization proves to be a significant driver of SDG reporting in emerging economies but does not have the same effect in advanced countries. From a practical perspective, the study suggests that governments and organizations should prioritize digitalization strategies and governance frameworks to enhance sustainability reporting and better align with the global development goals set out in the 2030 Agenda.

JEL classification: Q5, Q01

Keywords: sustainable development goals (SDG); sustainability reporting; digitalization; corporate governance

* Corresponding author. Address: Department of Accounting and Audit, Faculty of Economics and Business Administration, Babes-Bolyai University, Teodor Mihali str., Cluj-Napoca, Romania Email: cristina.palfi@econ.ubbcluj.ro

1. Introduction

The increasing focus on sustainability and the pursuit of the Sustainable Development Goals (SDGs) has become a central agenda for policymakers, businesses, and civil society alike. At the heart of this shift lies the recognition of digitalization as a transformative force in driving progress toward sustainability. Digital technologies, including Artificial Intelligence (AI), Big Data, the Internet of Things (IoT), and Information and Communication Technology (ICT), have rapidly reshaped economies, societies, and environments across the globe. These technologies, when strategically integrated, offer significant potential to advance the SDGs by enhancing transparency, optimizing resource use, and improving social well-being (Kostetskyi, 2021; Gouvea et al., 2018). The interplay between digitalization and the SDGs is particularly critical as it empowers organizations to disclose their sustainability practices, monitor progress, and ensure accountability.

However, despite the promising role of digitalization, the relationship between digital technologies and SDG reporting remains underexplored in the academic literature. While some studies have highlighted the importance of digitalization for corporate transparency (Kostetskyi, 2021) and the role of SDG reporting in driving sustainability (Walker et al., 2019), few have examined the combined effects of digital technologies, governance structures, and reporting practices on achieving the SDGs (Del Río Castro et al., 2021). Moreover, while governance is acknowledged as a fundamental driver for shaping organizational behaviors and promoting sustainability (Gerged et al, 2023; Gómez and Garcia, 2020), the nuanced role of digitalization in strengthening or hindering the effectiveness of governance in SDG reporting remains unclear.

Our paper addresses these gaps in the literature by exploring the joint and individual effects of digitalization, governance, and national culture on SDG reporting. We aim to contribute to the growing body of research by examining how these factors when considered together, influence SDG disclosures across different regions and economies. Specifically, our study seeks to answer the following research questions: *(1) What role does digitalization play in enhancing SDG reporting? (2) To what extent does corporate governance moderate the relationship between digitalization and SDG reporting?*

The originality of this study lies in its holistic approach to understanding the interplay between digitalization, governance, and SDG reporting. By integrating insights from stakeholders' theory and resilience theory, this research offers a comprehensive theoretical and empirical framework for analyzing the drivers of sustainability reporting. Previous studies have often focused on these concepts in isolation, but this paper aims to explore their interconnectedness and provide a more nuanced understanding of how digitalization can act as both a facilitator and a moderator in the SDG reporting process.

Our findings provide compelling evidence that digitalization significantly enhances SDG reporting, particularly in emerging economies where digital infrastructure is expanding rapidly. In contrast, the impact of digitalization is less pronounced in advanced economies, where reporting practices are more established, and digitalization has already been integrated into organizational practices. Furthermore, while governance does play a role in shaping SDG reporting, its moderating effects appear to be insignificant compared to the direct influence of digitalization. These results

underline the importance of fostering digital transformation in emerging economies to ensure more comprehensive and transparent sustainability reporting.

This paper makes several contributions to the literature. First, it extends the understanding of how digitalization influences SDG reporting by analyzing the moderating role of governance. Second, it provides empirical evidence on the effectiveness of digitalization in different economic contexts, offering valuable insights for policymakers, businesses, and regulators aiming to enhance sustainability practices. Lastly, the study highlights the importance of integrating digitalization into sustainability reporting frameworks, which can ultimately contribute to more resilient and sustainable societies. The implications of these findings are far-reaching, offering a roadmap for organizations and governments to align their strategies with the 2030 Agenda and accelerate progress toward the SDGs.

The paper is structured as follows: Section 2 outlines the theoretical background and hypotheses, Section 3 covers the methodology, including data collection and model specification, Section 4 presents the empirical results, and Section 5 concludes with key insights, limitations, and suggestions for future research.

1. Literature review and hypotheses development

Sustainable development and SDG reporting

Sustainable development emphasizes the interconnectedness of economic prosperity, environmental stewardship, and social equity, recognizing that progress in these areas must be balanced to ensure long-term well-being for current and future generations (Del Rio Castro et al., 2021). This concept underpins the Sustainable Development Goals (SDGs), a global framework aimed at addressing pressing issues such as poverty, inequality, and environmental degradation through key pillars like planet, people, peace, prosperity, and partnerships (Dalby et al., 2019). The SDGs encourage businesses to integrate sustainability into their strategies, fostering innovative solutions that benefit stakeholders and society (Garcia-Meca and Martinez-Ferrero, 2021; Gunawan et al., 2021).

As a response to stakeholders' growing interest in non-financial performance, sustainability reporting has evolved to go beyond traditional financial metrics. This shift reflects an increasing demand for transparency on environmental, social, and governance (ESG) impacts (Adams and Abhayawansa, 2021)). Over time, sustainability reporting has expanded, driven by regulatory developments like the EU's Directive 2014/95/EU, which mandated non-financial disclosures for large companies, marking a significant move toward mandatory reporting (Dumay et al., 2019). The recent Corporate Sustainability Reporting Directive (2021) further emphasizes digital integration, allowing for automated reporting and reinforcing the role of digital technology as a critical tool for sustainable development (La Torre et al., 2018).

In this context, digitalization is increasingly recognized as a driver for achieving SDGs and enhancing the transparency, accessibility, and accuracy of sustainability reports. By supporting innovative approaches to longstanding challenges, digital technologies contribute to creating sustainable business environments, allowing countries to pursue improved living standards while supporting business success aligned with the SDGs (Farinha et al., 2018).

Digitalization and SDG reporting – insights from stakeholders and resilience theories

Digitalization plays an increasingly vital role in achieving the Sustainable Development Goals (SDGs) by transforming how organizations approach sustainability reporting. The stakeholder theory provides a foundation for understanding how digital advancements can influence sustainability practices. This theory emphasizes the importance of transparent disclosure to meet stakeholders' growing demand for non-financial information, amplifying their voices and accountability expectations (Barnett et al., 2020). Alongside stakeholder theory, resilience theory also underscores the role of digitalization in enhancing corporate adaptability. Digital tools can help companies build resilience in response to unforeseen crises like financial downturns or the COVID-19 pandemic, making sustainable practices an integral component of long-term organizational stability (Gillespie-Marthaler et al., 2019).

The integration of digital technologies such as AI, IoT, and big data accelerates sustainable reporting, enabling more accessible and data-driven disclosures that support the SDGs (Filho et al., 2023; Del Rio Castro et al., 2021). By enhancing transparency, digitalization fosters an environment where stakeholders, particularly investors, can drive economic, social, and environmental goals. For emerging economies, digitalization presents an opportunity to bridge gaps in sustainable governance and empower stakeholders to champion SDG-related initiatives (Lichtenthaler, 2021). Prioritizing digital advancement in policy-making can thus lead to more robust national and organizational frameworks for sustainable growth.

Moreover, digital technologies contribute to sustainable development by enabling a circular economy, promoting resource efficiency, and supporting evidence-based decision-making (Del Rio Castro et al., 2021). The impact of digitalization on economic growth and sustainability has been widely recognized as a catalyst for achieving the SDGs. By streamlining information-sharing and enabling enhanced environmental, social, and governance (ESG) evaluations, digitalization helps organizations measure and improve their sustainability performance, further aligning with global goals (Kiron and Unruh, 2018).

The convergence of digitalization and sustainability represents a transformative path forward, allowing organizations to better meet societal demands and adapt to environmental challenges (Del Rio Castro et al., 2021). This interplay creates opportunities for governments and businesses to embrace greener economic models, positioning digitalization as a critical driver for the SDGs and offering a promising route for sustained global growth and resilience (Mondejar et al., 2021).

Hypothesis development

In the aftermath of the COVID-19 pandemic, digitalization has become a critical factor in reshaping the way businesses, governments, and societies function, with digital technologies playing a central role in transforming operations and decision-making processes (Delgosha et al., 2021). Digital tools have the potential to drive greater efficiency, transparency, and value in reporting practices, enhancing both the quality and accessibility of information (Rozario and Thomas, 2019). In particular,

digitalization offers significant prospects for improving the harmonization of SDG reporting,

with the potential to revolutionize the way organizations measure and disclose their sustainability impacts.

Traditional reporting methods, particularly in the era of Big Data, are increasingly viewed as outdated (La Torre et al., 2018). With the power of digital technologies, companies and organizations are now able to generate and process data in ways that were previously unimaginable, enabling them to present more comprehensive and real-time insights into their economic, social, and environmental performance. For effective SDG reporting, however, it is essential to balance technological advancements with the need for stakeholders to easily interpret and understand the information being communicated (Smith, 2020). Digitalization, when properly leveraged, provides an opportunity for organizations to meet these demands while improving the quality of their sustainability disclosures.

The SDGs, which address global challenges such as poverty, inequality, and environmental sustainability, are a framework for sustainable development that transcends national boundaries. While achieving these goals may be more challenging for some countries and organizations, digitalization is increasingly seen as a tool that can bridge gaps by facilitating more effective and transparent reporting (Costanza et al., 2016; Fukuda-Parr and McNeill, 2019). Digital tools enable organizations to make meaningful progress toward the SDGs by improving business practices, fostering social inclusion, and supporting sustainable economic growth.

Digital technologies have already demonstrated their ability to advance the SDGs by addressing key challenges in areas such as education, health, clean energy, and economic growth (Mondejar et al., 2021). By improving data collection, enabling greater transparency, and providing new insights, digitalization plays an essential role in driving sustainability efforts. As such, we hypothesize that:

H_1: Digitalisation positively influences SDG reporting

Corporate governance plays a pivotal role in shaping sustainable development, as it serves as both a driving force for progress and a crucial element to integrate into development strategies. The relationship between governance and sustainable development is bidirectional, with effective governance structures enabling countries to address sustainability challenges more effectively, while sustainability itself requires strong governance frameworks to ensure its success. The level of governance within a country can significantly impact its economic and social development, and this, in turn, influences the quality and extent of sustainability reporting, including SDG disclosures (Stefanescu, 2021).

Governance structures are essential in shaping the environment in which sustainability reporting occurs. In countries with robust governance systems, there are fewer external pressures to drive change, as the internal regulatory and enforcement mechanisms are strong. These systems ensure compliance with sustainability standards and encourage organizations to adopt responsible practices (Gómez and Garcia, 2020). Conversely, in countries with weaker governance frameworks, characterized by poor transparency or high levels of corruption, the adoption and enforcement of sustainability reporting standards are often inconsistent, leading to national differences in the harmonization of SDG reporting (Stefanescu, 2021).

Governance structures also impact corporate social responsibility (CSR) practices and the overall transparency of organizations. In countries with strong political

stability, accountability, and transparent legal systems, businesses are more likely to adopt responsible behaviors and disclose relevant non-financial information (Cahan et al., 2016). This is because a stable governance environment allows organizations to operate securely and engage in environmentally friendly initiatives, which align with global sustainability goals (Jamali et al., 2020). In contrast, nations with weak governance systems, characterized by corruption and ineffective legal structures, often face challenges in fostering responsible corporate behavior and transparency (Pinheiro et al., 2022).

Considering the influence of governance on organizational behavior and sustainability, we hypothesize that corporate governance may strengthen, weaken, or reverse the impact of digital transformations on SDG reporting, as follows:

H_2: Corporate governance moderates the relationship between digitalisation and SDG reporting

2. Methodology

Sample and data collection

This study includes 105 countries from the latest global ranking by the World Economic Forum (WEF, 2020). To analyze systematic effects from multiple perspectives, the sample was divided into advanced and emerging economies groups and further categorized by regions: Africa, Asia-Pacific, Europe, and the Americas. Among the countries studied, 42% were advanced economies, with nearly half showing trends of development advancement, and income distribution ranging between 30% and 70%, encompassing lower-middle to high-income groups. Detailed sample characteristics are present in Table 1.

Variable description

To explore the connections between *digitalization* and *SDG reporting,* the proposed model includes the following variables:

Dependent variable - SDG Reporting

Sustainable development aims to enhance present and future generations' well-being by promoting equality, inclusion, and sustainability, addressing interconnected global economic, social, and environmental challenges. The SDG Index, developed by Sachs et al. (2022), provides a multidimensional perspective on these challenges, measuring countries' progress through various indicators that reflect each SDG's achievement percentages. Despite critiques regarding qualitative data limitations, the SDG Index remains a widely used benchmark for assessing national performance on SDG reporting (Del-Aguila-Arcentales et al., 2022).

Table 1. Sample characteristics

Region[1)]	%	Income group[1)]	%	Development status[2)]	%	Development trend[2)]	%
Europe	50	Low	0	Emerging	42	Receding	5
Asia	25	Lower middle	6	Advanced	58	Slowly receding	23
America	15	Upper middle	24			Stable	18
Africa	10	High	70			Slowly advancing	29
						Advancing	25

[1)] World Bank (2022)
https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html
[2)] World Economic Forum (2020)
https://www.weforum.org/reports/the-inclusive-development-index-2020

Independent variable – Digitalization

Digitalization plays a crucial role in encouraging organizations to align with the Sustainable Development Goals (SDGs) and to report their progress, supporting greater transparency and accountability in sustainability efforts (Rosati and Faria, 2019). The widespread adoption of digital technologies and IT innovations has facilitated more effective communication and improved information-sharing, enhancing reporting practices (Hilali et al., 2019). In this context, we draw upon the Digital Adoption Index (DAI) developed by the World Bank (2016) to reflect the transformative impact of recent technological advances that have spurred the development of innovative business models, reinforcing companies' commitment to sustainability (Piscielli et al., 2018). Subsequently, for the *robustness analysis,* we relied on the Digital Competitiveness Index (DCI) recently developed by IMD World Digital Competitiveness (2021), as it has recently gained increased attention as a catalyst for effective digital transformation that can provide a competitive advantage in both business environments and national economies (Stankovic et al., 2021).

