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INDEX

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Maintaining resilience while seizing opportunities

*Boštjan Vasle**

In the past years, our economy and financial system have experienced severe external shocks, which have been weathered well, given the strong support from economic policies. More recently, they showed high resilience to a decisive tightening of our monetary policy in response to persistently high inflation that has been caused by supply shocks and a robust post-pandemic demand recovery. While inflation in the euro area is steadily approaching our target and as we are contemplating the start of a gradual reduction in our policy rates, the prospect of achieving a soft landing is globally becoming increasingly promising. However, uncertainties and risks persist, particularly those associated with geopolitics, exuberance in some asset markets and the effects of monetary tightening that might still be in the pipeline.

Several structural changes are taking place in parallel, which will have transformative effects on our economy and financial system. Accelerated digitization, climate change, green transition and fragmentation of trade and investment along geopolitical lines may not advance in a linear manner. In addition to the opportunities some of them offer, they also pose risks. That said, it is important that we generate an environment, where we would be able to operate successfully despite increased uncertainty and more frequent shocks.

For policymakers creating such conditions entails ramping up buffers in different policy areas: monetary, fiscal and macroprudential. We must regain or enhance our capacity to effectively respond to future shocks and bolster the resilience of the economy and financial system against climate, health, geopolitical and cyber risks. Related to the latter, the global rise in the number of cyber incidents, along with recent cyber attacks on public infrastructure in Slovenia, underscores this imperative. Progress is underway in the banking sector. In the last few quarters, Slovene banks have been strengthening their capital ratios by reallocating a significant portion of their record high profits to capital. At the end of 2023, Banka Slovenije introduced a higher, so-called positive neutral rate for the countercyclical capital buffer. A buffer rate requirement of 1% instead of 0% in a "cyclically neutral risk environment" will further enhance the capital resilience of our banks. Additionally, at Banka Slovenije, we are increasingly focusing on cyber risks in the banking sector. We have recently developed a set of tools designed to identify and mitigate cyber risks. In collaboration with ECB, we will soon complete our first stress tests of cyber resilience of the banks. We are also advancing in the measurement, management and monitoring of climate-related risks to protect price stability and the safety of banks.

After years of operating in crisis mode, it is time to come to terms with higher uncertainty and devote more attention to structural challenges that have taken a back seat in recent years. These include low growth of labour productivity and aging of the population. In general, there is a growing need for investments to capitalize on advancements in IT and AI, facilitate green transition, fortify strategic autonomy and defence capabilities. The urgency to address the investment gap in the private sector is particularly evident. Meeting substantial funding needs will require a robust financial sector and its further development. While banks currently benefit from a competitive edge through digital transformation and fintech adoption, these advancements may eventually become essential for their survival.

* Boštjan Vasle, Governor, Banka Slovenije

UDK 004.8:336.71

Navigating the AI Frontier: Generative AI and Organisational Transformations

*Maja Škrjanc**

In the last few years, the banking sector has witnessed a seismic shift due to the rapid development of Gen AI technologies. Advancements in hardware capabilities, coupled with an exponential increase in data availability, have fuelled the rise of sophisticated LLM models. Although they are now playing a pivotal role in enhancing customer interactions and streamlining regulatory compliance, the sector faces significant challenges, including a skills gap in the AI workforce and the need for stringent ethical and regulatory compliance. To address these issues, the role of the Responsible AI Champion is being introduced, promoting ethical AI use, and ensuring that AI deployments are both innovative and responsible. This role is central to navigating the complexities of AI integration, balancing technological advancement with risk management and compliance, thereby safeguarding the industry's integrity, and advancing its technological forefront. The integration of AI is set to transform banking operations dramatically, enhancing efficiency and customer service while fostering significant personal and professional growth opportunities.

JEL G21 O33

Section 1: The Rapid Development of Generative AI (Gen AI)

Over the past two years, the field of artificial intelligence, particularly generative AI technologies, has seen explosive growth, significantly impacting the banking sector. This period has been characterised by remarkable advancements in hardware capabilities, exponential growth in data availability, and the rapid evolution of Large Language Models (LLMs).

In terms of hardware, the increase in processing power is staggering. Today's high-end GPUs, specialised for AI tasks, offer processing capabilities equivalent to thousands of laptops back in 2000. To put this in perspective, a single modern GPU can perform operations up to 100 teraflops, while an average laptop used in year 2000 struggled to reach even 1 gigaflop. Comparatively, a modern high-end smartphone now possesses more computing power than desktop computers from the early 21st century, highlighting the dramatic advancements in both personal and professional computing technology. This significant improvement in processing power enables the handling of complex AI computations at speeds previously unattainable, which is crucial for training and deploying large-scale AI models. Most of these powerful models, including those underpinning LLMs, are trained on vast server farms located in cloud infrastructures, allowing for scalable, flexible computing

* Maja Škrjanc, Institut Jožef Stefan

resources that are essential for managing the enormous computational demands. However, this immense processing capability comes with high energy consumption, raising concerns about the resulting CO2 emissions and the environmental impact of scaling up AI technologies. Data availability has similarly expanded, with banks and financial institutions now managing and processing data in the range of multiple terabytes to petabytes. This vast reservoir of data, including transaction histories, customer interactions, and regulatory reports, provides the essential ingredients needed to train more robust and precise AI models.

The landscape of LLMs has also evolved significantly. OpenAI's GPT-4 (OpenAI, 2022), for instance, with its billions of parameters trained on diverse internet texts, has shown capabilities that include generating human-like text, making reasoned arguments, and even creating content from scratch. Another notable model is Llama (Touvron at all, 2023), designed to run locally on devices rather than requiring powerful cloud-based infrastructure. This local processing capability offers significant advantages in terms of data privacy and operational speed, allowing sensitive financial data to be processed securely on-premises without the latency associated with data transmission to and from the cloud.

Comparatively, the human brain is estimated to have around 86 billion neurons, each capable of numerous connections and interactions. Current LLMs, despite their vast number of parameters—GPT-4 boasts about 175 billion—are still far from matching the complex interconnectivity and processing power of the human brain. However, the speed at which LLMs are growing in size and complexity is noteworthy, with substantial increases in model size from one iteration to the next.

LLMs are trained using vast amounts of data from the internet, including books, websites, and other texts, in a process known as unsupervised learning. They learn to predict the next word in a sentence based on the words that came before it, gradually improving their ability to understand and generate human-like text as they process more text. This training process also involves fine-tuning the models to specific tasks to enhance their accuracy and utility in applications such as customer service, content creation, and complex problem-solving.

In Europe, initiatives such as the development of Mistral (Mistral AI, 2023) alongside Germany's Aleph Alpha (Aleph Alpha, 2019) and Helsinki-based Silo AI (SiloAI, 2024), are shaping a unique approach to LLMs. These projects differ from their US counterparts by offering their models as open-source tools, promoting a decentralised, community-based approach to AI development. This does not only facilitate wider collaboration and innovation within the AI community but also aligns with the European values of transparency and access in technological advancements.

The competitive landscape of AI is thriving with entities like Google's Bard (Google, 2023) and Baidu's ERNIE (Baidu Research, 2023), each also comprising billions of parameters. These models are trained on extensive datasets to perform a wide array of tasks from language translation to complex problem solving, showcasing the depth and breadth of AI capabilities today. With new generative AI solutions emerging almost daily, these advancements are not only enhancing operational efficiencies but are also redefining the boundaries of what automated systems can achieve especially when we think about personalised banking and risk management.

As these technologies continue to mature, their integration into daily banking operations is set to unlock unprecedented levels of efficiency, enhance customer engagement, and ensure rigorous compliance with regulatory standards, heralding a new era in the financial landscape.

As we continue to harness these technological advancements, it becomes increasingly important to address the challenges they bring. This necessity leads us directly into the complexities and hurdles of integrating such powerful technologies within the banking sector.