Control variables

To analyze harmonized sustainability reporting under digitalization, we identified five macroeconomic factors and selected control variables based on their relevance to each type of influence.

Governance: Governance plays a critical role in enhancing reporting and ensuring harmonization, as highlighted by international accounting standards. In this study, governance quality is measured using the average of the six *Worldwide Governance Indicators (WGI)* (World Bank, 2020). Following Pinheiro et al. (2022), the behavior of companies reflects the governance environment of the country in which they operate, with stronger enforcement mechanisms - such as regulatory quality and the rule of law - being essential for effective reporting. As sustainability reporting, particularly on the SDGs, is often linked to corporate reputation and legitimacy (Cahan et al., 2016), we expect a positive impact of governance quality on SDG reporting.

Economic development: Economic development is crucial for sustainable growth, industrialization, and innovation, but also linked to the well-being of

individuals, addressing issues like poverty reduction, food security, and health. To measure it, this study uses the *Inclusive Development Index (IDI)* developed by the World Economic Forum (2020), which is well-suited for assessing countries' economic progress, particularly regarding sustainability and its associated goals (Gupta and Vegelin, 2016). We expect a positive influence of the economic development pillar of sustainability on the reporting of SDG progress, as countries with stronger economic sustainability are likely to report more effectively on their achievements.

Social development: Human development, focuses not just on economic growth but on people's capabilities and well-being, making it a powerful tool for evaluating a country's overall progress (Rosati and Faria, 2019; Xiao et al., 2018). This study uses the *Human Development Index (HDI)* established by the United Nations (2019), which has become the official index for governments to measure progress toward the SDGs. We expect a positive influence of the social sustainability pillar on reporting.

Environmental performance: It provides a clear picture of how effectively countries address environmental challenges and meet their sustainability targets. This study uses the *Environmental Performance Index (EPI)* developed by the Yale Center for Environmental Law and Policy (Wolf et al., 2022). The EPI is commonly employed as a national scale to measure countries' ability to set and achieve policy goals related to environmental health and ecosystem vitality (Rosati and Faria, 2019; Xiao et al., 2018). We expect a positive influence, as sustainability reporting serves as an incentive to promote environmental initiatives and reflect countries' progress and achievements in environmental performance.

Model specification

This study examines the impact of digitalization (DAI) on SDG reporting and its interaction with corporate governance (WGI).

Table 2. Variables description

Variable	Abbrev.	Description (scale)
SDG score[1)]	SDG	Total progress towards achieving all 17 SDGs (ranges from 0 to 100)
Digital Adoption Index[2)]	DAI	Countries' digital adoption across three dimensions of the economy: people, government, and business (ranges from 0 to 1)
Digital Competitiveness Index[3)]	DCI	Capacity and readiness to adopt and explore digital technologies for economic and social transformation (ranges from 0 to 100)
Worldwide Governance Indicators[4)]	WGI	Quality of governance across countries and over time (ranges from -2.5 to 2.5)
Inclusive Development Index[5)]	IDI	Level of growth and development growth (based on a 1-7 scale: 1=worst and 7=best)
Human Development Index[6)]	HDI	Level of social development (ranges from 0 to 1)
Environmental Performance Index[7)]	EPI	Level of environmental health and ecosystem vitality (ranges from 0 to 100)

Variable	Abbrev.	Description (scale)

[1] SDG Index and Dashboard https://dashboards.sdgindex.org/chapters/part-2-the-sdg-index-and-dashboards
[2] World Bank https://www.worldbank.org/en/publication/wdr2016/Digital-Adoption-Index
[3] IMD World Digital Competitiveness https://www.imd.org/centers/wcc/world-competitiveness-center/
[4] Worldwide Governance Indicators https://www.worldbank.org/en/publication/worldwide-governance-indicators
[5] World Economic Forum https://www.weforum.org/publications/the-global-competitiveness-report-2020/
[6] United Nations https://hdr.undp.org/content/human-development-report-2019
[7] Yale Center for Environmental Law and Policy https://epi.yale.edu

The baseline model (Model 1) for testing *hypothesis* H_1, which analyzes the role of digitalization (DCI) on the SDG Index, is set as follows:

$$SDG_i = \beta_0 + \beta_1 DAI_i + \beta_2 X_i + \varepsilon_i$$

where i represents the country; β_0 is the intercept; the term X_i represents control variables (economic, social, environmental, and governance factors); while ε_i signifies an error term.

To test hypothesis H_2, we expand the model to include an interaction term for digitalization and governance *(DAI*WGI)*:

$$SDG_i = \beta_0 + \beta_1 DAI_i + \beta_1 WGI_i + \beta_2 (DAI*WGI)_i + \beta_3 X_i + \varepsilon_i$$

Detailed definitions and data sources of the variables are presented in Table 2.

3. Results

This section presents the study's findings, starting with descriptive statistics and multicollinearity results. We then provide hypothesis testing outcomes using OLS regression for both baseline and moderating models, followed by an analysis of heterogeneity across country sub-samples. Finally, we confirm the robustness of our results through additional analyses using alternative variables.

Descriptive statistics

The descriptive analysis shows an average SDG score of 69.86, with a high of 85.9 in an advanced economy and a low of 40.9 in an emerging one. Table 3 details statistics for independent variables, distinguishing between developed (28% of sample) and emerging economies (72%). Emerging countries have an average SDG score of 65.92, while advanced countries average 79.71. Digitalization measures, DAI and DDCI, are also lower in emerging economies (0.05 and 46.48) than in advanced ones (0.76 and 77.89), mirroring trends seen across all control variables due to varying development levels.

Table 3. Descriptive statistics

	SDG	*DAI*	*DCI*	*WGI*	*IDI*	*EPI*	*HDI*
Emerging economies							
N	75	75	48	75	72	75	75
Mean	65.92	.05	46.48	-0.31	3.73	41.82	0.68
Std. Dev	8.64	0.15	10.43	0.54	0.57	10.15	0.12
Variance	74.67	0.12	108.85	0.30	0.33	103.20	0.01
Advanced economies							
N	30	30	29	30	29	30	30
Mean	79.71	0.76	77.89	1.27	5.11	73.44	0.92
Std. Dev	3.46	0.07	9.61	0.40	0.62	5.88	0.02
Variance	11.97	0.01	92.42	0.16	0.38	34.66	0.01

Given the relatively high correlations between several variables (see Table 2), we calculated the Variance Inflation Factor (VIF) and checked it against correlation tolerance (1/VIF). Variables with a tolerance below 0.1 and/or a VIF above 9 indicated a high degree of collinearity between them. The tests showed critical values for HDI (0.089/11.14), pointing to multicollinearity issues that could lead to unstable estimates, consistent with prior research, which has already shown that digitalization and digital innovations influence human development and/or GDP per capita (Stremousova and Buchinskaia, 2019), both with a notable main and interactive effect on sustainability outcomes (Gouvea et al., 2018).

Hypothesis test results

This sub-section tests our hypotheses using a simple OLS regression model, with a summary of results in Table 4. The baseline model (Model 1) assesses the impact of digitalization (DAI) on SDG reporting (Hypothesis H1), while the moderating model (Model 2) explores the interaction effect between digitalization and country governance on the same SDG score (Hypothesis H2). Table 3 follows a hierarchical estimation procedure: Model (0) includes only control variables, Models (1a) and (2a) focus on the independent variables and their moderation effect, respectively, and Models (1b) and (2b) present results for all variables combined.

Model (1a) shows that digitalization positively influences SDG outcomes across countries. The coefficients are statistically significant, and this positive impact remains robust when controlling for various country-specific factors in Model (1b). Therefore, digitalization plays an important role in advancing SDG progress, demonstrating a strong, meaningful relationship between DAI and the SDG score.

Table 4. Estimated results from the regression analysis

	Baseline model			*Moderating model*	
Variables	**Model (0)**	**Model (1a)**	**Model (1b)**	**Model (2a)**	**Model (2b)**
IDI	3.781***		2.535**		3.249**
	(0.849)		(13.002)		(4.448)
EPI	0.262***		0.219***		0.104**
	(0.047)		(0.060)		(0.875)
WGI	2.072***		-1.605*	1.575***	-2.037
	(0.898)		(1.002)	(0.918)	(0.776)
DAI		26.055***	27.376***	31.258***	25.564**
		(4.567)	(4.677)	(4.516)	(3.625)
DAI*WGI					-0.029
					(0.058)
Constant	34.503	42.295***	32.633	45.740	62.788
	(2.163)	(2.625)	(3.549)	(2.625)	(7.914)
Observations	105	105	105	105	105
R-squared	0.759***	0.813***	0.833***	0.830***	0.851***

*Significance *10%; **5% and ***1%. p-values reported in brackets.*

These findings support *hypothesis* H_1, demonstrating that technological advancements foster innovative business models that strengthen companies' commitment to sustainability (Piscielli et al., 2018). Digital transformations balance economic, social, and environmental factors, contributing to sustainable growth and alignment with the SDGs. Examples like AI in agriculture, smart water management, and blockchain technology to fight corruption (Goralski and Tan, 2020; Palomares et al., 2021) show how digital technologies drive SDG progress. Our results confirm that countries embracing digital technologies also improve their reporting practices, reflecting the broader trend of increased reporting in the digital age. Technologies like Big Data and XBRL have standardized taxonomies, enhancing corporate social responsibility and sustainable strategies (Seele, 2016). Digitalization supports organizational resilience, ensuring sustainability even in uncertainty, and improves stakeholder engagement and management policies (Miceli, 2021). Overall, our results validate that digitalization significantly influences sustainability reporting, enriching prior evidence and confirming our hypothesis that digitalization positively impacts sustainability reporting across macroeconomic determinants.

The control variable results also provide valuable insights. Better environmental health, ecosystem vitality, and higher economic progress were found to increase the likelihood of SDG reporting. These findings align with prior studies, confirming that environmental and economic sustainability are key drivers of sustainability reporting (Faccia et al., 2021). Countries facing greater environmental challenges (e.g., pollution, global warming) are under more pressure to act sustainably and are more inclined to report on SDGs (Rosati and Faria, 2019). Similarly, economically advanced countries, with more resources and public pressure, are more likely to report on sustainability (Ali et al., 2017). These results support stakeholder-oriented approaches that promote

transparent reporting on financial, social, environmental, and governance matters (Barnett et al., 2020). Developed economies, with greater resilience and access to new technologies, can enhance long-term value creation and sustainable development by supporting digitalization investments for broader social, economic, and environmental benefits.

Model (1b) tests the impact of digitalization (DAI) and corporate governance (WGI) on SDG reporting, exploring how their interaction moderates this relationship. As outlined in *hypothesis* H_2, we expect that corporate governance could either strengthen, weaken, or reverse the relationship between digitalization and SDG outcomes. To test this, we ran a modified regression model (Model 2) that included an interaction term (DAI*WGI), using the same estimation procedure as the baseline model.

The results show a negative moderation effect based on the sign of the interaction term. However, this effect is not statistically significant, suggesting that, contrary to our expectations, the interaction between digitalization and governance does not meaningfully influence SDG progress. As a result, we reject *hypothesis* H_2.

It is not surprising that governance enforcement mechanisms are insufficient to drive sustainability reporting, as these practices remain voluntary and digitalization presents ongoing challenges for many governance systems. For instance, while EU Member States were expected to lead SDG implementation and improve public governance, their Digital Government capacity was inadequate (Janowski, 2016). Given digitalization's key role in sustainable development, governments must invest more in aligning it with SDG objectives, as delayed adoption of digital technologies could worsen inequalities and impede sustainable development.

Robustness analysis

To explore the robustness of our results, we conducted the same analysis (see Table 5) using an alternative measure of digitalization, namely the Digital Competitiveness Index (DCI), developed by IMD World Digital Competitiveness (2021). This index assesses a country's ability to adopt and leverage digital technologies across various sectors, driving successful transformations in government, business models, and society. We choose due to its increasing recognition as a key driver of digital transformation, offering a competitive advantage in both business environments and national economies (Stankovic et al., 2021).

Our estimations strongly support the main analysis according to the variance explanation power. The independent variable (DCI) remains statistically significant, showing a positive influence, though with a lower significance (p-values < 0.05), while the interaction term confirms that corporate governance does not have any moderation effect on between digitalization and SDG reporting.

In conclusion, the robustness analysis confirms the initial findings, with only minor changes in the significance of the variables. Digital competitiveness emerges as a key driver for achieving the SDGs, promoting cultural and multidimensional changes across businesses and societies (Del Rio Castro et al., 2021). Furthermore, digitalization not only enhances sustainability reporting practices but also accelerates the achievement of specific SDGs through innovative technologies (Kunkel and Tyfield, 2021).

Table 5. Estimated results from the regression analysis with alternative variable

	Baseline model			*Moderating model*	
Variables	**Model (0)**	**Model (1a)**	**Model (1b)**	**Model (2a)**	**Model (2b)**
IDI	3.936***		3.894***		2.241**
	(1.249)		(1.263)		(1.131)
WGI	0.391***		0.526	2.408*	-0.797
	(0.529)		(1.542)	(1.717)	(1.347)
DCI		0.231*** (0.056)	0.209**	0.248***	0.310**
			(0.850)	(0.081)	(0.061)
DCI*WGI					0.079
					(0.077)
Constant	42.462	48.219	43.735	57.491	41.688
	(3.129)	(1.551)	(4.882)	(4.253)	(4.206)
Observations	105	105	105	105	105
R-squared	0.724***	0.782***	0.721***	0.631***	0.795***

*Significance *10%; **5% and ***1%. p-Values reported in brackets.*

Heterogeneity analysis

A potential critique of our analysis is the varying impact of digitalization on SDG reporting across different country characteristics. To address this, we explored the heterogeneity of digitalization's effect by analyzing two sub-samples: emerging vs. advanced economies, based on the Inclusive Development Index (IDI), and by region (Africa, Asia-Pacific, Europe, and America) following The World Bank's classification. We re-estimated the baseline model for each group to better understand how economic development and regional context influence the relationship between digitalization and SDG reporting.

The heterogeneity analysis results by countries' development status (Table 6) reveal that digitalization significantly impacts SDG reporting in emerging economies (Model A), with DAI showing a positive effect ($p<0.01$) and strong predictive power (79.4%). In contrast, advanced economies (Model B) show no significant results, suggesting that digitalization does not enhance sustainability reporting in these countries.

In advanced economies, strong legal frameworks and public pressure already drive sustainability practices and reporting, reducing the need for digitalization to play a key role. However, emerging economies face weaker governance and regulatory challenges. Despite this, companies have used digital technologies—like blockchain, mobile apps, and AI—to promote corporate social responsibility and address SDG targets, particularly in areas like education, poverty reduction, and infrastructure (Forcadell and Aracil, 2019; Mhlanga, 2021). These technologies have helped bridge policy gaps, supporting sustainable development in regions with limited resilience.
Overall, digitalization is a crucial driver of sustainability in emerging economies, where it compensates for institutional and regulatory weaknesses, enabling progress toward SDG goals.

Table 6. Regression results for the heterogeneity analysis by development status

	Model A			*Model B*	
Variables	***Advanced***	***Emerging***	**Variables**	***Advanced***	***Emerging***
DAI	20.926***	5.743	DCI	0.317***	-0.133
	(6.282)	(7.798)		(0.109)	(0.088)
IDI	4.836***	-0.697	IDI	6.524***	1.401
	(1.257)	(1.593)		(1.621)	(1.299)
EPI	0.272***	0.143			
	(0.083)	(0.134)			
WGI	-0.525	2.405	WGI	-0.209	4.429*
	(1.179)	(2.335)		(1.707)	2.220
Observations	*35*	*75*		*35*	*75*
R-squared	0.096***	0.794***		0.292***	0.666***

*Significance *10%; **5% and ***1%. p-Values reported in brackets.*

The regional analysis (Table 7) confirms the heterogeneity in digitalization's impact based on development levels. In developing countries, such as those in Africa (e.g., Egypt, Ghana, Kenya), digital policies aimed at boosting productivity, job creation, and sustainable transformation have advanced SDG attainment (ElMassah and Mohieldin, 2020). Similarly, digitalization has supported SDG progress in Nigeria, driven by stakeholder commitment and e-governance (Ufua et al., 2021).

Table 7. Regression results for the heterogeneity analysis by region

Variables	***Model C (Africa)***	***Model D (Asia-Pacific)***	***Model E (Europe)***	***Model F (America)***
DAI	25.898**	4.650	4.614	-9.594
	(11.864)	(6.796)	(8.114)	(19.825)
IDI	5.338**	2.004	-0.593	3.469
	(2.429)	(2.144)	(1.039)	(3.999)
EPI	0.422**	0.272**	0.147*	-0.385*
	(0.178)	(0.103)	(0.078)	(0.174)
WGI	2.022	-1.029	2.261	0.202
	(1.969)	(1.804)	(1.519)	(2.103)
Observations	24	24	35	17
R-squared	729***	632***	.618***	.850***

*Significance *10%; **5% and ***1%. p-Values reported in brackets.*

In Asia, rapid digital growth, particularly in China and ASEAN countries, has modernized business processes, with government policies promoting the digital economy (Chen et al., 2022). However, digitalization has become less crucial for transparency and sustainability reporting in these regions. In Europe, North America,

and Japan, the knowledge economy and the COVID-19 pandemic have accelerated digital transformation, driving both economic growth and sustainability. Overall, digitalization is a key growth driver for developing nations, fostering sustainable development.

4. Conclusion

In today's world, characterized by rapid changes and uncertainties, sustainability reporting has emerged as a vital tool for aligning business activities with the real needs of stakeholders and enhancing system resilience. Digitalization, by enabling unprecedented interconnectivity among business processes, organizations, societies, and stakeholders, provides the backbone for present and future development. This study explores the complex relationship between digitalization and sustainability reporting, offering a holistic approach to understanding how various macroeconomic factors - governance, economics, environmental concerns, and social dynamics - impact sustainability reporting practices across countries. We propose that digitalization functions as a central, overarching factor influencing these practices, providing the catalyst for systemic change in sustainability efforts globally.

Our findings offer several important contributions to the literature. First, we highlight the significant role that digitalization plays in enhancing SDG reporting, confirming the hypothesis that countries with higher digital adoption also demonstrate improved reporting practices. These countries not only report better on sustainability but also exhibit strong environmental health, ecosystem vitality, and sound economic performance. These findings align with previous studies suggesting that digitalization is a fundamental driver of societal transformation and economic growth. We also show that digital technologies are vital for accelerating progress, particularly in emerging economies, where digital adoption is a key enabler of sustainable development.

However, the study also revealed that governance did not play a substantial role in enhancing SDG reporting, which reflects the current voluntary nature of sustainability practices in many countries. This finding points to the need for a re-evaluation by both businesses and governments, who should consider accelerating efforts to align with the SDGs. Moreover, while sustainability has often been linked with resilience, our research demonstrates that digitalization provides the flexibility to navigate change and promote growth, ensuring the capacity to meet future sustainability challenges. These results underscore the transformative power of digitalization, particularly in emerging economies, and emphasize the need for global efforts to leverage digital tools for sustainable development.

Despite the promising findings, this study has some limitations that should be addressed in future research. Our sample, comprising 105 countries categorized as advanced or emerging, is limited by its scope, and future studies could expand the sample to include more nations or focus on specific regions, such as the EU, OECD, or Asia-Pacific. Furthermore, while our analysis controls for several macroeconomic factors, the impact of omitted variables remains a possible avenue for further exploration. Testing our model on different datasets or conducting region-specific studies could yield valuable insights into the nuances of digitalization's impact on sustainability reporting.

The implications of our findings are both theoretical and practical. From a theoretical perspective, we contribute to the ongoing debate on the interplay between

digitalization, governance, and sustainability reporting. Our study provides a clearer understanding of the role digital technologies play in advancing SDG reporting, offering a foundation for future research in this area. Practically, our findings offer valuable guidance to policymakers, businesses, and regulatory bodies. Governments and organizations should consider developing more robust frameworks to support the harmonization of sustainability reporting practices, encouraging global alignment with the 2030 Agenda. Digitalization and governance frameworks must be strategically integrated to ensure that businesses can align their reporting with the SDGs and contribute meaningfully to sustainable development.

References

Adams, C.A., Abhayawansa, S. (2021) Connecting the COVID-19 pandemic, environmental, social and governance (ESG) investing and calls for 'harmonisation' of sustainability reporting, *Critical Perspectives on Accounting,* 82, 102309.

Ali, W., Frynas, J.G., Mahmood, Z. (2017) Determinants of corporate social responsibility (CSR) disclosure in developed and developing countries: A literature review, *Corporate Social Responsibility and Environmental Management*, 24, 273–294.

Barnett, M.L., Henriques, I., Husted, B.W. (2020) The rise and stall of stakeholder influence: How the digital age limits social control, *Academy of Management Perspectives,* 34(1). 48-64.

Cahan, S.F., De Villiers, C., Jeter, D.C., Naiker, V., Van Staden, C.J. (2016) Are CSR disclosures value relevant? Cross-Country evidence, *European Accounting Review*, 25(3), 579-611.

Chen, Y., Li, J., Zhang, J. (2022) Digitalisation, data-driven dynamic capabilities and responsible innovation: An empirical study of SMEs in China. *Asia Pacific Journal of Management*. Available at https://doi.org/10.1007/s10490-022-09845-6

Costanza R., Daly L., Fioramonti L., Giovannini E., Kubiszewski I., Fogh Mortensen L., Pickett K.E., Vala Ragnarsdottir K., De Vogli R., Wilkinson R. (2016) Modelling and measuring sustainable wellbeing in connection with the UN Sustainable Development Goals. *Ecological Economics,* 130, 350–355.

Dalby, S., Horton, S., Mahon, R., Thomaz, D., Dalby, S., Horton, S., Mahon, R., Thomaz, D., (2019) Achieving the sustainable development goals: global governance challenges In: *Routledge Studies in Sustainable Development*, Routledge.

Del Rio Castro, G.D., Fernández, M.C.G., Colsa, Á.U. (2021) Unleashing the convergence amid digitalization and sustainability towards pursuing the Sustainable Development Goals (SDGs): A holistic review, *Journal of Cleaner Production,* 280, 122204.

Del-Aguila-Arcentales S, Alvarez-Risco A, Jaramillo-Arévalo M, De-la-Cruz-Diaz M, Anderson-Seminario M. (2022) Influence of social, environmental and economic Sustainable Development Goals (SDGs) over continuation of entrepreneurship and competitiveness, *Journal of Open Innovation: Technology, Market, and Complexity*. 8(2), 73.

Delgosha, M.S., Saheb, T., Hajiheydari, N. (2021) Modelling the asymmetrical relationships between digitalisation and sustainable competitiveness: A Cross-country configurational analysis, *Information Systems Frontiers*, 23, 1317–1337.

Dumay, J., La Torre, M., Farneti, F. (2019) Developing trust through stewardship: Implications for intellectual capital, integrated reporting, and the EU Directive 2014/95/EU, *Journal of Intellectual Capital,* 20(1), 11-39.

ElMassah, S., Mohieldin, M. (2020) Digital transformation and localizing the Sustainable Development Goals (SDGs), *Ecological Economics,* 169, 106490.
Faccia, A., Manni, F., Capitanio, F. (2021) Mandatory ESG reporting and XBRL taxonomies combination: ESG ratings and income statement, a sustainable value-added disclosure, *Sustainability,* 13(16), 8876.
Farinha, L., Ferreira, J.J.M., Nunes, S. (2018) Linking innovation and entrepreneurship to economic growth, *Competitiveness Review*, 28(4), 451–475.
Filho, W.L., Yang, P., Eustachio, J.H.P.P., Azul, A.M., Gellers, J.C., Gielczyk, A., Dinis, M.A.P., Kozlova, V. (2023), Deploying digitalisation and artificial intelligence in sustainable development research, *Environment, Development and Sustainability*, 25, 4957–4988.
Forcadell, F.J., Aracil, E. (2019) Can multinational companies foster institutional change and sustainable development in emerging countries? A case study, *Business Strategy and Development*, 2(2), 91-105.
Fukuda-Parr, S., McNeill, D. (2019) Knowledge and politics in setting and measuring the SDGs: introduction to special issue, *Global Policy*, 10, 5-15.
Garcia-Meca, E., Martinez-Ferrero, J. (2021) Is SDG reporting substantial or symbolic? An examination of controversial and environmentally sensitive industries, *Journal of Cleaner Production,* 298, 126781.
Gerged A.M., Beddewela, E.S., Cowton, C.J. (2023) Does the quality of country-level governance have an impact on corporate environmental disclosure? Evidence from Gulf Cooperation Council countries, *International Journal of Finance and Economics*, 28(2), 1179-1200.
Gillespie-Marthaler, L., Nelson, K.S., Baroud, H., Kosson, D.S., Abkowitz, M. (2019) An integrative approach to conceptualizing sustainable resilience, *Sustainable and Resilient Infrastructure,* 4(2), 66–81.
Gnanaweera, K.A.K., Kunori, N. (2018) Corporate sustainability reporting: Linkage of corporate disclosure information and performance indicators, *Cogent Business & Management*, 5(1).
Gómez, N. A., García, S. M. (2020) Governance and type of industry as determinants of corporate social responsibility disclosures in Latin America, *Latin American Business Review,* 21(1), 1-35.
Gouvea, R., Kapelianis, D., Kassicieh, S. (2018) Assessing the nexus of sustainability and information & communications technology, *Technological Forecasting and Social Change,* 130, 39-44.
Gunawan, J., Permatasari, P., Tilt, C. (2020) Sustainable development goal disclosures: do they support responsible consumption and production?, *Journal of Cleaner Production,* 246, 118989.
Gupta, J., Vegelin, C. (2016) Sustainable development goals and inclusive development, *International Environmental Agreements: Politics, Law and Economics,* 16, 433–448.
Hilali, W.E., Manouar, A.E., Idrissi, M.J.I. (2020) Reaching sustainability during a digital transformation: a PLS approach, *International Journal of Innovation Science*, 12(1), 52-79.
IMD World Competitiveness Center (2021). World Digital Competitiveness Ranking. https://www.imd.org/centers/wcc/world-competitiveness-center/
Janowski, T. (2016). Implementing Sustainable Development Goals with Digital Government – Aspiration-capacity gap, *Government Information Quarterly*, 33(4), 603-613,

Kiron, D., Unruh, G., Reeves, M., Kruschwitz, N., Rubel, H., ZumFelde, A. M. (2017) Corporate sustainability at a crossroads, *MIT Sloan Management Review, Cambridge,* 58(4).

Kostetskyi, P. (2021) Does digitalization lead to better transparency: Bibliometric approach, *Business Ethics and Leadership,* 5(3), 102-107.

Kunkel, S., Tyfield, D. (2021) Digitalisation, sustainable industrialisation and digital rebound – Asking the right questions for a strategic research agenda, *Energy Research & Social Science,* 82,102295.

La Torre, M., Sabelfeld, S., Blomkvist, M., Tarquinio, L., Dumay, J. (2018) Harmonising nonfinancial reporting regulation in Europe: practical forces and projections for future research, *Meditari Accountancy Research,* 26(0), 598-621.

Lichtenthaler, U. (2021) Digitainability: The combined effects of the megatrends digitalization and sustainability, *Journal of Innovation Management.* 9(2). 64-79.

Mhlanga D. (2021) Artificial Intelligence in the Industry 4.0, and Its Impact on Poverty, Innovation, Infrastructure Development, and the Sustainable Development Goals: Lessons from Emerging Economies?, *Sustainability,* 13(11), 5788.

Miceli A., Hagen B., Riccardi M.P., Sotti F., Settembre-Blundo D. (2021) Thriving, not just surviving in changing times: How sustainability, agility and digitalization intertwine with organizational resilience, *Sustainability,* 13(4). 2052.

Mondejar, M.E., Avtar, R., Lellani Baños Diaz, H., Kant Dubey, R., Esteban, J., Gómez-Morales, A. (2021) Digitalization to achieve sustainable development goals: Steps towards a smart green planet, *Science of The Total Environment,* 794, 148539.

Palomares, I., Martínez-Cámara, E., Montes, R., et al. (2021) A panoramic view and swot analysis of artificial intelligence for achieving the sustainable development goals by 2030: progress and prospects, *Applied Intelligence,* 51, 6497–6527.