Section 2: Navigating the AI Revolution in Banking

As banks integrate advanced AI technologies, they encounter a spectrum of new challenges that necessitate a proactive and thoughtful approach to technology adoption. The rapid evolution of AI capabilities has made it imperative for financial institutions to address associated risks and ethical considerations diligently.

One of the foremost challenges is the competence in AI within the workforce. The demand for AI expertise significantly exceeds the available supply, making it difficult for banks to attract and retain the necessary talent. This gap is not only in technical skills but also in the ability to implement AI solutions effectively while complying with regulatory standards. Consequently, banks are compelled to invest in training and development programmes to upskill their existing workforce, ensuring employees are both technologically proficient and ethically aware of AI's potential and limitations.

The implementation of AI also presents various hurdles. Legal and regulatory compliance is particularly challenging, as banks must navigate a complex and ever-changing landscape of laws that vary by jurisdiction. These challenges are compounded by the need for effective change in management strategies to integrate AI into the existing systems. Such integration requires a cultural shift within organisations to support continuous learning and adaptation to new technologies. Moreover, banks must develop robust mechanisms to identify and mitigate risks associated with AI, such as biases in decision-making processes and vulnerabilities in AI-driven systems.

Organiational culture also needs to evolve to support the ethical use of AI. Banks must establish continuous monitoring mechanisms to assess the performance and impact of AI technologies. This involves not only technical audits but also feedback loops that allow for the refinement of AI applications based on real-world experiences and outcomes. Promoting a culture that prioritises ethical considerations in the use of AI is vital, ensuring transparency in AI-driven decisions, fairness in algorithmic processes, and accountability for the outcomes of AI systems.

As banks venture further into this AI-driven era, they face challenges that require comprehensive strategies encompassing technical implementation, workforce development, and ethical governance. Successfully addressing these challenges will enhance their operational efficiency and fortify their reputation in an increasingly competitive and regulated market.

The challenges mentioned in Section 2 underscore the critical need for dedicated roles within organisations to oversee AI deployment and ethical adherence. This leads us to the emergence and significance of the newly introduced role of Responsible AI Champion.

Section 3: Responsible AI Champion (RAI)

The role of a Responsible AI Champion (Microsoft, 2023) (Telefonica Tech, 2020) has emerged as crucial in recent years, driven by the need for ethical and effective AI deployment. This development responds to the accelerating integration of wide range of AI technologies necessitating careful oversight to align with both ethical standards and regulatory compliance. As AI continues to permeate deeper into the banking landscape, the introduction of this role could serve as a proactive measure to manage the complexities and potential risks associated with these technologies.

Although the RAI was initially implemented in telco organizations, the same principles applies also to financial institutions. The Responsible AI Champion acts as the cornerstone of a bank's AI governance framework, tasked with overseeing the ethical implementation of AI technologies. This role includes ensuring all AI deployments are in line with ethical guidelines that prioritise fairness, transparency, and accountability. By doing so, the Champion helps build trust among customers and stakeholders, enhancing the bank's reputation for responsible innovation. Additionally, they navigate the complex landscape of both local and international regulations pertaining to AI, such as data protection laws and bias mitigation requirements, ensuring compliance across all operations.

The Champion also plays a critical role in cross-departmental coordination, acting as a liaison between technology teams, management, and external auditors and supervisors. This ensures that AI solutions are developed and deployed in a manner that supports the bank's broader business objectives without compromising ethical values or compliance with regulatory standards. Furthermore, they lead educational initiatives to raise awareness about the ethical dimensions of AI among employees, fostering a culture that prioritises responsible AI use. Regular monitoring and auditing of AI systems to ensure ongoing compliance with both internal and external standards are also key responsibilities, along with adapting practices in response to technological advancements and regulatory changes.

Implementing the role of a Responsible AI Champion involves overcoming several challenges. Resistance from some departments might occur as they may perceive the oversight of a Responsible AI Champion as a hindrance to innovation or an increase in bureaucracy. Additionally, the interdisciplinary nature of the role requires a rare combination of technical AI knowledge, understanding of regulatory environments, and ethical reasoning.

The Champion must balance the drive for technological advancement with risk management, ensuring that AI deployments enhance customer value without introducing new risks. They must interact effectively with various departments, including IT for technical deployment, legal for compliance issues, human resources for training programs, and customer service to understand user feedback and concerns.

The establishment of a Responsible AI Champion is a forward-thinking response to the complexities introduced by AI in the banking sector. It underscores a commitment to ethical practices, enhances regulatory compliance, and positions the bank as a leader in responsible innovation. As AI continues to evolve, the role of the Responsible AI Champion will be crucial in steering banks toward sustainable and ethical AI integration, thereby safeguarding both their reputations and their customers. This role not only ensures that banks navigate the AI landscape with a strong ethical compass but also solidifies their position at the forefront of technological advancement in the financial industry.

The role of the Responsible AI Champion helps address many of the operational and ethical challenges associated with AI in banking. With this foundation, we can explore specific instances where generative AI has proven its value in enhancing banking services and regulatory processes.

Section 4: Gen AI solutions proves value in Banking sector

Gen AI is increasingly becoming a transformative force in the banking sector, reshaping both customer-facing services and regulatory compliance processes. This section highlights two pivotal applications of Gen AI within distinct banking contexts—one in retail banking and the other in regulatory supervision. Both examples demonstrate the potential of Gen AI to enhance efficiency and accessibility, yet they also underscore the challenges and regulatory considerations that must be addressed to harness this technology effectively.

Example 1: Enhancing Customer Interactions at ING (McKinsey, 2023): ING, a global bank based in the Netherlands, routinely manages 85,000 customer interactions weekly through phone and online chat. Historically, only about 45% of these interactions were resolved using their existing chatbot, leaving many customers waiting for live agent support. To improve this situation, ING partnered with an external firm to develop a Gen AI-enhanced chatbot over seven weeks. This advanced system not only retrieves and ranks information to offer tailored responses but also includes built-in guardrails for handling sensitive queries. Initial tests showed substantial improvements in response efficiency and customer satisfaction, significantly reducing wait times without compromising security. ING's initiative represents a strategic step towards integrating sophisticated AI tools in customer service, with plans to expand these capabilities globally.

Example 2: Advancing Supervisory Technologies at the ECB (ECB, 2023)**:** The European Central Bank (ECB) has leveraged Gen AI to revolutionize banking supervision, developing 14 applications and platforms that now serve over 3,500 users across the ECB and EU Member States' supervisory authorities. A standout innovation among these is a tool that converts plain language inquiries into executable code, allowing supervisors without programming skills to access specific data points from the ECB's extensive "data lake." This tool is part of a broader suite of applications, such as Athena for textual analysis and GABI for big data analytics, which collectively enhance the ability of supervisors to perform their roles more effectively and inclusively.

Challenges of Gen AI

Gen AI presents several challenges that transcend specific use cases and impact the broader banking industry. One major concern is the accuracy and reliability of AI-generated outputs, often referred to as AI "hallucinations," where the AI produces false or misleading information. These inaccuracies can severely impact decision-making processes, leading to significant financial repercussions if not adequately addressed. Another challenge is ensuring that AI systems are resistant to biases that can skew results and lead to unfair outcomes. Additionally, the integration of Gen AI requires substantial investments in technology and training, presenting cost-related challenges, especially for smaller institutions. Finally, the rapid evolution of AI technology necessitates continual updates and maintenance to ensure systems remain effective and secure against emerging threats.

EU Regulatory Framework for Gen AI

The deployment of Gen AI in the financial sector is subject to increasing scrutiny under EU regulations, which aim to ensure that these technologies are used responsibly and ethically. The emerging EU regulatory framework for AI emphasises transparency, accountability, and enhanced oversight. This framework includes strict requirements for AI systems that have significant impacts, ensuring that they do not compromise the privacy and rights of individuals. Furthermore, the framework mandates thorough documentation and testing of AI technologies to verify their safety and efficacy before widespread deployment. In addition to these requirements, the upcoming regulations will also introduce guidelines focused mainly on enforcing good practices that financial institutions should already be following, not merely in response to regulatory demands. This approach underscores the EU's commitment to fostering responsible innovation while protecting consumers and maintaining the integrity of the financial system.