Pinheiro, A.B., Oliveira, M.C., Lozano, M.B. (2022) The mirror effect: influence of national governance on environmental disclosure in coordinated economies, *Journal of Global Responsibility,* 13(4), 380-395.

Piscicelli, L., Ludden, G.D.S., Cooper, T. (2018) What makes a sustainable business model successful? An empirical comparison of two peer-to-peer goods-sharing platforms, *Journal of Cleaner Production*, 172, 4580-4591.

Rosati, F., Faria. L.G.D. (2019) Addressing the SDGs in sustainability reports: the relationship with institutional factors, Journal *of Cleaner Production*, 215, 1312–1326.

Rozario, A.M., Thomas, C. (2019) Reengineering the Audit with Blockchain and Smart contracts, *Journal of Emerging Technologies in Accounting,* 16(1): 21–35.

Sachs, J.D., Lafortune, G., Kroll, C., Fuller, G., Woelm, F. (2022) *From crisis to sustainable development: the SDGs as roadmap to 2030 and beyond. Sustainable Development Report 2022*. Cambridge: Cambridge University Press.

Seele, P. (2016) Digitally unified reporting: how XBRL-based real-time transparency helps in combining integrated Sustainability reporting and performance control, *Journal of Cleaner Production,* 136, 65-77.

Stankovic, J. J., Marjanovic, I., Drezgic, S., Popovic, Z. (2021) The Digital Competitiveness of European Countries: A Multiple-Criteria Approach, *Journal of Competitiveness,* 13(2), 117–134.

Stefanescu, C.A. (2021), Transposition of Directive 2014/95/EU – Do macroeconomic determinants affect non-financial reporting harmonisation?, *Journal of Financial Reporting and Accounting,* 19(5), 861-884.

Stremousova, E., Buchinskaia, A. (2019), Some approaches to evaluation macroeconomic efficiency of digitalisation, *Business, Management and Education,* 17(2), 232-247.

Ufua, D., Emielu, E., Olujobi, O., Lakhani, F., Borishade, T., Ibidunni, A., Osabuohien, E. (2021) Digital transformation: A conceptual framing for attaining Sustainable Development Goals 4 and 9 in Nigeria*, Journal of Management & Organization,* 27(5), 836-849.

United Nations (2019). Human Development Index. https://hdr.undp.org/data-center/human-development-index#/indicies/HDI

Walker, J., Pekmezovic, A., Walker, G (2019) *Sustainable Development Goals: Harnessing business to achieve the SDGs through finance, technology, and law reform*. John Wiley & Sons Ltd.

Wolf, M.J., Emerson, J.W., Esty, D.C., de Sherbinin, A., Wendling, Z. A. (2022). Environmental Performance Index. Yale Center for Environmental Law & Policy. https://epi.yale.edu/

World Bank (2016). Digital Adoption Index. https://www.worldbank.org/en/publication/wdr2016/Digital-Adoption-Index

World Bank (2020). Worldwide Governance Indicator. www.govindicators.org

World Economic Forum (2020). The Inclusive Development Index 2020 - Summary and data highlights. https://www.weforum.org/reports/the-inclusive-development-index-2018/

Xiao, C., Wang, Q., van der Vaart, T., van Donk, D.P. (2018) When does corporate sustainability performance pay off? The impact of country-level sustainability performance, *Ecological Economics*. 146, 325-333.

STUDIA UNIVERSITATIS BABEŞ-BOLYAI OECONOMICA
VOLUME 69, ISSUE 3, 2024, pp. 43-55
DOI: 10.2478/subboec-2024-0014

CULTURAL TIGHTNESS-LOOSENESS AND STOCK MARKET INTEGRATION

Anita TODEA*
Babes-Bolyai University, Romania

Alexandru TODEA
Babes-Bolyai University, Romania

Abstract. This study examines the relationship between Cultural Tightness-Looseness (CTL) and stock market integration, focusing on a sample of 36 markets from 2004 to 2022. The analysis demonstrates that "loose" cultures, characterized by greater social flexibility, exhibit higher levels of financial integration with the global market. This relationship remains robust after controlling for alternative cultural determinants, such as genetic distance and Hofstede's dimensions. Additionally, the study investigates CTL's moderating effect on the relationship between global uncertainty and stock market integration. The findings reveal that in "loose" countries, the impact of global uncertainty on integration is less pronounced, suggesting a buffering effect. The results, validated through alternative specifications and robustness tests, extend the literature by identifying CTL as a unique cultural determinant of financial integration, distinct from long-term cultural barriers like genetic distance. These insights have implications for understanding market behavior under varying cultural and uncertainty conditions.

JEL Classifications: F15; F36; G15; O50

Keywords foreign portfolio investments; foreign bias; unfamiliarity; cultural tightness/looseness.

1. Introduction

The integration of local stock markets with the world market is an essential process for modern economies, opening access to financial resources and facilitating international capital flows. Among the of this integration are improved access for local companies to external funding and diversification of financing sources. This access

* Corresponding author. Address: Faculty of Economics and Business Administration, Babeş-Bolyai University, 58-60, Teodor Mihali Street, 400591, Cluj-Napoca, Romania, E-mail: anita.todea@econ.ubbcluj.ro

to global capital can stimulate private sector development and investments, reducing dependency on local financing and encouraging long-term economic growth. Additionally, stock market integration allows for better allocation of financial resources, enhancing the efficiency and liquidity of local markets and facilitating the transfer of knowledge and technology through the attraction of international investors (Stulz, 2005; Calessens, 2003). However, integrating local stock markets with the world market also brings a series of challenges. By opening up to global capital flows, local economies become more exposed to external shocks, such as sudden fluctuations in interest rates or asset prices. These shocks can amplify internal market volatility and create financial instability. Furthermore, a globally integrated stock market can attract speculative capital, which may be quickly withdrawn during times of crisis, leading to significant imbalances. Beyond these risks, stock market integration can deepen economic inequalities, favoring large corporations that have access to international financing, while small and medium enterprises remain dependent on local markets (Obstfeld, 2004; Kose et al., 2009).

In an increasingly interconnected global economy, stock market integration has become a central research theme, with significant implications for financial stability, efficient capital allocation, and risk diversification at the international level. Stock market integration reflects the degree to which national barriers are reduced, facilitating capital flows and promoting economic and financial convergence across markets. Literature suggests that higher integration between capital markets can reduce capital costs and contribute to more efficient allocation of financial resources but may also introduce greater vulnerability to global shocks (Bekaert and Harvey, 1995; Stulz, 1999).

The primary determinants of capital market integration encompass formal institutions, including political, economic, and institutional factors, as well as global financial uncertainty as an international factor (Bekaert et al., 2011; Lehkonen, 2015). Culture, as an informal institution, shapes human behavior and is undoubtedly an informal factor that can help explain varying levels of stock market integration. In this regard, Todea and Todea (2003) demonstrated that long-term cultural barriers, measured by genetic distance, are strongly associated with the degree of integration.

In this study, we demonstrate that cultural tightness-looseness (CTL) is also strongly associated with the level of stock market integration, with CTL serving as an additional cultural factor that complements long-term cultural barriers.

Cultural Tightness-Looseness (CTL)—defined as the degree of strictness or flexibility of social norms and tolerance toward behaviors that deviate from these norms—represents one such factor with potential impact on the openness of national markets to the global marketplace. In countries characterized by a “loose” culture, social norms are more flexible, and there is greater tolerance for behavioral diversity and for risks associated with international exchanges. Conversely, in “tight” countries, norms are stricter, and tolerance for unconventional behavior and risks is lower, which may limit economic openness and capital market integration (Gelfand et al., 2011). Existing literature highlights the importance of cultural norms in shaping the economic and financial behavior of a country (La Porta et al., 1997; Guiso et al., 2006). Cultural Tightness-Looseness can influence not only individual and organizational behaviors but also the openness of capital markets, as “loose” economies tend to be more open to cross-border interactions and are less constrained by strict rules on

foreign investments. In this context, a low level of "tightness" can facilitate capital market integration since culturally relaxed societies are more likely to accept and adopt the structures and practices specific to global markets. Thus, the first hypothesis of this study is:

- *H1: There is a positive relationship between "loose" culture and stock market integration.*

In addition to its direct effect, CTL may play a moderating role in the relationship between stock market integration and global uncertainty. High levels of global uncertainty, reflected by indicators such as International Political Risk, VIX, US Money supply growth or TED spread (see Lehkonen, 2015), significantly affect capital flows and financial market stability. In contexts marked by high uncertainty, countries with higher levels of "tightness" tend to show greater resistance to volatility, which may lead to capital withdrawals and increased volatility. On the other hand, countries with a "loose" (flexible) culture may moderate the negative effects of global uncertainty on integrated markets, as higher cultural flexibility promotes greater tolerance toward international uncertainty and risks (Gelfand et al., 2011). Therefore, the second hypothesis of this study is:

- *H2: Cultural Tightness-Looseness (CTL) moderates the relationship between stock market integration and global uncertainty, such that the effect of uncertainty on markets is less pronounced in "loose" countries.*

Using panel data from 39 countries for the period 2004-2022, the results validate the two formulated hypotheses and contribute to the literature in multiple directions. First, a new cultural factor (i.e., CTL) is identified, adding to those already highlighted in the literature, such as cultural, religious, or linguistic distances (see Patell et al., 2022 for a detailed survey). Second, this study aligns with the literature that emphasizes the role of culture in the incorporation of information into stock prices (Eun et al., 2015; Todea, 2022; Todea and Todea, 2023). Lastly, this study connects the literature on CTL to international finance (Todea and Harin, 2023).

2. Data and variables

2.1. Sample

The sample consists of 36 stock markets, comprising 17 developed and 19 emerging markets. The selection of this sample results from applying three successive filters. The first filter considered all stock markets that currently have or previously held either developed or emerging market status, according to MSCI classifications. The second filter retained only countries that maintained one of these two statuses—developed or emerging—for at least half of the period analyzed (2004-2022). The third filter finalized the sample by including only those markets for which measures of the primary variable of interest, Cultural Tightness-Looseness (CTL), were available. Table 1 presents the country structure of the final sample, the stock market indices used in measuring integration, and statistics regarding the average integration and CTL values.

Table 1. The sample structure and statistics

Country	Stock index	Integration	CTL
Developed Markets			
Austria	ATX	0.8967	75.80
Belgium	BEL 20	0.8891	119.80
Canada	TSX 60	0.8866	84.60
Denmark	OMX 20	0.9021	65.50
Finland	OMX 25	0.7939	74.50
France	CAC 40	0.9475	99.60
Germany	DAX 30	0.9163	82.90
Ireland	ISEQ 20	0.8712	71.20
Italy	FTSE-MIB	0.9191	67.80
Japan	Nikkei 225	0.9742	43.30
Netherlands	AEX 25	0.9222	78.90
Portugal	PSI 20	0.8367	78.60
Singapore	STI 30	0.9475	55.20
Spain	IBEX 35	0.9039	83.90
Sweden	OMX 30	0.8581	87.90
U.K.	FTSE 100	0.8353	89.30
U.S.	SP 500	0.8005	58.00
Emerging Markets			
Argentina	Merval 25	0.3159	75.00
Chile	IGPA	0.3945	86.80
Czech Republic	PX	0.5619	59.60
Egypt	EGX 30	0.0807	3.90
Greece	ATHEX	0.4125	58.30
Hungary	BUX 20	0.4340	42.80
India	Nifty 50	0.3465	43.70
Indonesia	LQ45 Index	0.3441	3.10
Korea (South)	Kospi 50	0.5192	20.10
Mexico	IPC 35	0.5029	74.70
Morocco	MASI	0.1517	0.00
Pakistan	KSE 100	0.0391	0.00
Peru	BVL 25	0.3389	52.30
Philippines	PSEi 30	0.2851	31.50
Poland	WIG20	0.5396	42.80
Russia	RTS index	0.3974	57.20
Saudi Arabia	Tadawul	0.1005	22.40
South Africa	JSE 40	0.6081	67.60
Turkey	BIST 30	0.3004	12.50

2.2. Dependent variable: stock markets integration

We utilize a *stock market integration* measure based on a multi-factor APT model developed by Pukthuanthong and Roll (2009). Their approach assumes that if markets are perfectly integrated with the global market, their assets will be equally exposed to the same global shocks. Consequently, the measure of integration is derived from the R-squared value of a multi-factor model. To construct this measure,

we extract daily closing prices of stock market indices, denominated in USD, for the period from January 2003 to December 2022, using the Refinitiv Eikon database. The global factors, totaling 10, are derived through Principal Components Analysis (PCA) from the return series of 20 developed market stock indices, along with 1-day lagged returns from the U.S. to adjust for nonsynchronous trading due to time zone differences. Similar with Todea and Todea (2023), we excluded Finland, Israel, and New Zealand from the developed market sample due to their relatively small share of global stock market capitalization. For each year from 2003 to 2021, we calculate and rank the eigenvectors and eigenvalues. The first 10 principal components explain over 85% of the cumulative eigenvalues. These principal components, which represent the global factors, are then estimated from the returns of stock market indices for the subsequent calendar year. This procedure is repeated annually, producing global factors for the period 2004–2022. Finally, we estimate adjusted R-squared values by regressing the annual daily returns of each stock market index against the global factors.

2.3. Independent variables

2.3.1. Cultural tightness looseness

In this study, we employed the combined *CTL* (Cultural Tightness-Looseness) index introduced by Uz (2015). This index is based on data from the 2000 survey wave conducted by the European Values Study Group and the World Values Survey Association (EWVS). Uz (2015) developed three CTL indices to capture cultural variation: the domain-specific index, the domain-general index, and the combined index. The combined index was created by organizing survey questions into relevant domains and calculating the average standard deviation of these variables. This computation was further refined using emic weights, which reflect the significance of each domain as reported by respondents in each country.

To ensure the reliability of the selected questions, Uz applied a thorough filtering process and found that the weighted averages of standard deviations in the domains of work, family, and religion best represented cultural tightness-looseness, collectively accounting for 54.4% of the variance in CTL. Out of the three indices, we selected the combined CTL index due to its superior performance compared to the other measures (Uz, 2015). In our dataset, Morroco and Pakistan emerged as the "tightest" nation, with a CTL index of 0, while Belgium was the "loosest," with a CTL index of 119.8.