Section 5: New Paradigms Introduced by Gen AI

Gen AI is reshaping the workforce landscape in unexpected ways, challenging preconceived notions about which jobs and which types of workers are most impacted by automation and artificial intelligence. Two new paradigms have emerged as GenAI continues to evolve and integrate into various sectors, particularly in the banking industry.

Paradigm 1: Impact on Creative and Routine Jobs

Historically, it was anticipated that AI would primarily affect "blue-collar" workers, automating manual and routine tasks traditionally associated with these roles. However, the reality has proven to be quite different. Gen AI's capabilities extend far beyond simple task automation; it is profoundly influencing creative roles as well. With its ability to process and generate complex data and content, Gen AI serves as a potent tool for creative and knowledge-intensive jobs. For instance, in the banking sector, Gen AI assists in drafting financial reports, analysing investment opportunities, or even developing new financial products, tasks that typically require high levels of creativity and expert knowledge. Simultaneously, Gen AI continues to excel as an assistant for routine tasks, streamlining operations like data entry, transaction processing, or customer query handling, thereby freeing up human workers to focus on more strategic activities.

Paradigm 2: The Shift in Workforce Demographics
The initial belief that younger workers would be more advantageous in an AI-driven workplace due to their familiarity with technology is being reconsidered. As Gen AI systems require oversight, the verification of outputs, and nuanced decision-making, there is an increasing appreciation for the skills and experience that older, more seasoned workers bring to the table. These workers often possess critical thinking, judgment, and a depth of industry knowledge that are crucial for effectively managing and guiding AI operations. In banking, where decision accuracy is paramount, the expertise of experienced professionals in overseeing Gen AI outputs is invaluable. They ensure that the AI's recommendations are sensible, compliant with regulations, and beneficial for customers, reflecting an understanding that comes from years of nuanced, real-world experience.
These shifts highlight a broader trend in AI integration where the focus is on complementarity between human and machine rather than substitution. The evolving paradigms emphasize the importance of leveraging the unique strengths of both younger and older employees to create a more dynamic, effective workforce that is equipped to harness the full potential of Gen AI technologies. This approach not only maximises the benefits of AI but also mitigates the risks associated with its limitations, leading to better outcomes for businesses and their clients.

Conclusion

As the banking sector embarks on a transformative journey with Gen AI, it is imperative to navigate both the immense opportunities and the significant challenges this technology presents. The integration of Gen AI into financial services is reshaping operations, enhancing capabilities, and introducing new paradigms in workforce dynamics. However, alongside these technological advancements, it is crucial to address the ethical implications and ensure the responsible usage of AI. Ethical governance, transparency, and accountability must be at the core of AI deployments to maintain trust and integrity within the financial system.
One effective solution to address these challenges is the introduction of a Responsible AI Champion within organisations. This role can spearhead the ethical deployment of AI technologies, ensuring that AI systems are implemented responsibly and in alignment with regulatory standards while also serving as a bridge between AI technology and business objectives. Simultaneously, the development of Gen AI should not overshadow the importance of traditional AI systems such as KYC initiatives, credit scoring, fraud, AML solutions using predictive Machine Learning models. There is a critical need to foster synergy between traditional AI and Gen AI solutions to maximize their respective strengths. This synergy can lead to substantial added value, enhancing not just organisational efficiency but also customer satisfaction and regulatory compliance.
Moreover, this new AI era offers profound opportunities for personal and professional growth at an individual level. As AI technologies evolve, they provide financial professionals with tools to free themselves from mundane tasks, delve deeper into creative and strategic pursuits, and develop skills that are pivotal in the digital age. Embracing this shift can lead to significant personal development and career advancement within the evolving landscape of financial services.

References

(OpenAI, 2022), *Introducing ChatGPT*. Available at: https://openai.com/blog/chatgpt .

(Touvron at all, 2023), *Llama 2: Open Foundation and Fine-Tuned Chat Models*. Available at: https://arxiv.org/abs/2307.09288 .

(Mistral AI, 2023), *Frontier AI in your hands*. Available at: https://mistral.ai/ .

(Aleph Alpha, 2019), *Sovereignty in the AI era*. Available at: https://aleph-alpha.com/ .

(SiloAI, 2024), *Europe's open language model Poro: A milestone for European AI and low-resource languages*. Available at: https://www.silo.ai/blog/europes-open-language-model-poro-a-milestone-for-european-ai-and-low-resource-languages .

(Google, 2023), *An important next step on our AI journey*. Available at: https://blog.google/technology/ai/bard-google-ai-search-updates/ .

(Baidu Research, 2023) *ERNIE Bot: Baidu's Knowledge-Enhanced Large Language Model Built on Full AI Stack Technology*. Available at: http://research.baidu.com/Blog/index-view?id=183 .

(Microsoft,2023) *Governing AI: A Blueprint for the Future*. Available at:https://query.prod.cms.rt.microsoft.com/cms/api/am/binary/RW14Gtw .

(Telefonica Tech, 2020) *A new organizational role for Artificial Intelligence: the Responsible AI Champion*. Available at: https://telefonicatech.com/en/blog/a-new-organizational-role-for-artificial-intelligence-the-responsible-ai-champion .

(McKinesy, 2024) *Scaling gen AI in banking: Choosing the best operating model.* Available at: https://www.mckinsey.com/industries/financial-services/our-insights/scaling-gen-ai-in-banking-choosing-the-best-operating-model .

(McKinsey, 2023) *Banking on innovation: How ING uses generative AI to put people first*. Available at: https://www.mckinsey.com /industries/financial-services/how-we-help-clients/banking-on-innovation-how-ing-uses-generative-ai-to-put-people-first .

(ECB, 2023) *Suptech: thriving in the digital age*. Available at: https://www.bankingsupervision.europa.eu/press/publications/newsletter/2023/html/ssm.nl231115_2.en.html .

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The impact of automation and artificial intelligence on Slovenia's labour market: a look at the recent past and foreseeable future

*Gonzalo Caprirolo**

So far, from the technological point of view automation and programable artificial intelligence have and continue to be the main factors driving the occupational change in the labour force. Their impact seems to have been biased towards high-skilled labour and their effect on employment mixed. In some activities and industries, it has been complementary to job creation and in others lead to job displacement. Employment structure and past labour dynamics do not differ significantly from those in other EU countries. Labour shares of major occupation groups have increased mainly for Professionals and Service and sales workers whose most used skill is working with digital devices. Most labour transition originate from occupations where the skills most used involve finger dexterity, hard physical work and are related to human interaction with machines. Labour share in Low-technological industries has decreased in favour of those with higher technological complexity.

JEL J24 O33

This article looks at the impact of occupational automation and digital transformation on the labour market. It reviews major trends in employment and through its interaction with productivity developments, assess the impact of the technological and digital progress on the labour force. It looks at labour composition in different activities and industries as well as to occupational change. Based on existing labour markets projections provides some insight on the potential impact of generative artificial intelligence.

The broad context in which the impact of automation and Artificial Intelligence (AI) on the labour force will continue unfolding is one in which population is ageing, and there is a forceful policy drive towards transition to green technologies and a push for enhancement of digital skills. In Slovenia the impact of demographic change in the labour market is already visible.