2.3.2. Control variables

In selecting control variables, we drew upon influential studies in the literature, particularly those by Bekaert et al. (2011) and Lehkonen (2015), which identify key determinants of integration through econometric selection procedures. Following the approach of the recent study by Todea and Todea (2023), we adopted the variables identified by Lehkonen (2015) in the final column of Table V on page 2064. Detailed descriptions of these variables can be found in Appendix 2 of Lehkonen (2015). We introduced a few modifications to this list. Due to the unavailability of the *Risk Profile*

from the ICRG Table 3, we used the sum of the six components capturing risk profile data as provided by the Political Risk Services International Country Risk Guide (PRS), and accessed from World Bank Database.. For *Equity Market Openness*, we employed the *Equity Inflow Restrictions* measure developed by Fernandez et al. (2016), which we rescaled to ensure that a higher value indicates greater openness.

Among these control variables, those capturing international uncertainty—namely *International Political Risk*, *TED Spread*, *VIX*, and *U.S. Money Growth*—will be the focus of interest in analyzing the effect of their interaction with CTL on stock market integration, as outlined in Hypothesis 2.

3. Empirical results

To examine the association between CTL and stock market integration, we will use pooled country-year data in the following format:

$$Integration_{l,t} = \alpha_0 + \alpha_1 CTL_{l,t} + \mathrm{B}X + cTrend + \varepsilon_{l,t}$$

where $Integration_{l,t}$ is stock market integration of local country l in year t; $CTL_{l,t}$ is Cultural Tightness Looseness of country l 1; X is a vector of control; *Trend* is deterministic trend; $\varepsilon_{l,t}$ is the residual variable. Such a model can be estimated using various methods, but for the main results, we opted for pooled OLS, following the approach of Lehkonen (2015) and Todea and Todea (2023). To account for the potential presence of intragroup correlation and heterogeneity, we adjusted the standard errors of the parameters using the cluster option by country.

The association between CTL and stock market integration is analyzed in Table 2. In the baseline model presented in Column (1), the positive and significant coefficient of the CTL variable suggests that looser countries are more strongly integrated with the global market compared to tighter countries. To complement the statistical significance with economic relevance, we estimated standardized beta coefficients for the baseline model in Column (2). The results indicate that CTL has one of the largest marginal effects, comparable only to that of the Risk Profile. Specifically, a one-standard-deviation increase in CTL corresponds to a 34.59% rise in stock market integration.

In Column (3) of Table 2, we investigated the CTL–Integration relationship while accounting for the potential presence of endogeneity. In this study, endogeneity may arise for two reasons. First, the CTL variable of interest may be measured with error, as it is derived from WVS surveys. Second, despite the inclusion of numerous control variables, the issue of omitted variable bias persists due to cross-sectional heterogeneity. Since CTL is time-invariant, it does not allow for the use of fixed effects in the cross-section. The potential endogeneity stemming from reverse causality between CTL and Integration is unlikely, given that CTL evolves slowly over time and cultural traits developed long before the emergence of stock markets.

Table 2. The impact of cultural tightness-looseness on the stock markets integration

	(1) Base model	(2) Beta (%)	(3) 2SLS	(4) Developed markets	(5) Emerging markets
Cultural tightness looseness (CTL)	0.0036*** (4.02)	34.59	0.0059*** (2.99)	0.0002 (0.24)	0.0031*** (3.23)
Political risk	0.1416*** (3.10)	39.27	0.0204 (0.24)	-0.0656 (-1.20)	0.0721* (1.77)
Openness	0.1974** (2.09)	17.84	0.1302** (2.18)	0.1610 (1.32)	0.0258 (0.51)
International Political Risk	0.0017* (-1.67)	-3.31	0.0005 (0.55)	-0.0011 (-1.17)	0.0029*** (-2.76)
Legal origin (French)	0.0136 (0.25)	2.15	-0.0754 (-0.79)	-0.0423 (-0.75)	0.0083 (0.18)
Past Equity Market Returns	0.0149 (1.20)	1.53	0.0327* (1.82)	0.0195 (1.28)	0.0241* (1.73)
Local crisis	-0.0737* (-1.97)	-7.53	-0.0969** (-2.56)	0.0122 (1.23)	-0.0712*** (-2.72)
Exchange rate	-0.1349* (-1.66)	-3.62	-0.2762*** (-3.51)	-0.0901 (-1.62)	-0.1060 (-1.32)
Local Market Turnover	0.0006*** (2.94)	12.89	0.0007** (2.26)	-0.0001 (-1.43)	0.0004* (1.83)
Inflation	-0.0029** (-2.23)	-6.95	-0.0048*** (-3.00)	-0.0023 (-1.12)	-0.0023** (-2.25)
Past Local GDP Growth	0.0030 (1.10)	3.65	0.0066* (1.86)	0.0016* (1.69)	0.0060* (1.87)
TED Spread	-0.0094 (-0.57)	-1.61	-0.0172 (-1.03)	-0.0124 (-1.04)	0.0438** (1.99)
VIX	0.0091*** (6.40)	18.33	0.0108*** (7.73)	0.0052*** (4.76)	0.0137*** (9.98)
U.S. Money Growth	0.2614** (2.59)	4.21	0.2963** (2.29)	0.0056 (0.08)	0.3568** (2.34)
Phones	0.0015*** (3.11)	18.12	0.0016*** (4.10)	0.0003 (0.88)	0.0010 (1.61)
Life Expectancy (log)	-0.7999 (-0.80)	-8.44	0.4862 (0.52)	3.7061*** (3.09)	-1.4862* (-1.96)
Population Growth	0.0178 (1.06)	6.08	0.0371*** (3.24)	0.0033 (0.68)	-0.0643** (-2.35)
Trend	-0.0004 (-0.17)	-0.73	-0.0039* (-1.70)	-0.0048*** (-3.02)	-0.0010 (-0.35)
N	684	684	684	323	361
Adj./Centered R2	0.765	0.765	0.754	0.318	0.592

Notes: In brackets are the *t* of the regression coefficients based on standard errors estimated with country cluster. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels

In order to address the potential endogeneity of the CTL variable, we employed a two-stage least squares (2SLS) approach, using *Kinship* and *Religion Fractionalization* as instrumental variables. The kinship index is from Enke (2019), and the values for religion fractionalization are from Alesina et al. (2003). The use of 2SLS is particularly

relevant in this context, as it allows us to mitigate the bias that could arise from measurement errors and omitted variable bias, both of which are concerns when analyzing the relationship between CTL and stock market integration. The choice of Kinship and Religion Fractionalization as instruments is grounded in theoretical considerations related to the factors that shape cultural tightness-looseness. Kinship, as a form of social structure, plays a key role in defining the norms and values that underpin a society's cultural characteristics. Societies with strong kinship ties tend to emphasize conformity and social control, which can be associated with higher cultural tightness. On the other hand, societies with weaker kinship structures often exhibit more individualistic tendencies, contributing to greater cultural looseness. Kinship ties, therefore, are likely to be correlated with CTL but not directly with stock market integration, making them a valid instrument in this context. Religion Fractionalization, similarly, provides an important cultural dimension that influences societal norms and behaviors. Societies with high religious diversity often face greater challenges in terms of social cohesion, which can lead to more relaxed cultural norms and lower levels of social control, thus contributing to cultural looseness. Conversely, societies with more homogeneous religious beliefs tend to exhibit tighter social norms and greater conformity. As with kinship, religion fractionalization is theoretically connected to CTL but is not likely to be directly related to stock market integration, making it an appropriate instrument.

In Column (3) of Table 2, the 2SLS results confirm a strong positive association between CTL and stock market integration, reinforcing our main findings. This suggests that, after addressing the endogeneity concerns, the relationship between CTL and market integration remains robust, and the choice of Kinship and Religion Fractionalization as instruments is validated. Thus, these results further strengthen the validity of our analysis and underscore the importance of cultural factors in explaining variations in stock market integration across countries.

Developed markets exhibit a very high level of integration with the global market, and at the same time, the majority of these markets tend to be more loose than tight. In contrast, emerging markets show much greater variability in both integration and CTL. It is therefore likely that the CTL-Integration association observed across the full sample is primarily driven by emerging markets. To investigate this, we re-estimated the baseline model separately for developed and emerging markets. The results in Columns (4) and (5) of Table 2 show that the CTL coefficient is positive and significant only in the case of emerging markets, thus confirming our hypothesis.

In Table 3, we investigated Hypothesis 2 of this study by considering interaction effects and introducing the product of CTL with various measures of global uncertainty: in Column 1, the interaction between CTL and the International Risk Profile; in Column 2, between CTL and the TED Spread; in Column 3, between CTL and the VIX; and in Column 4, between CTL and U.S. Money Growth. To improve the interpretation of the parameters of the interacting variables, they were centered.

The results show that, in all cases, the coefficients of the product terms between CTL and the uncertainty variables are negative and statistically significant. The negative sign of these interactions suggests that, at a certain level of global uncertainty, countries with higher CTL (looser countries) become less integrated into global financial markets, meaning they respond less to global external factors. This phenomenon can be explained by the cultural characteristics of looser countries, which, although more flexible and tolerant of change, may not absorb external shocks

as efficiently as tighter societies, despite being more open to external influences. In looser cultures, characterized by more flexible social norms and a more relaxed attitude toward risk, financial markets may be less anchored in traditional behaviors and more vulnerable to changes in the global economic environment. This suggests that, in the face of significant increases in global uncertainty, these countries might integrate external factors less effectively into their economic behaviors, leading to a decrease in financial market integration. In contrast, countries with a lower CTL (tighter countries), which are characterized by more rigid social norms and greater risk aversion, may respond more consistently and stably to global uncertainty, incorporating external shocks more rapidly into their stock markets. Therefore, the interaction between CTL and uncertainty variables indicates that, in the context of global economic and political uncertainty, looser nations are less exposed to global shocks than tighter ones.

Table 3. Impact of CTL on Integration with global determinants interaction terms

	(1) Interaction with International Political Risk	(2) Interaction with TED Spread	(3) Interaction with VIX	(4) Interaction with U.S. Money Growth
Cultural tightness looseness (CTL)	0.0036*** (4.00)	0.0036*** (3.96)	0.0036*** (4.05)	0.0036*** (4.02)
International Political Risk	0.0017* (1.68)			
TED Spread		-0.0101 (-0.61)		
VIX			0.0091*** (6.47)	
U.S. Money Growth				0.2639*** (2.68)
CTL × International Political Risk	-0.0001* (-1.78)			
CTL × TED Spread		-0.0008* (-1.93)		
CTL × VIX			-0.0001** (-2.51)	
CTL × U.S. Money Growth				-0.0044* (-1.68)
Control variables	Yes	Yes	Yes	Yes
N	684	684	684	684
Adj. R2	0.765	0.767	0.768	0.765

Notes: In brackets are the *t* of the regression coefficients based on standard errors estimated with country cluster. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

4. Robustness tests

In the baseline regression presented in Column (1) of Table 2, we employed pooled OLS to align with the methodology adopted in relevant studies from the literature (Lehkonen, 2015; Todea and Todea, 2023). While there are numerous arguments both for and against the use of OLS, we sought to strengthen the robustness of our

baseline results by employing alternative specifications and estimation methods. In Column (1) of Table 4, we continued to use OLS but replaced the deterministic trend with year fixed effects to account for temporal variations. Column (2) of Table 4 shifts focus to potential cross-sectional heterogeneity that might not be fully captured by the selected control variables. Given that CTL is time-invariant, we opted for random effects instead of fixed effects. To address potential endogeneity concerns, we instrumented CTL using *religion fractionalization* and *kinship*, as shown in Column (3) of Table 4. Finally, recognizing the strong persistence of the Integration variable, we employed the system GMM estimator in Column (4) of Table 4. The positive and statistically significant coefficient of CTL across all these alternative specifications corroborates the baseline regression results and lends strong support to Hypothesis 1 of the study.

Table 4. Alternative estimation methods

	(1) Time fixed effects	(2) Random effects	(3) Random effects with IV	(4) GMM system
Cultural tightness looseness (CTL)	0.0035*** (3.65)	0.0047*** (4.84)	0.0053** (2.45)	0.0044** (2.88)
Control variables	Yes	Yes	Yes	Yes
N	684	684	684	684
Adj./Centered R2	0.785	0.732	0.761	-

Notes: In brackets are the *t* of the regression coefficients based on standard errors estimated with country cluster. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

In all the empirical results presented, we measured the strictness-flexibility of social norms using Uz's (2015) CTL combined index, chosen for its superiority in facilitating international comparisons relative to the other two measures developed by Uz (2015). To further validate our findings, we estimated the baseline regression using alternative measures of CTL. Specifically, in Columns (1) and (2) of Table 5, we employed the CTL domain-specific index and the CTL domain-general index, respectively. The positive and statistically significant coefficients of these alternative measures further support Hypothesis 1, reinforcing the robustness of our results.

CTL captures a cultural component that may be strongly correlated with long-term cultural differences (proxied by genetic distance) or cultural values. However, in the final two columns of Table 5, we demonstrate that CTL is a distinct construct that explains stock market integration independently of these factors.

In Column (3) of Table 5, we controlled for genetic distance from the world market, a variable shown to be strongly associated with stock market integration (Todea and Todea, 2023). In Column (4), we included the five cultural dimensions developed by Hofstede (2010), which are potentially correlated with CTL. The positive and statistically significant coefficient of CTL in both columns indicates that the strictness-flexibility of social norms, as measured by CTL, represents a unique informal institution associated with integration, distinct from long-term cultural barriers or cultural values. These findings suggest that the results of this study are complementary to those of Todea and Todea (2023).

Table 5. Impact of CTL on Integration: other tests

	(1)	(2)	(3)	(4)
CTL domain-specific	0.0031*** (2.92)			
CTL domain-general		0.0021*** (3.06)		
Cultural tightness looseness (CTL)			0.0036*** (4.09)	0.0046*** (5.45)
Genetic distance			-1.4247 (-0.49)	
Individualism				-0.0005 (-0.47)
Uncertainty Avoidance				-0.0026*** (-2.77)
Power distance				-0.0010 (-0.94)
Masculinity				0.0020*** (2.64)
Long term-orientation				0.0028** (2.55)
Control variables	Yes	Yes	Yes	Yes
N	684	684	684	684
Adj. R2	0.761	0.769	0.772	0.810

Notes: In brackets are the *t* of the regression coefficients based on standard errors estimated with country cluster. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

5. Conclusions

This study provides a novel contribution to the literature by exploring the relationship between Cultural Tightness-Looseness (CTL) and stock market integration, positioning it as a distinct cultural determinant beyond the framework established by Todea and Todea (2023). While their research highlighted the significant role of genetic distance as a long-term cultural barrier affecting stock market integration, our investigation shifts the focus to the flexibility of social norms as captured by the CTL index. This focus reveals new insights into the cultural underpinnings of market behaviors, demonstrating that CTL is an independent and complementary construct to genetic distance in explaining cross-country variations in integration levels.