A broad idea of the impact of automation and impact of digital technologies including AI on employment can be obtained by first looking at the employment dynamic by mactivity and industry in Slovenia's post EU accession period 2005-2022. In this period, total employment increased by 152 thousand. Employment increased in 12 activities and the largest

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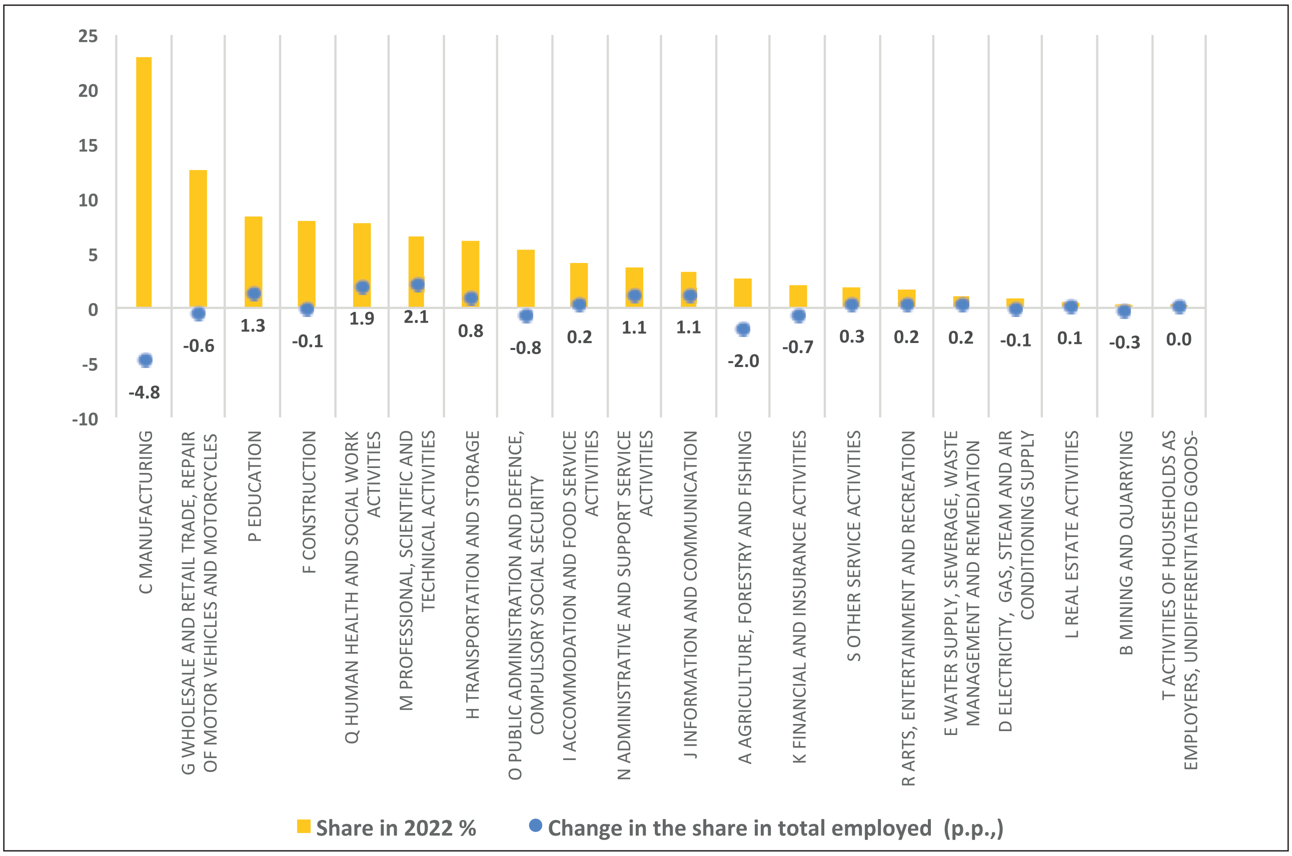
increases were in: Professional activities; Human health activities; Education; Information and communication, and Administrative and support services. The labour market shares decreased in 8 activities with the bulk of it taking place in: Manufacturing; Agriculture; Public administration; Financial sector, and Wholesale and retail trade (Figure 1). At the industry level, employment increased by 214 thousand in 28 industries and decreased by 62 thousand in 14 industries. About 60% of the increase took place in: Non-market services (Health and Education); business services (Legal account and consultancy and Computer programming); Construction; Whole and retail trade and; Accommodation and catering (Figure 2). Employment decreased in primary activities (Agriculture and Mining), Textile and Wood and Printing Industries, Computer Equipment and Financial Industries. In terms of labour market share, a similar pattern to that of the change in the number of employed is found, with the shares of non-market and business services increasing. However, the relative increase in the market share of construction is smaller while that of wholesale and retail trade decreased.

The labour dynamics in terms of labour shares by type of activity do not differ from those in other EU countries in the period 2005-2021. When looking at the change in labour market shares in 21 activities in Slovenia and comparing them with those in Germany and the EU average countries it is possible to observe that the dynamics are similar. With labour market shares of services increasing while those of production decreasing in the three cases. In particular, labour shares increased in business and non-marketed services, professional services, health and social care, and education. Notice also that the dimension of the increase in the labour share of ICT activity is the same in the three cases (Figure 3). Comparing Slovenia's industries labour market shares with those of the EU average in 2021 suggests that the ranking is similar, with Slovenia exhibiting higher labour shares in the manufacturing and education sectors and lower shares in distribution and transport and health care (Figure 4).

Looking at occupations, the bulk of the increase in *the number of the employed* in Slovenia in the period 2010-2022[1], was in Professionals and Service and sales workers (64%) the rest of the increase is in more labour-intensive occupations. When looking *at labour shares of occupations*, except for Plant and machine operators, which share marginally increased by 0.1 p.p., they increased only for Professionals and Service and sales workers (Figure 5). The

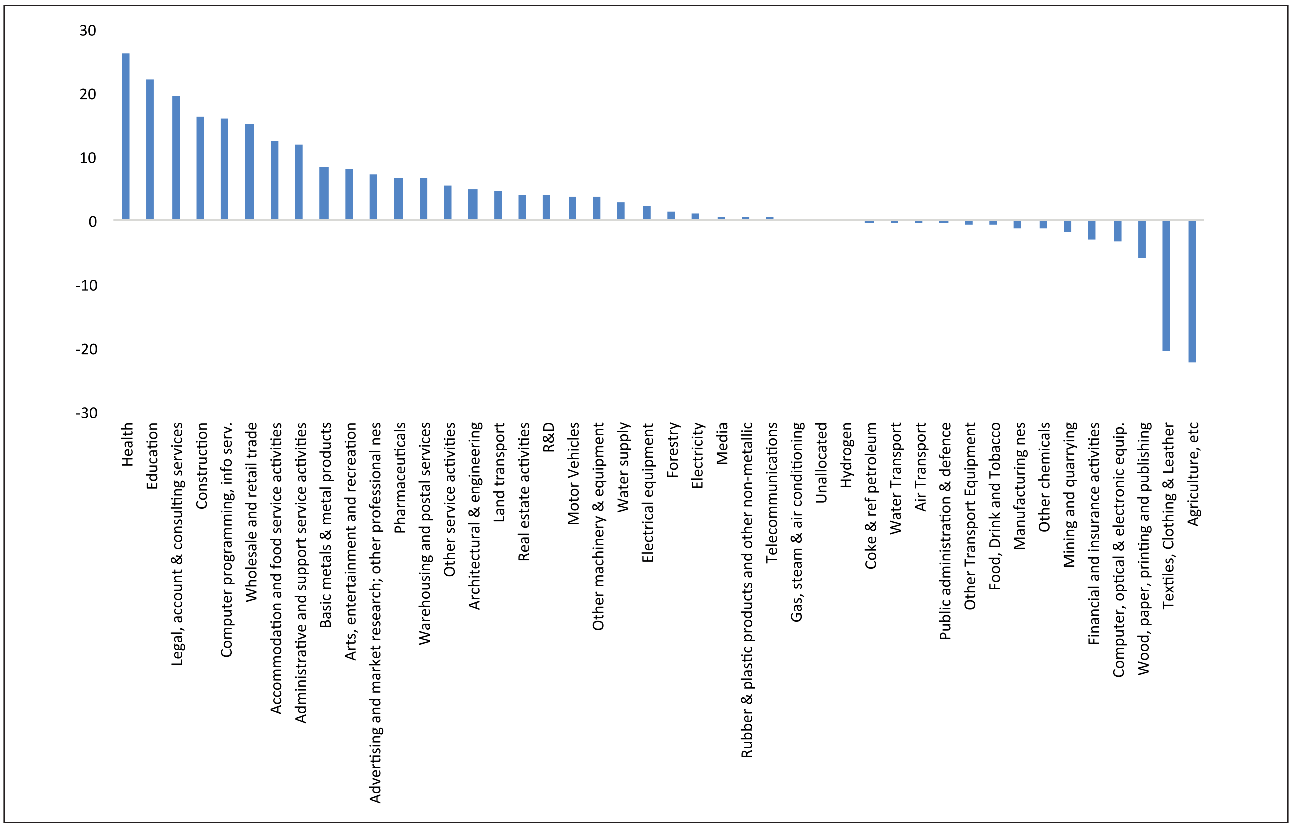
[1] Period for which information is available.

Figure 1: Labor share in 2022 (percent) and change in the labor share (2005-2022), percentage points



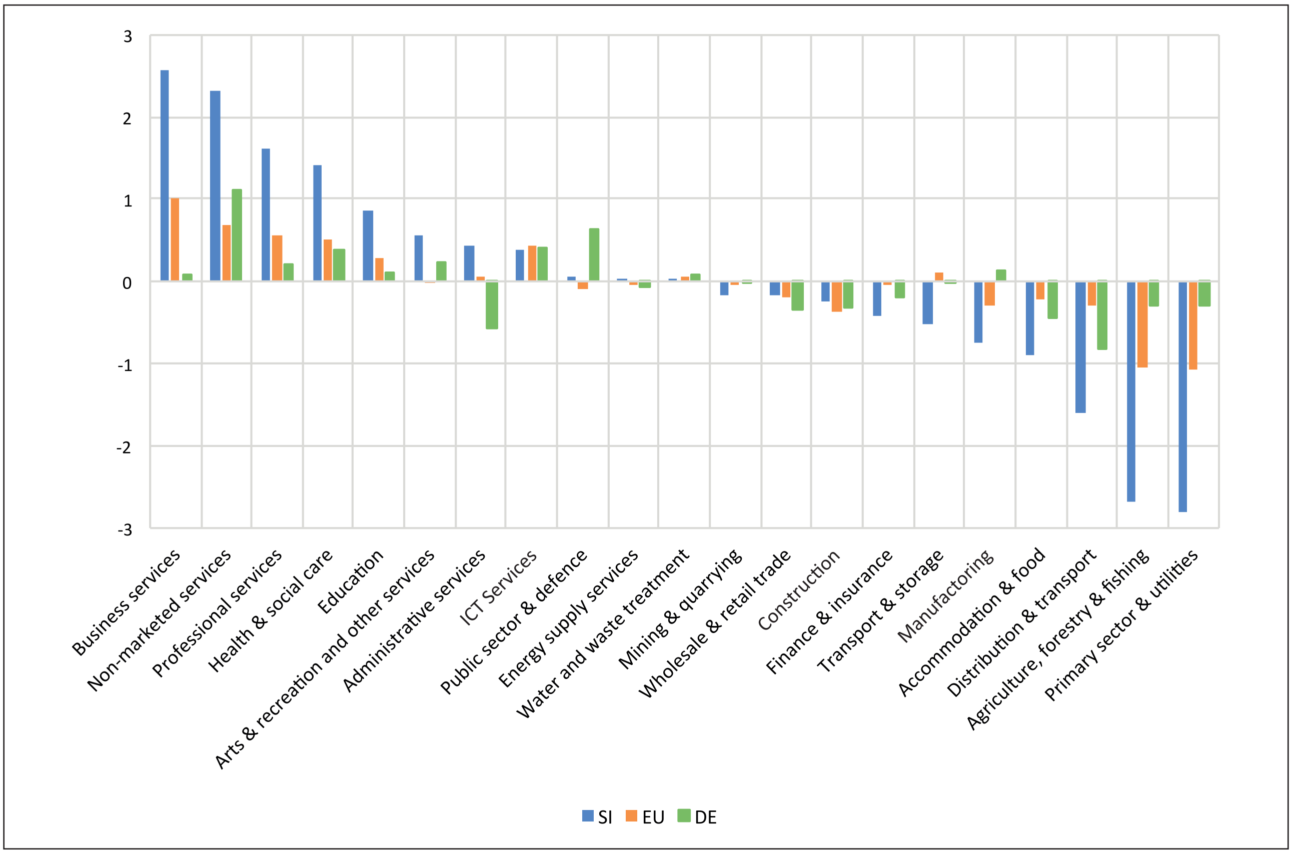
Source: SORS. Own calculation.

Figure 2: Change in employment 2005-2022, thousands



Source: SORS. Own calculation.

Figure 3: Change in labor market shares 2021-2011, percentage points



Source: Eurostat. Own calculation.

increase was particularly large for Professionals (4.7 p.p.). The occupations whose labour shares decreased significantly were: Managers[2]; Technicians and associate professionals and Skilled agricultural, forestry and fishery workers.

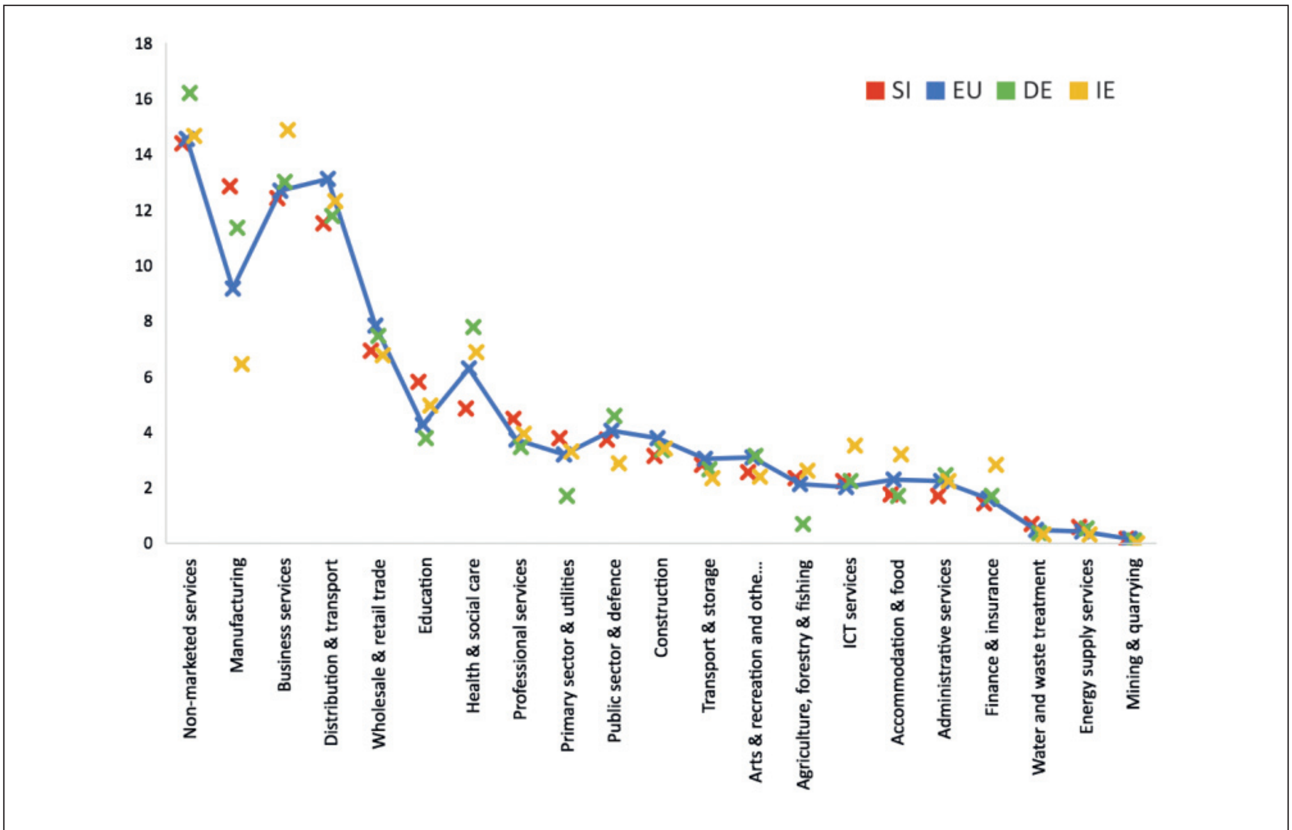
To get some insight about the impact of automation and AI on the observed dynamics of occupations, it is relevant to look at the type of the most used skill by those who all or most of their working time use a specific skill in a given occupation. For the group of Professionals, whose number and labour share increased, the skill most used is working with digital devices (Figure 6). For Service and sell workers, the skill most used is verbal communication with people outside the organization. For those whose labour share has decreased such as Craft workers and Elementary occupation the skill most used involve finger dexterity and hard physical work. For Technicians and associate professionals whose number has increased but labour share decreased significantly (1.3%), the most used skill is working with digital devices.[3]