Our findings robustly validate both hypotheses. Hypothesis 1, which posits a positive relationship between “loose” culture and stock market integration, is consistently supported across various model specifications. The positive and statistically significant coefficients of the CTL index, even when controlling for factors such as genetic distance and Hofstede’s cultural dimensions, underscore the unique role of CTL in shaping integration. Furthermore, the robustness checks—ranging from alternative measures of CTL to addressing potential endogeneity—strengthen the credibility of this result. Hypothesis 2, which asserts that CTL moderates the relationship between stock market integration and global uncertainty, is also validated. The interaction terms between CTL and various measures of global uncertainty, including International Risk Profile, TED Spread, VIX, and U.S. Money Growth, consistently exhibit negative

and statistically significant coefficients. These results suggest that “loose” countries, characterized by greater social flexibility, respond less strongly to external shocks, integrating global uncertainty into their markets to a lesser extent than “tight” countries. This moderating role of CTL highlights its potential to buffer the adverse effects of global uncertainty on financial markets.

The originality of this study lies in its integration of CTL as a novel explanatory variable in financial market integration research. By demonstrating that CTL operates as an independent cultural determinant, distinct from long-term barriers like genetic distance, this research broadens the scope of cultural economics. The findings also have practical implications for policymakers and investors, suggesting that cultural characteristics should be considered when assessing the resilience of financial markets to global uncertainty.

References

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., Wacziarg, R., 2003. "Fractionalization." *Journal of Economic Growth*, 8, 155-194.

Bekaert, G., & Harvey, C. R., 1995. "Time-Varying World Market Integration." *Journal of Finance*, 50(2), 403-444.

Bekaert, G., Harvey, C. R., Lundblad, C. T., & Siegel, S., 2011. "What Segments Equity Markets?" *Review of Financial Studies*, 24, 3847-3890.

Claessens, S., & Laeven, L., 2003. "Financial Development, Property Rights, and Growth." *Journal of Finance*, 58(6), 2401-2436.

Enke, B., 2019. "Kinship, Cooperation, and the Evolution of Moral Systems." *The Quarterly Journal of Economics*, 134(2), 953-1019.

Eun, C. S., Wang, L., & Xiao, S., 2015. "Culture and R2." *Journal of Financial Economics*, 115(2), 283-303.

Fernandez, A., Klein, M.W., Rebucci, A., Schindler, M., & Uribe, M., 2016. "Capital Controls Measures: A New Dataset." *IMF Economic Review*, 64(3), 548-574.

Guiso, L., Sapienza, P., & Zingales, L., 2006. "Does Culture Affect Economic Outcomes?" *Journal of Economic Perspectives*, 20(2), 23-48.

Hofstede, G. H., Hofstede, G. J., & Minkov, M., 2010. *Cultures and Organizations: Software of the Mind*. McGraw-Hill, New York.

Kose, M. A., Prasad, E., Rogoff, K., & Wei, S., 2009. "Financial Globalization: A Reappraisal." *IMF Staff Papers*, 56(1), 8-62.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W., 1997. "Trust in Large Organizations." *American Economic Review*, 87(2), 333-338.

Lehkonen, H., 2015. "Stock Market Integration and the Global Financial Crisis." *Review of Financial Studies*, 19, 2039-2094.

Obstfeld, M., & Taylor, A. M., 2004. *Global Capital Markets: Integration, Crisis, and Growth*. Cambridge University Press.

Pukthuanthong, K., & Roll, R., 2009. "Global Market Integration: An Alternative Measure and Its Application." *Journal of Financial Economics*, 94, 214-232.

Stulz, R. M., 1999. "Globalization, Corporate Finance, and the Cost of Capital." *Journal of Applied Corporate Finance*, 12(3), 8-25.

Stulz, R. M., 2005. "The Limits of Financial Globalization." *Journal of Finance*, 60(4), 1595-1638.

Todea, A., 2022. "Ancestry Barriers to the Cross-Border Diffusion of Global Market Information." *Financial Research Letters*, 49, 103151.
Todea, A., & Todea, A., 2023. "Genetic Distance and Stock Market Integration." *Journal of Behavioral and Experimental Finance*, 39, 100827.
Todea, A., & Harin, C., 2024. "The Influence of Cultural Norms on International Equity Allocation." *The European Journal of Finance*, 30(12), 1362-1385.
Uz, I., 2015. "The Index of Cultural Tightness and Looseness Among 68 Countries." *Journal of Cross-Cultural Psychology*, 46(3), 319-335.

STUDIA UNIVERSITATIS BABEȘ-BOLYAI OECONOMICA
VOLUME 69, ISSUE 3, 2024, pp. 56-72
DOI: 10.2478/subboec-2024-00015

EXPLORING THE LINK BETWEEN ROMANIAN ACCOUNTING STUDENTS' GOAL ORIENTATIONS, SELF-EFFICACY, TEST ANXIETY AND PERFORMANCE: A CLUSTER ANALYSIS APPROACH

Camelia-Ancuța MÜLLER[*]
Babeș-Bolyai University, Romania

Abstract: This empirical study examines the relationship between learning motivation, self-efficacy, test anxiety, and academic performance in the context of a Financial Accounting course, using Achievement Goal Theory (AGT) as a framework. A sample of 149 second-year students enrolled in the Accounting and Management Information Systems program completed a questionnaire based on the Motivated Strategies for Learning Questionnaire (MSLQ). The data were analyzed using correlation, cluster analysis, and ANCOVA. The results confirmed significant differences between four motivational profiles: mastery, performance, multiple goals, and low motivation, regarding their impact on self-efficacy, test anxiety, and performance. The findings suggest that students with multiple goals achieve better academic outcomes, emphasizing the importance of a multidimensional approach to learning motivation.

JEL classification: A22, I23, M41.

Keywords: financial accounting education; learning motivation; self-efficacy; test anxiety; academic performance; Achievement Goal Theory.

1. Introduction

The relationship between student motivation, academic performance, and emotional well-being has been extensively explored in educational psychology. Understanding the factors that influence academic success is particularly critical in higher education, where students encounter increasingly complex academic demands. In this context, Achievement Goal Theory (AGT) provides a valuable framework for examining how different types of learning motivation influence academic outcomes.

[*] Corresponding author. Address: Faculty of Economics and Business Administration, Babeș-Bolyai University, Teodor Mihali 58-60 street, RO-400591, Cluj-Napoca, Romania, E-mail: anca.muller@econ.ubbcluj.ro

Over time, several theories have been developed to explain learning motivation, but three are internationally recognized as the most representative: Self-Determination Theory, Attributional Theory, and Achievement Goal Theory. The latter, AGT, is central to the present study and has been the foundation of numerous scientific investigations aimed at describing and explaining achievement behavior (Dull et al., 2015).

In accounting education, where the curriculum requires advanced problem-solving skills and high levels of technical proficiency, the distinction between mastery and performance goals becomes particularly salient. Mastery-oriented students are more likely to engage in deep learning strategies, focusing on understanding the material and improving their skills. In contrast, performance-oriented students tend to prioritize high grades or outperforming peers, often at the expense of thorough comprehension. This divergence in learning approaches can significantly impact students' academic achievements, self-efficacy, and test anxiety.

As the importance of fostering effective learning strategies in accounting education grows, it becomes crucial to understand how different goal orientations—mastery and performance—affect students' self-efficacy, test anxiety, and performance outcomes. By examining these relationships, educators can design more effective interventions that enhance student motivation, reduce anxiety, and ultimately improve academic achievement.

The literature highlights that understanding how students are motivated, and structuring courses to positively influence student motivation, can significantly enhance student engagement and learning. As Svinicki and McKeachie (2014) suggest, the reasons why students vary in their motivation is a compelling question, and several theoretical frameworks offer valuable insights. The present study builds on this existing knowledge by exploring the less-researched area of accounting education.

This study examines the relationships between learning motivation, self-efficacy, test anxiety, and academic performance using a sample of 149 second-year students enrolled in the Accounting and Management Information Systems program at Babeș-Bolyai University. By conducting a comprehensive analysis of students' motivational profiles, this research aims to provide new insights into the impact of mastery and performance goals on academic outcomes within a financial accounting course.

In this study, the same instrument employed by Dull et al. (2015) was applied to a new cohort of accounting students at the Faculty of Economics and Business Administration, Babeș-Bolyai University. The objective is to evaluate the relevance and applicability of previous findings in a different academic and cultural context, offering further insights into the influence of goal orientation on academic performance in accounting.

Based on these considerations, we formulated the following research question: What are the academic learning motivations in Romania within the field of accounting, and how do they influence student outcomes?

2. Literature Review

2.1 Achievement Goal Theory

Achievement Goal Theory (AGT) rapidly emerged as one of the most prominent frameworks in motivation research following its introduction in the early 1980s (Urdan and Kaplan, 2020). Four scholars, Carole Ames, Carol Dweck, Martin Maehr, and John Nicholls, are widely credited with developing AGT. Their work highlighted that students define success in different ways. Some students view success as learning, understanding, or developing new skills—an internal standard for achievement. This orientation often encourages deeper engagement with learning materials and resilience in the face of obstacles. Conversely, students who define success as outperforming others or appearing intelligent adopt an external, socially comparative standard, which can lead to shortcuts in learning, such as cheating, or avoidance of challenging tasks (Urdan and Kaplan, 2020).

AGT differentiates between two primary types of goals: mastery (learning) goals and performance goals (Nicholls, 1984; Dweck and Leggett, 1988). Mastery goals emphasize developing competence through learning and understanding, while performance goals focus on demonstrating competence relative to others. Research consistently shows that these goals have distinct implications for academic behaviors and outcomes (Harackiewicz et al., 1998; Senko et al., 2011).

Given the difficulty in shifting students away from performance-driven motivations, educators might better serve students by emphasizing mastery of knowledge rather than attempting to reduce performance goals entirely (Haynes et al., 2008; Dull et al., 2015). Ramburuth and Mladenovic (2004) further suggest that a combination of approaches, rather than a strict focus on either mastery or performance, may be optimal in fields like accounting, where both deep conceptual understanding and technical detail are essential.

In accounting education, the adoption of mastery versus performance goals significantly impacts student motivation and academic outcomes. Dull, Schleifer, and McMillan (2015) found that accounting students who adopt mastery goals exhibit higher levels of intrinsic motivation and self-efficacy, while performance-goal-oriented students tend to experience increased test anxiety, often leading to surface learning strategies that hinder long-term retention (Pintrich and DeGroot, 1990).

2.2 Key Self-Report Instruments in Achievement Goal Theory Research

Several prominent scholars in the field of AGT have developed self-report questionnaires to assess students' achievement goal orientations. These instruments have become central to AGT research, offering insights into how students' goals influence their motivation, learning behaviors, and academic outcomes. Some of the most widely used instruments include those developed by Nicholls et al. (1985), Ames and Archer (1988), Midgley et al. (2000), and Elliot and Church (1997).

Nicholls, Patashnick, and Nolen's (1985) questionnaire was among the first to distinguish between task and ego orientations, laying the groundwork for future research into how these orientations affect student motivation. Ames and Archer

(1988) designed a questionnaire rooted in Ames' theoretical model, which interprets goal orientations as processes shaped by the learning environment. Their work demonstrated how classrooms emphasizing mastery goals promote adaptive motivational patterns.

The Patterns of Adaptive Learning Scales (PALS), developed by Midgley et al. (2000), is one of the most widely used tools in AGT research, offering a comprehensive view of how achievement goals interact with the classroom environment. Elliot and Church (1997) further refined AGT with the Achievement Goals Questionnaire (AGQ), introducing the 2x2 framework that distinguishes between mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance goals.

The Motivated Strategies for Learning Questionnaire (MSLQ), developed by Pintrich and colleagues in the late 1980s, is another critical tool, assessing both cognitive and motivational components of student learning. The MSLQ has been instrumental in AGT research, offering a broad understanding of how students regulate their learning in response to their goals.

Four notable studies have used the MSLQ to assess accounting students' learning strategies and motivation. These include research by Opdecam et al. (2012), Becker (2013), Dull et al. (2015), and Papageorgiou (2022), each providing valuable insights into how achievement goal orientations and self-regulated learning strategies influence academic outcomes in accounting education.

2.3 Self-Efficacy and Test Anxiety

The concept of self-efficacy was introduced by Albert Bandura (1977) as part of his broader theory of social cognitive learning. Self-efficacy refers to an individual's belief in their ability to successfully perform a task or achieve a goal. Studies have consistently shown that students with high self-efficacy are more motivated to persist in challenging tasks and achieve higher academic outcomes (Zimmerman, 2000). In accounting education, where technical skills and problem-solving are critical, self-efficacy is a strong predictor of success (Hart and Wang, 2016).

Self-efficacy can be shaped by several key factors, including mastery experiences (successes achieved through effort), vicarious experiences (observing others succeed), and verbal encouragement (Miller, 2014, p. 170). As students become more confident in their abilities, they are more likely to engage in effective learning strategies, improving their academic outcomes.

On the other hand, test anxiety—often linked to performance goals—is a well-documented affective outcome. Students who focus on outperforming peers or demonstrating competence in high-stakes environments tend to experience elevated levels of test anxiety, which negatively impacts performance (Cassady and Johnson, 2002). Accounting, as a field where exams play a significant role in evaluating success, is particularly prone to this phenomenon. Research by Daniels et al. (2008) shows that interventions aimed at fostering mastery goals can help reduce test anxiety and improve academic performance in accounting courses.

2.4 Cluster Analysis in Achievement Goal Theory

In AGT research, cluster analysis is commonly used to identify different combinations of mastery and performance goals. Due to the lack of a standardized instrument to assess multiple-goal orientation, researchers often evaluate mastery and performance goals independently, subsequently merging the results through statistical methods like cluster analysis (Daniels et al., 2008).