Looking at job transition between occupations (2017-2021) can provide additional information on their underlying drivers including that of automation. In that period, most of the transition between occupation on average originated from the following occupation groups: Craft and related trade workers; Elementary occupations; Service and sales workers and; Plant and machine operators (Figure 7). Except for Craft and related trade workers, the net outflow into other occupations was positive. A common feature in the group of occupations from which the bulk of the workers shifted away or decreased on yearly average (Craft and related trade workers, Service and sales workers and Plant and machine operators) is that the most used skills involve finger dexterity and hard physical work and are related to human interaction with machines. Within those groups these are the case of: Metalworkers and machine mechanics (average outflow 540 employees); Machine and plant operators and assemblers (average outflow of 307 employees) and; Plant and products (average outflow of 120 employees). In the case of Service and sales workers the sizable net outflow is mainly explained by workers shifting away from the occupation of Sales assistance. Such dynamic could be explained by the effect of digitalisation and other drivers such as the level of remuneration.

2 The decrease is explained primarily by occupations in Production and specialised services managers (0.7 p.p.,) and Hospitality, retail and other services managers 0.5 p.p.,).

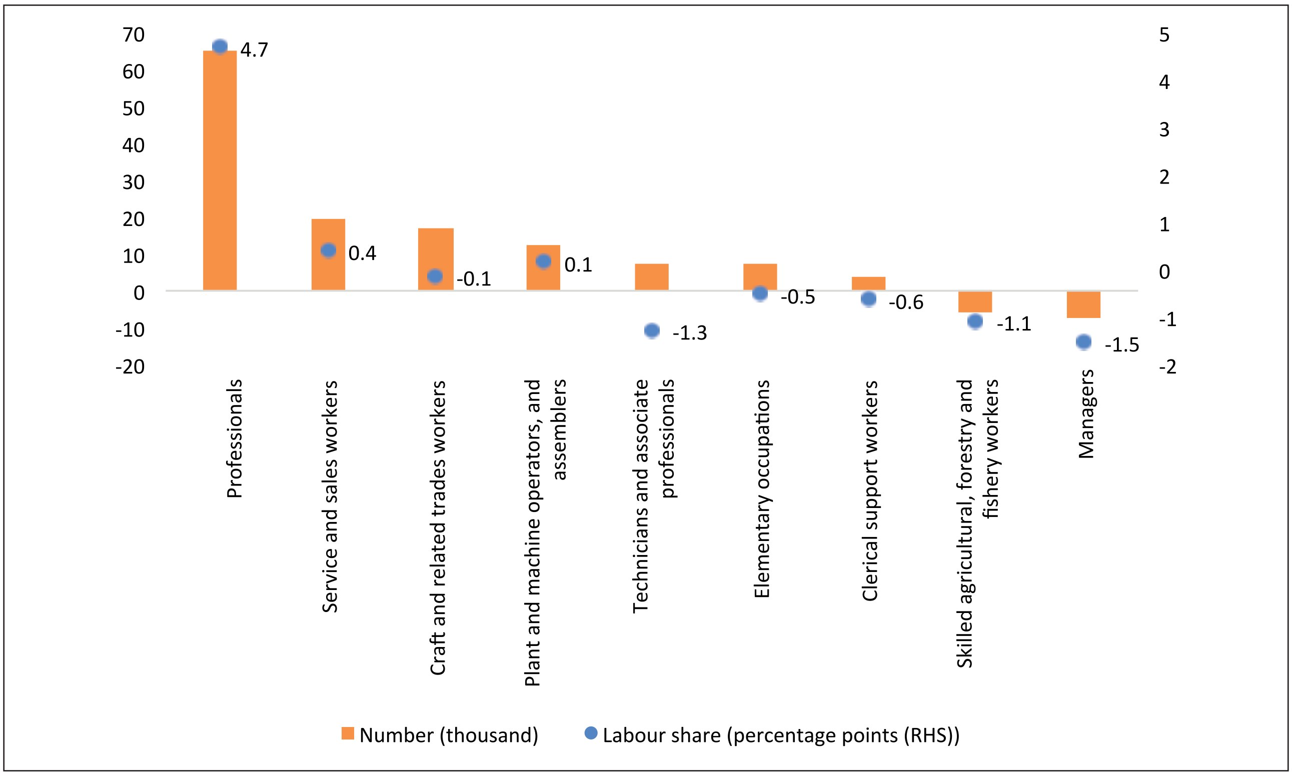
3 The bulk of the decrease among Technicians and associate professionals concerns the occupation of Business and administration associate professionals (1.1 p.p.,).

Figure 4: Labor market share by sector 2021



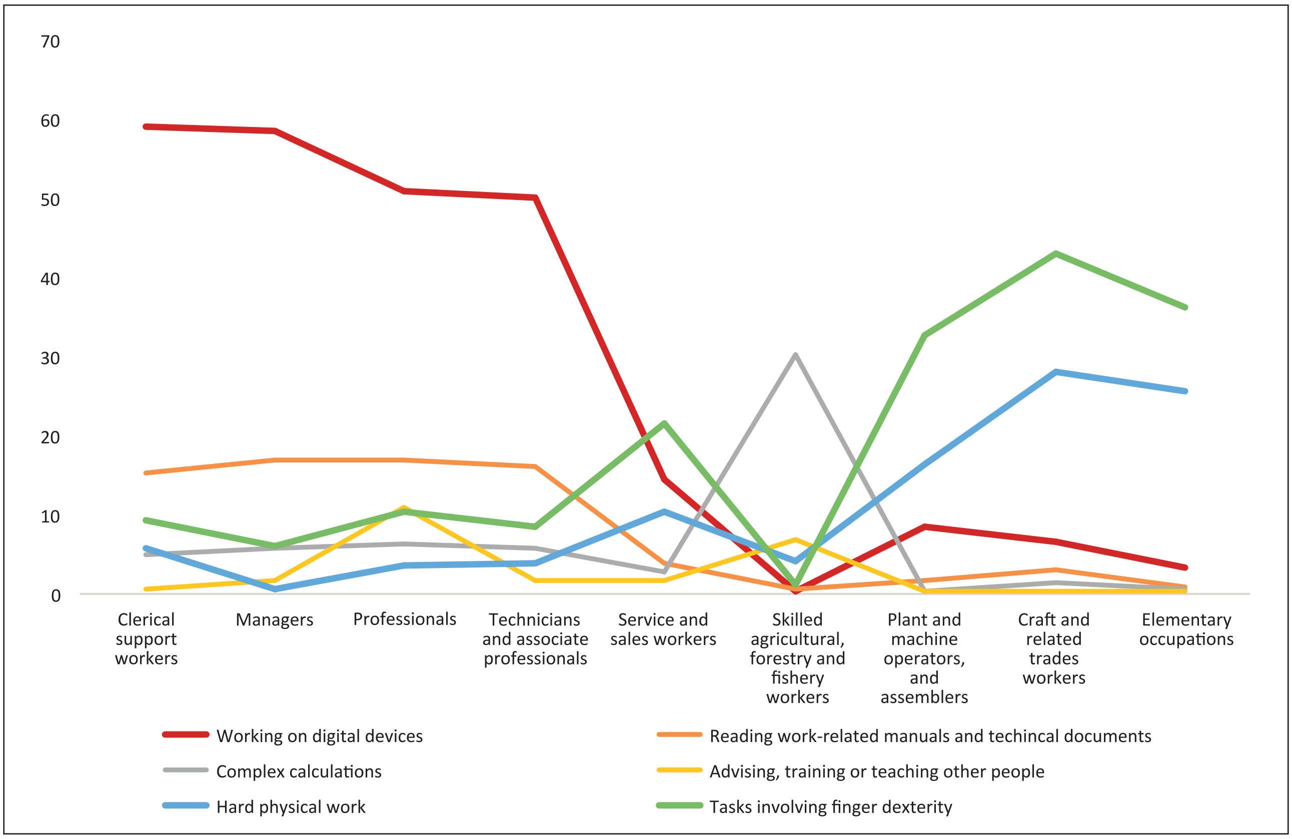
Source: Eurostat. Own calculation.