Dull et al. (2015) applied cluster analysis in accounting education, identifying students who pursued both mastery and performance goals, termed "multiple goal" students. These students exhibited higher levels of self-efficacy and better academic outcomes than students pursuing only one type of goal. This result aligns with the wider body of educational research, highlighting the significance of employing a multidimensional framework when addressing learning motivation (Senko et al., 2011).

2.5 Research Hypotheses

Building on the theoretical insights and empirical findings from the literature, this study aims to explore the specific relationships between students' achievement goal orientations—mastery and performance—and key academic outcomes such as self-efficacy, test anxiety, and performance in the context of a financial accounting course. Given the complex demands of accounting education, where both deep conceptual understanding and high-stakes evaluations are critical, understanding how students' motivational profiles influence these outcomes is crucial for educators and researchers alike. Previous studies (Dull et al., 2015; Pintrich and DeGroot, 1990) have shown that mastery-oriented students tend to exhibit higher self-efficacy and engage in deeper learning strategies, while performance-oriented students often experience higher levels of test anxiety and adopt surface learning approaches. In this context, the following hypotheses are proposed to examine the predictive power of students' goal orientations on their academic success and emotional well-being:

H1: Students' motivational orientations toward learning serve as predictors of self-efficacy in a financial accounting course.
H2: Students' motivational orientations toward learning are related to their levels of test anxiety in a financial accounting course.
H3: Students' motivational orientations toward learning are predictive of their anticipated performance (grade) in a financial accounting course.
H4: Students' motivational orientations toward learning serve as predictors of their actual performance (grade) in a financial accounting course.

3. Research Design

The study involved 149 students (118 female and 31 male) enrolled in the second year of the Accounting and Management Information Systems program at the Faculty of Economics and Business Administration of the Babeș-Bolyai University in Cluj-Napoca. The study was undertaken after the end of the exam session related to the winter semester 2020-2021, i.e. in the 2nd week of the second semester of the academic year.

Table 1: MSLQ-based questions included in the questionnaire

Mastery goal orientation or intrinsic goal orientation
1. In a course like this, I prefer materials that really challenge me so that I can learn new things.
2. In a course like this, I prefer course materials that arouse my curiosity, even if it is difficult to learn.
3. The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.
4. When I have the opportunity in this class, I choose assignments that I can learn even if they do not guarantee a good grade.
Performance or extrinsic goal orientation
5. Getting a good grade in this subject is the most satisfying thing for me.
6. The most important thing for me right now is to improve my overall average, so my main concern in this course is getting a good grade.
7. If possible, I want to get better grades in this subject than most other students.
8. I want to do well in this subject as it is important to show my ability/performance to my family, friends, employer or others.
Self-efficacy for learning and performance
9. I think I will get an excellent grade in this subject.
10. I am sure I can understand even the most difficult content in the material provided.
11. I am confident that I can learn the basic concepts taught in this course.
12. I am confident that I can understand the most complex material presented by the teacher in this course.
13. I am confident that I can do an excellent job on the assignments and tests in this course.
14. I expect to do well in this subject.
15. I am sure I can master the skills that are taught in this subject.
16. Considering the difficulty of this course, the teacher and my abilities, I think I will do well in this class.
Test anxiety
17. When I take a test, I think about how poorly I do compared to other students.
18. When I take a test, I think about items in other parts of the test that I cannot answer.
19. When I take tests I think about the consequences of failure.
20. I have an anxious, upset feeling when taking an exam.
21. I feel my heart beating fast when I take an exam.

The data were collected through an anonymous questionnaire posted on the faculty's Moodle educational platform (within the Financial Accounting 2 course) and were further processed in the SPSS statistical program. The questionnaire included a total of 30 questions, of which the first 21 were based on the MSLQ (Motivated Strategies for Learning Questionnaire), well established in the literature for approximately 30 years for investigating students' motivational learning strategies (Pintrich and DeGroot, 1990). These questions (Table 4) aim to measure mastery goal orientation or intrinsic goal orientation (first 4), performance orientation or extrinsic goal orientation (questions 5-8), self-efficacy regarding learning and performance achievement (questions 9-16) and test anxiety (questions 17-21).

For these questions a Likert scale from 1 to 7 was used (1 - “not at all true for me” - 7 “very true for me”). The aggregate variables for each of the four investigated aspects are given by the mean value of the answers to the questions (variables) that refer to the respective aspect, i.e. those that compose the aggregate variable. By means of factor analysis (Varimax rotation method in SPSS), the goodness-of-fit of the measurement scales of the four aggregate variables was analyzed. From the results obtained, considering the threshold of 0.6 for an item to be part of an aggregate variable, it was found that all items grouped appropriately to form the aggregate variable, except item (question) 3 which aims to measure the Mastery goal. As a result, this question was removed from the related aggregate variable in order not to distort the results obtained.

The last 9 questions of the questionnaire refer to the grades obtained/expected in the courses Basic Accounting (BA) and Financial Accounting 1 (FA1). (whole numbers from 1 to 10, except the grade in the midterm exam in Financial Accounting 1 where the values are in 0.5 point increments), the overall average at the end of the first year of study (values from 1 to 10 in 0.5 point increments), the profile of the high school graduated (Real - Mathematics, Real - Natural Sciences, Humanities, Economics) and gender. These questions (excluding the expected grade and the final grade in Financial Accounting 1) are included in the questionnaire as potential covariates in the research (to account for their possible effect on the dependent variables analyzed).

Table 2: Descriptive statistics

Variable	N	Min.	Max.	Average	Standard deviation
Mastery	149	1.33	7.00	4.7966	1.27587
Performance	149	1.00	7.00	4.4379	1.48782
Self - efficacy	149	1.00	7.00	4.5772	1.24494
Test - anxiety	149	1.00	7.00	4.1302	1.54901
Expected grade in FA 1	149	4.00	10.00	7.4228	1.62822
Final grade in FA 1	147	3.00	10.00	6.9388	1.61001
Grade for the midterm exam in FA 1	144	0.50	10.00	6.0035	2.26133
Final grade in BA	148	4.00	10.00	8.5000	1,36775
Overall average year 1	148	5.50	10.00	8.2568	1.03261

To explore the univariate relationships among all pertinent variables, correlation analysis was performed. Additionally, cluster analysis was employed to categorize students and identify their achievement goal profiles (also known as learning motivation profiles), based on variables assessing mastery and performance goals. Subsequently, ANOVA and ANCOVA were utilized to assess whether, and to what extent, the identified groups (i.e. achievement goal profiles) differed in self-efficacy, test anxiety, expected grade, and final grade in the Financial Accounting 1 course.

4. Results

4.1 Correlation analysis

The correlations between the 11 variables measured in this study are presented in Table 3. The existence in general of a significant level of correlation between the dependent variables and the covariate variables (the overall average of the first year of study, the final grade in the Basic accounting course and the grade in the midterm examination in the Financial accounting 1 course) is an argument for using them as covariate (control) variables. As for the variables high school graduation profile and gender, they show a significant correlation only with the dependent variables self-efficacy and test anxiety. Female respondents show a higher level of test anxiety (mean 4.32) than male respondents (mean 3.37).

Table 3: Matrix of correlations between variables

	Mastery	Performance	Self-efficacy	Test anxiety	Final grade in FA1	Expected grade in FA1	Midterm exam grade in FA1	Final grade BA	Overall average year 1	High school profile
Mastery										
Performance	.187*									
Self-efficacy	.546**	.379**								
Test anxiety	-.182*	.149	-.238**							
Final grade in FA1	.389**	.263**	.547**	-.153						
Expected grade in FA1	.368**	.264**	.541**	-.202*	.611**					
Midterm exam grade in FA1	.306**	.202*	.505**	-.076	.734**	.565**				
Final grade in BA	.149	.162	.321**	-.076	.535**	.522**	.425**			
Overall average year 1	.203*	.183*	.333**	-.046	.664**	.602**	.535**	.616**		
High school profile	.198*	.090	.215*	-.070	.043	.075	.184*	-.012	-.064	
Gender	.059	-.108	.128	-.268**	-.006	.057	-.002	-.052	-.189*	.205*

* Significant correlation at the 0.05 level ** Significant correlation at the 0.01 level

There is a significant ($p<0.05$) but low intensity (0.187) correlation between the variable measuring mastery goals and the variable measuring performance goals. This suggests that accounting students aiming for high grades are also driven to understand and master the subject matter (Dull et al., 2015). This positive association aligns with the notion of a multi-goal learning approach (Daniels et al., 2008).

As for the correlations between the variables measuring the mastery goals respectively the performance goals and the four dependent variables (self-efficacy, test anxiety, expected grade in FA1 and final grade in FA1), they are statistically significant, except for the correlation between the performance goals and test anxiety variables. The strongest correlation in this context is between the variable mastery goals and the variable self-efficacy (0.546).

4.2 Formatting groups (clusters)

Following the approach employed by Dull et al. (2015) and Daniels et al. (2008), clusters were generated using the standardized scores (z-scores) for the variables that measure mastery and performance goals. In SPSS, the k-means clustering technique was applied to produce a four-group/cluster solution. This method seeks to minimize variance within clusters while maximizing variability between them. Consistent with the findings of Daniels et al. (2008), the four clusters represent distinct combinations of goals. The centroid values of the clusters are presented in Table 4.

Table 4: Centroid values of groups/clusters

Type of objective	Group/Cluster 1 Multiple goals	Group/Cluster 2 Mastery	Group/Cluster 3 Performance	Group/Cluster 4 Low motivation
Mastery	0.97902	0.41573	-0.75864	-1.15762
Performance	0.85918	-0.68417	0.81830	-1.11433
N	37	50	37	25

Group/cluster 1 is referred to as ‘Multiple Goals’ due to the positive centroid values, indicating that students in this cluster exhibit above-average scores for both mastery and achievement variables. Group/cluster 2 is named ‘Mastery’ because the average score for the mastery goal (knowledge/competence) is higher than the performance goal, as reflected by the positive centroid for mastery and the negative centroid for performance. In contrast, Group/cluster 3 is labeled “Performance”, emphasizing performance as the primary goal. Group/cluster 4 is labeled as “Low motivation”, as both centroid values are negative. Thus, these four groups/clusters represent four possible combinations of students’ goal orientation or motivation profiles in the Financial Accounting discipline. The one-way ANOVA statistical test applied in SPSS showed that the four groups/clusters differed significantly ($p<0.001$) for both variables. Descriptive statistics related to the groups/clusters are presented in Table 5.

Table 5: Descriptive statistics for groups/clusters

Variable	N	Min.	Max.	Average	Standard deviation
Grup/Cluster 1 Multiple goals					
Mastery	37	5.00	7.00	6.0457	.68617
Performance	37	4.50	7.00	5.7162	.77092
Self - efficacy	37	3.50	7.00	5.6273	.90443
Test - anxiety	37	1.00	6.80	4.2973	1.64696
Expected grade in FA1	37	4.00	10.00	7.8378	1.48162
Final grade in FA1	37	4.00	10.00	8.2432	1.40249
Midterm exam grade in FA1	37	2.00	10.00	6.9730	1.87804
Final grade in Basic Accounting	37	5.00	10.00	8.7838	1.15795
Overall average year 1	36	6.50	10.00	8.5278	1.04160
Group/Cluster 2 Mastery					
Mastery	50	4.33	6.67	5.3270	.65445
Performance	50	1.00	4.50	3.4200	.92090
Self - efficacy	50	2.00	6.88	4.5776	1.14534
Test - anxiety	50	1.60	6.20	3.6480	1.43232
Expected grade in FA1	50	3.00	10.00	6.7600	1.59796
Final grade in FA1	50	4.00	10.00	7.1200	1.56022
Midterm exam grade in FA1	48	1.00	10.00	5.6458	2.54316
Final grade in Basic Accounting	50	4.00	10.00	8.2800	1.53915
Overall average year 1	50	6.00	10.00	8.1300	1.03416
Group/Cluster 3 Performance					
Mastery	37	1.33	4.67	3.8286	.76861
Performance	37	4.25	7.00	5.6554	.70551
Self - efficacy	37	2.00	5.75	4.2019	1.04752
Test - anxiety	37	1.00	7.00	4.5784	1.60540
Expected grade in FA1	35	3.00	10.00	6.8286	1.58087
Final grade in FA1	37	4.00	10.00	7.5946	1.70717
Midterm exam grade in FA1	34	2.50	9.50	6.1324	1.94356
Final grade in Basic Accounting	36	5.00	10.00	8.5556	1.38243
Overall average year 1	37	1.33	4.67	3.8286	.76861
Grup/Cluster 4 Low motivation					
Mastery	25	1.67	4.33	3.3196	.92915
Performance	25	1.75	4.25	2.7800	.67438
Self - efficacy	25	1.00	4.88	3.5776	1.02392
Test - anxiety	25	1.80	6.40	4.1840	1.35391
Expected grade in FA1	25	4.00	8.00	6.1200	1.30128
Final grade in FA1	25	5.00	9.00	6.5600	1.41657
Midterm exam grade in FA1	25	.50	8.50	5.0800	2.16833
Final grade in Basic Accounting	25	5.00	10.00	8.4400	1.26095
Overall average year 1	25	5.50	9.00	7.9400	.85781

Post hoc ANOVA and t-tests for pairwise comparisons between clusters, conducted in SPSS, indicate that each group is significantly distinct from the others, with one exception: the 'Multiple Goals' and 'Performance Goal' clusters show similarly high-performance goal scores (5.71 and 5.65, respectively). However, the 'Multiple Goals' cluster demonstrates a significantly higher mastery goal score compared to the 'Performance Goal' group.

Subsequent analyses were conducted to examine the relationship between group/cluster membership and various academic outcome variables. These analyses aimed to draw inferences about how different combinations of mastery and performance goals influence self-efficacy (a motivational outcome), test anxiety (an affective outcome), expected grade (a cognitive outcome), and final grade (a behavioral outcome) in the Financial Accounting 1 course.