Figure 5: Change in occupations' number and labor share, 2010-2022



Source: SORS. Own calculation.

Figure 6: Share of employed (%) by job skills, all or most of the working time spent, occupational groups (ISCO), 2022



Source: SORS. Own calculation.

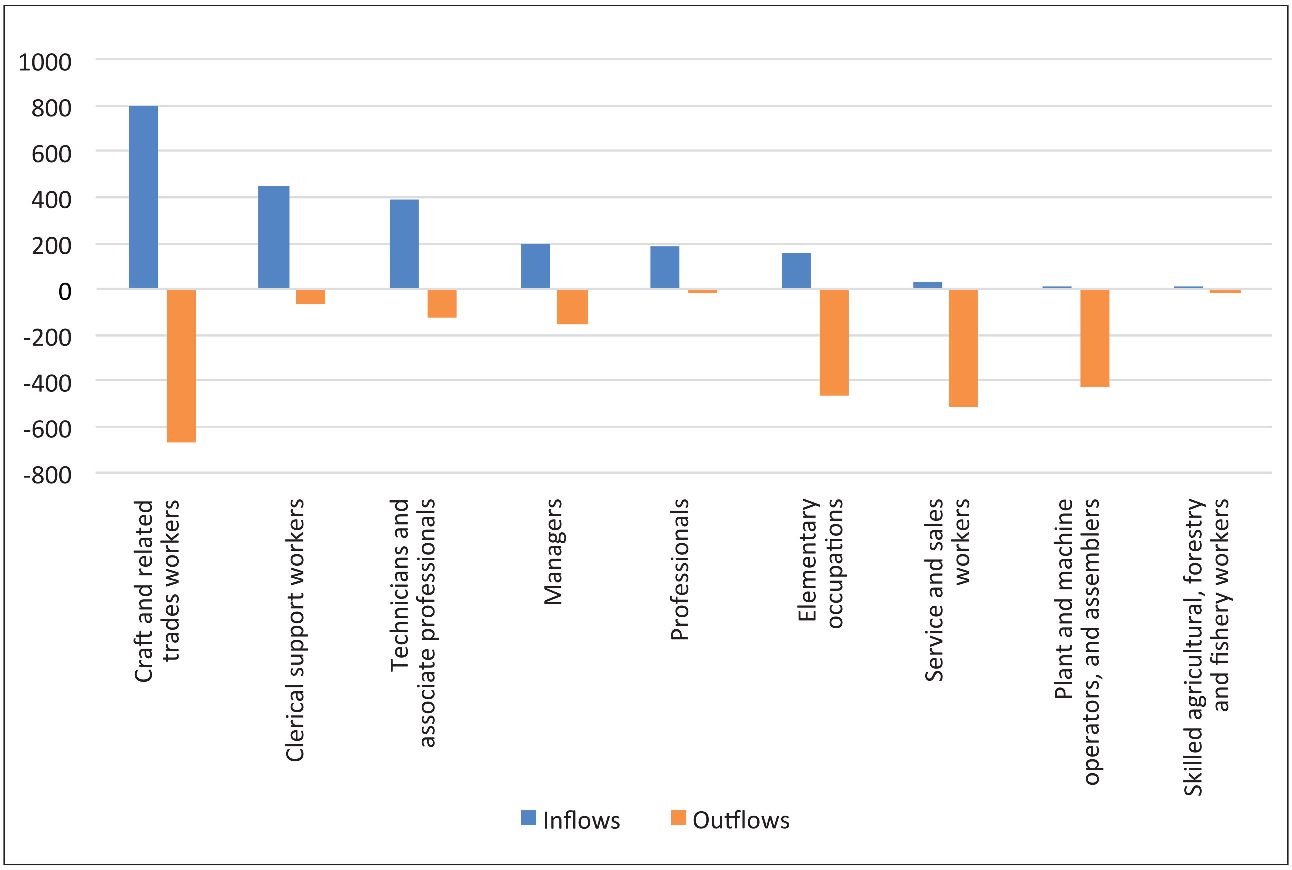
In the case of Craft and related trades workers, where the yearly average job transition inflow was significant, the bulk of it was into occupations of construction (642 employees) and into Assemblers and repairers of electrical and electronic equipment (152 employees). In the case of the occupational group of Clerical support workers the inflow was into the occupation of office administration clerks (376 employees) and, in the occupational group of Technicians and associate professionals, the inflow was into occupations of Business and management professionals.

Given that the Manufacture activity has the largest labour market share in total activities (23% in 2022) and automation and digitalization seems to play an important role in overall employment dynamics (Borowiecki et.al 2023), it is relevant to zoom into employment developments in this activity. Manufacture is the activity that experienced the

largest decreased in terms of both number of employed (14.4 thousand) and of labour market share (5%) in the period 2005-2022. This activity has undergone important transformation due to structural change in relative competitiveness but also is affected by automation and artificial intelligence. Employment in the manufacturing activity decreased in 8 industries by 36 thousand in the period under consideration. Industries where employment decreased the most are: Textile; Printing and publishing; Manufacture of electronic products; food and; chemical excluding pharmaceutical products. Employment increased by 21 thousand in the following industries: Basic metals; Pharmaceutical products; Motor vehicles and manufacture of vehicles and; Electronic equipment. Looking at employment dynamics in industries classified according to its technological content [4] indicates that during 2005-2022 there was a strong decrease in the number (33.1 thousand) and the share of employed in

[4] Based on the Eurostat classification, four groups of industries are classified according to their technological complexity: (i) high-technology pharmaceuticals (C21), manufacture of ICT equipment (C26), (ii) medium-high-technology chemicals (C20), manufacture of electrical equipment (C27), manufacture of other machinery and equipment (C28), manufacture of vehicles and vessels (C29-30), (iii) medium-low-technology manufacturing of coke and petroleum products (C19), manufacture of rubber and plastic products (C22), Manufacture of other non-metallic mineral products (C23), Manufacture of basic metals (C24-25), Repair and assembly of machinery and equipment (C33), (iv) Low-tech food industry (C10-11), Manufacture of tobacco products (C12), Manufacture of textiles (C13-14), Manufacture of leather (C15), Manufacture of wood products (C16), Manufacture of paper and printing (C17-18), Manufacture of furniture and other miscellaneous manufacturing (C31-32). In the following analysis, we do not show and analyse companies in the manufacture of tobacco products and the manufacture of coke and petroleum products, which together accounted for only around 0.007% of value added and employment of manufacturing companies in 2022.