4.3 Comparison of target groups/clusters with outcome variables

In order to examine the associations between group/cluster membership and the five academic outcomes measured by self-efficacy, test anxiety and expected grade and final grade, analysis of covariance (ANCOVA) was used. The ANCOVA models included the goal groups (multiple goals, knowledge mastery goal, performance goal, and low motivation) as independent variables, academic outcomes as dependent variables, and the five covariate variables discussed above (overall average in year 1 of study, final grade in the Basic accounting course and grade in the midterm exam in the Financial accounting 1 course, profile of the high school graduated, and gender) (Table 6).

Table 6: Analysis of covariance: main effects of clusters and covariate variables

	Mean Square	F	Sig.	η^2
Self-efficacy				
Cluster	13.823	16.647	.000	.273
Overall Average year 1	.215	.259	.612	.002
Midterm exam grade FA1	14.132	17.020	.000	.113
Final grade BA	1.869	2.251	.136	.017
High school profile	.005	.006	.938	.000
Gender	3.643	4.387	.038	.032
Test anxiety				
Cluster	6.630	3.152	.027	.066
Overall Average year 1	.452	.215	.644	.002
Midterm exam grade FA1	1.279	.608	.437	.005
Final grade BA	.599	.285	.595	.002
High school profile	.022	.010	.919	.000
Gender	21.641	10.288	.002	.072
Note expected				
Cluster	4.800	3.488	.018	.073
Overall Average year 1	19.693	14.310	.000	.097

	Mean Square	F	Sig.	η^2
Midterm exam grade FA1	17.579	12.773	.000	.088
Final grade BA	5.966	4.335	.039	.032
High school profile	.754	.548	.460	.004
Gender	8.488	6.168	.014	.044
Final note				
Cluster	3.991	4.727	.004	.097
Overall Average year 1	16.726	19.810	.000	.130
Midterm exam grade FA1	53.809	63.732	.000	.326
Final grade BA	3.552	4.208	.042	.031
High school profile	2.422	2.868	.093	.021
Gender	1.647	1.950	.165	.015

Finally, pairwise comparisons of clusters were examined using Tukey's difference tests to determine the nature (significant/non-significant) of any differences between clusters (Table 7).

Table 7: Pairwise comparisons of clusters (Tukey's test)

Dependent variable	Cluster	Cluster	Difference in averages	Standard error	Sig.
Self-efficacy	3	1	-1.42541*	.24299	.000
		4	.62429	.27059	.101
		2	-.37571	.22665	.350
	1	3	1.42541*	.24299	.000
		4	2.04970*	.27059	.000
		2	1.04970*	.22665	.000
	4	3	-.62429	.27059	.101
		1	-2.04970*	.27059	.000
		2	-1.00000*	.25601	.001
	2	3	.37571	.22665	.350
		1	-1.04970*	.22665	.000
		4	1.00000*	.25601	.001
Test anxiety	3	1	.28108	.35336	.856
		4	.39438	.39349	.748
		2	.93038*	.32959	.028
	1	3	-.28108	.35336	.856
		4	.11330	.39349	.992
		2	.64930	.32959	.204
	4	3	-.39438	.39349	.748
		1	-.11330	.39349	.992
		2	.53600	.37229	.477
	2	3	-.93038*	.32959	.028
		1	-.64930	.32959	.204
		4	-.53600	.37229	.477

Dependent variable	Cluster	Cluster	Difference in averages	Standard error	Sig.
Expected grade in FA1	3	1	-.64865	.35767	.271
		4	1.03459	.39829	.050
		2	.47459	.33361	.487
	1	3	.64865	.35767	.271
		4	1.68324*	.39829	.000
		2	1.12324*	.33361	.005
	4	3	-1.03459	.39829	.050
		1	-1.68324*	.39829	.000
		2	-.56000	.37683	.449
	2	3	-.47459	.33361	.487
		1	-1.12324*	.33361	.005
		4	.56000	.37683	.449
Final grade in FA1	3	1	-1.00927*	.35806	.028
		4	.70857	.39765	.286
		2	.06857	.33467	.997
	1	3	1.00927*	.35806	.028
		4	1.71784*	.39315	.000
		2	1.07784*	.32931	.007
	4	3	-.70857	.39765	.286
		1	-1.71784*	.39315	.000
		2	-.64000	.37197	.317
	2	3	-.06857	.33467	.997
		1	-1.07784*	.32931	.007
		4	.64000	.37197	.317

* Significant difference ($p<0.05$)

Self-efficacy. Significant differences in self-efficacy were observed among the goal groups, supporting hypothesis H1. The ‘multiple goals’ cluster demonstrated significantly higher self-efficacy compared to the ‘mastery,’ ‘performance,’ and ‘low motivation’ clusters (Table 7). Additionally, the ‘mastery’ cluster exhibited significantly higher self-efficacy than the ‘low motivation’ cluster.

Test anxiety. The goal clusters differ significantly with respect to test anxiety, thus confirming the H2 hypothesis, but only the difference between the ‘performance’ cluster (highest level 4, 57) and the ‘mastery’ cluster (lowest level 3, 64) is statistically significant (Table 7).

Expected grade in Financial Accounting 1. The goal groups differ significantly in terms of expected grade, which confirms hypothesis H3. The cluster “multiple goals” shows a significantly higher level of expected grade than the clusters “mastery”, and “low motivation” (Table 7).

Final grade in Financial Accounting 1. Significant differences in final grades were found across the goal groups, supporting hypothesis H4. The “multiple goals” cluster shows a significantly higher final score compared to the “mastery of knowledge goal,” “performance goal,” and “low motivation” clusters (see Table 7). No statistically significant differences were observed in the other pairwise comparisons between clusters in terms of final grade.

Covariate variables. The main effects of the covariate variables shown in Table 6 indicate that gender is significant. The data showed that male students typically had higher self-efficacy (4.86 vs. 4.5) as well as higher expectations of the grade they would receive (7.70 vs. 7.34), and female students typically had higher test anxiety (4.32 vs. 3.37). Final grades, however, were on average roughly equal between male and female students. (For reasons of space we have not presented descriptive statistics broken down by respondents' gender.)

Regarding high school profile, the data in Table 6 indicate that this variable does not show a significant effect on the dependent variables. The covariate variables targeting grades/average show a significant impact on the expected grade as well as on the final grade. In addition, the grade in the partial examination of Financial Accounting 1 shows a significant effect on the self-efficacy variable.

5. Research Conclusions, Contributions and Perspectives

This paper describes an empirical study on achievement goal theory and the relationship between learning motivation and self-efficacy, test anxiety and performance (outcomes). The study was conducted on a group of 149 students enrolled in the second year of the Accounting and Management Informatics degree program, who completed an anonymous online questionnaire that included 30 questions aimed at measuring mastery orientation, performance orientation self-efficacy for learning and performance achievement (and test anxiety, as well as grades obtained/expected in the courses Basic Accounting and Financial Accounting 1, overall average at the end of year 1, profile of the high school they graduated from and gender.

In this study, cluster analysis was employed to categorize students and identify their achievement goal profiles (also referred to as motivational learning profiles), based on variables measuring mastery and performance goals. Subsequently, ANOVA and ANCOVA were conducted to assess whether, and to what extent, the identified groups (i.e., achievement goal profiles) differed in self-efficacy, test anxiety, expected grade, and final grade in the Financial Accounting 1 course.

The obtained results confirmed the four hypotheses formulated, indicating that belonging to the identified groups/clusters ("Multiple objectives", "Mastery", "Performance" and "Low motivation") is significantly associated with the dependent variables (self-efficacy, test anxiety, expected grade and final grade in Financial Accounting 1). Students in the 'Multiple Objectives' cluster had on average significantly higher values for the variables self-efficacy, expected grade and final grade than students belonging to the other clusters. This indicates that a combination of objectives is preferable to a single objective orientation approach (even if this is aimed at mastering knowledge/skills). This result contrasts with the results obtained by Dull et al. (2015) and Daniels et al. (2008) who found no significant differences between the respective groups (except for the 'low motivation' group). However, in our study, only the difference between the "Performance Goals" cluster (highest level 4.57) and the "Mastery Goals" cluster (lowest level 3.64) is statistically significant.

These findings suggest that students' learning approaches in (financial) accounting courses can affect their academic outcomes, and that the pathway to academic success is likely multidimensional. If instructors can shape the way students engage with the challenges of a course, they may significantly influence students' experiences, motivation, and academic performance (Dull et al., 2015).

Given the challenges in addressing the bias toward performance-oriented motivation (Haynes et al., 2008), educators might focus on enhancing students' motivation to master knowledge and skills, rather than attempting to diminish performance motivation or surface learning approaches. Instead, efforts could be directed toward reducing test anxiety. Regular use of these questionnaires could allow teachers to track the learning environment and support students in shifting towards a stronger emphasis on mastery of knowledge or deeper learning approaches, even if they cannot entirely steer students away from the performance-focused strategies they are accustomed to.

This study extends the existing body of research on Achievement Goal Theory (AGT) by examining its applicability within the context of accounting education, field where empirical research on student motivation remains relatively limited. Through the analysis of a cohort of Romanian accounting students, this paper contributes novel insights into how mastery and performance goal orientations influence self-efficacy, test anxiety, and academic performance. While previous studies, such as those by Dull et al. (2015) and Daniels et al. (2008), have highlighted the beneficial effects of multiple-goal orientations on academic outcomes, this research provides additional evidence in a different academic and cultural setting, thereby expanding the generalizability of AGT.

Moreover, this study emphasizes the importance of adopting a multidimensional approach to student motivation, particularly in technical fields like accounting, where both conceptual mastery and performance are critical to success. The findings reinforce the notion that a combination of mastery and performance goals leads to better academic outcomes, thereby offering practical implications for teachers seeking to design interventions that not only improve student learning strategies but also reduce test anxiety. These contributions are valuable for advancing understanding in both educational psychology and accounting education, and they offer a framework for further research on motivational profiles across diverse academic disciplines.

References

Ahmad Z., Anantharaman R. N., Ismail H. (2012) Students' motivation, perceived environment and professional commitment: an application of Astin's college impact model, *Accounting Education: An International Journal*, 21(2), 187-208

Ames C., Archer J. (1988) Achievement goals in the classroom: Students' learning strategies and motivation processes, *Journal of Educational Psychology*, 80(3), 260-267

Bandura A. (1977) Self-efficacy: Toward a unifying theory of behavioral change, *Psychological Review*, 84(2), 191-215

Bandura A. (1997) Self-Efficacy: The Exercise of Control, W.H. Freeman, New York

Becker L. (2013) Self-Regulated Learning Interventions in the Introductory Accounting Course: An Empirical Study. Issues in Accounting Education, 28(3), 435-460.

Cassady J. C., Johnson R. E. (2002) Cognitive test anxiety and academic performance, *Contemporary Educational Psychology*, 27(2), 270–295

Daniels L. M., Stupnisky R. H., Pekrun R., Haynes T. L., Perry R. P., Newall N. E. (2008) A longitudinal analysis of achievement goals: From affect to action, *Journal of Educational Psychology*, 100(3), 903–919

Dull, R. Schleifer L. McMillan J. (2015) Achievement Goal Theory: The Relationship of Accounting Students' Goal Orientations with Self-efficacy, Anxiety, and Achievement, *Accounting Education: an international journal*, 24(2), 152-174

Dweck C. S., Leggett E. L. (1988) A social-cognitive approach to motivation and personality, *Psychological Review*, 95(2), 256–273

Elliot A. J., Church M. A. (1997) A hierarchical model of approach and avoidance achievement motivation, *Journal of Personality and Social Psychology*, 72(1), 218-232

Elliot A. J., McGregor H. A. (2001) A 2x2 achievement goal framework, *Journal of Personality and Social Psychology*, 80(3), 501-519

Harackiewicz J. M., Barron K. E., Elliot A. J. (1998) Rethinking achievement goals: When are they adaptive for college students and why? *Educational Psychologist*, 33(1), 1-21

Hart D., Wang X. (2016) The impact of self-efficacy and anxiety on accounting students' perceptions of performance, *Accounting Education*, 25(3), 235–255

Haynes T. L., Daniels L. M., Stupnisky R. H., Perry R. P., Hladkyj S. (2008) The effect of achievement goals on mastery and performance learning in college students, *Journal of Educational Psychology*, 100(3), 903–919

Midgley C., Kaplan A., Middleton M. (2000) Performance-approach goals: Good for what, for whom, under what conditions, and at what cost? *Journal of Educational Psychology*, 92(1), 77-86

Miller M. D. (2014) Minds Online: Teaching Effectively with Technology, Harward University Press, Cambridge

Nicholls J. G. (1984) Achievement motivation: Conceptions of ability, subjective experience, task choice, and performance, *Psychological Review*, 91(3), 328–346

Nicholls J. G., Patashnick M., Nolen S. B. (1985) Adolescents' theories of education, *Journal of Educational Psychology*, 77(6), 683–692

Opdecam, E., Everaert P., Keer H. V., Buysschaert, F. (2012) Preferences for team learning and lecture-based learning among first-year undergraduate accounting students, *Research in Higher Education*, 53(4), 397-419

Papageorgiou E. (2022) Self-Regulated Learning Strategies and Academic Performance of Accounting Students at a South African University, *South African Journal of Higher Education*, 36 (1), 251-78

Pintrich P. R., DeGroot E. V. (1990) Motivational and self-regulated learning components of classroom academic performance, *Journal of Educational Psychology*, 82(1), 33-40

Pintrich P. R., Schunk D. H. (2002) Motivation in education: Theory, research, and applications. 2nd edition, Upper Saddle River, Merrill Prentice Hall, New Jersey

Ramburuth P., Mladenovic R. (2004) Exploring the relationship between students' orientations to learning, the structure of students' learning outcomes and subsequent academic performance, *Accounting Education*, 13(4), 507-527

Senko C., Hulleman C. S., Harackiewicz, J. M. (2011) Achievement goal theory at the crossroads: Old controversies, current challenges, and new directions, *Educational Psychologist*, 46(1), 26-47

Svinicki M., McKeachie W. J. (2014) McKeachie's Teaching Tips: Strategies, Research, and Theory for College and University Teachers, 14th Edition, Wadsworth Cengage Learning, Belmont

Urdan T., Kaplan A. (2020) The origins, evolution, and future directions of Achievement Goal Theory, *Contemporary Educational Psychology*, 61, 101864

Zimmerman B. J. (2000) Self-efficacy: An essential motive to learn, *Contemporary Educational Psychology*, 25(1), 82–91