Figure 7: Job transition between occupations (Yearly average)



Source: MOLFSAeO 2024. Own calculation.

low-technological industries (13 p.p. to 25%). In the cases of Medium-high and Medium-low technological industries, their number
increased (7.5 thousand and 9 thousand respectively) as well as their labour share (5.2 p.p., and 6.4 p.p., respectively). In the case of High-tech employment industries employment (2.4 thousand) and market share increased (1.5 p.p.,). More specifically, employment increased in Manufacture of basic pharmaceutical products (5.4 thousand) while it decreased in manufacture of ICT equipment (3 thousand).

Productivity and employment developments

Technological innovation in the form of automation and digitalization from the theoretical point of view can have ambiguous effect on employment. To the extent that innovation automates routine jobs it can lead to replacement of workers (Acemoglu and Restrepo 2018). However, it can also increase employment to the extent that most productive firms increase labour demand (Gregory, Salomons and Zierahn 2021). Similarly, the effect of digitalization and particularly artificial intelligence on different type of workers seems to be also ambiguous. Most of the research has focused on the effect on employment of programable artificial intelligence based on previous programming (robots, excel) that does not create new content as it is the case of "Generative" artificial intelligence (GenAI) that can identify patterns in huge data sets and generate new content - a capability often thought to be uniquely human. In particular, digitalization has been assessed as potentially resulting in labour market polarisation in which the demand for high-skilled workers increases at the expense of low-and middle skilled workers (Acemoglu and Restrepo 2020). Yet, the development of GenAI seems to challenge the perception that technological advancement affects mainly middle and, in some cases, low skilled jobs. According to It Cazzaniga et.al (2024) advanced AI can augment or replace high-skill jobs previously perceived as immune to automation.

While the use of GenAI is still in the early stage, it is spreading fast with significant potential applications for businesses wide-ranging. Thus, when looking at the impact of technological innovation in the recent past (2005-2022) in the form of automation and digitalisation this concerns primarily programable AI.

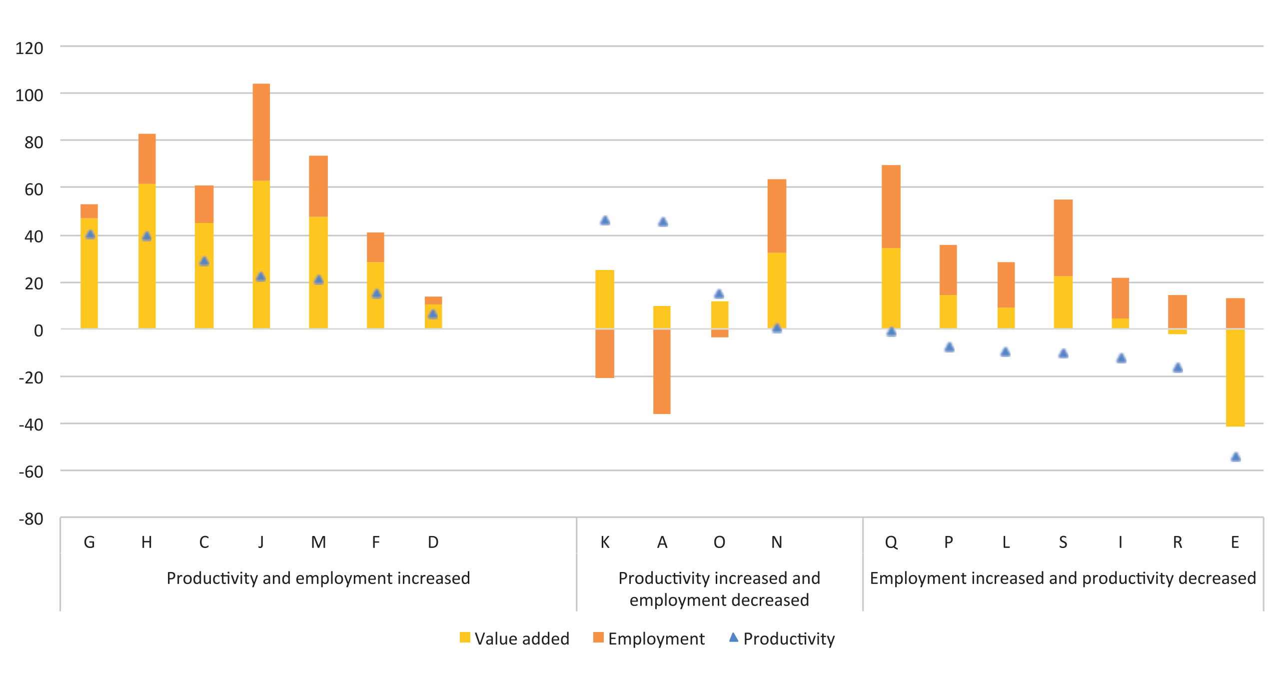
Developments of employment and productivity in the broad economic activities can provide further insight on how digitalisation and automation might have contributed, among other factors, to labour dynamics. Among other, factors that could influence the interaction between productivity and employment include: improvement in skills of the labour force; efficiency in the companies; better governance; ownership; broad competitiveness developments affecting specific sectors; policies and shocks.

Productivity growth performance of economic activities in the period 2011-2022 differ. By the interaction between the two variables performance in those activities can be classifies in in three groups (Figure 8): A group in which both productivity and employment increased; a second group in which productivity increased but employment decreased and; a third group where productivity decreased, and employment increased. The first group includes the following activities, which can be regarded as belonging to the traded sector: Wholesale and retail trade, repair of motor vehicles and motorcycles (G); Transportation and storage (H); Manufacturing (C); Information and communication (J); Professional, scientific and technical activities (M); Construction (F) and; Electricity, gas, steam and air conditioning supply (D). The second group includes: Financial and insurance activities (K); agriculture, forestry and fishing (A); Public administration and defence, compulsory social security (O) and; Administrative and support service activities (N). The last group consist of mostly non-tradable and tradable services: Human health and social work activities (Q); Education (P); Real estate activities (L); Other service activities (S); Accommodation and food service activities (I); Arts, entertainment and recreation (R); Water supply, sewerage, waste management and remediation activities (E).

Concerning the potential role of automation and use of AI it could be said that technological progress has been complementary to job creation in the first group. In the second group, where productivity is associated to job reduction, there are important structural changes besides the important role that digitalisation and automation might have played. In the case of financial activities, besides digitalistion the change in ownership and consolidation in the industry resulting in better governance and efficiency gains might had also played an important role. In the case of the agriculture, there is a secular decline in employment and associated with the increase in automation. In the case of activities where productivity decreased, which are mostly services, this can be explained by the nature of the activity relying importantly on labour. The ownership structure in some activities might also play an important role (Borowiecki et. Al., 2023).

To further disentangle the role that technological progress could have played on employment we look at skill improvement in the three groups identified above taking into account the described interaction between productivity

Figure 8: Productivity growth and its drivers 2011-2022, percentage change



Source: SORS. Own calculation

and employment. Figure 9 shows for the three groups of activities the change in the ratio of tertiary-skilled educated employees to that of low and middle skilled employees (i.e., skill ratio) in the period 2005-2022 and the ratio in 2022. There was skill improvement, as measured by the increase in the skill ratio, in all activities but, the ratio in 2022 is in general lower than 0.5 in activities relying on manual occupations or non-highly skilled traded services.[5] When looking at the group activities where productivity and employment increased, it seems that skill improvement played a reinforcing and complementary role to technological advancement on productivity. These also includes the activities of Transportation and storage (H) and Construction (F) where skills improve as reflected in the increase in the ratio, yet from low levels as reflected in the skill ratio in 2022. In the case of Wholesale and retail trade (G) and Manufacturing (C) the increase in the ratios were substantial despite of the relative low ratio in 2022, pointing out to an important contribution of digital technologies and automation as reflected in their high productivity growth rates (Figure 8). In the rest of activities, such as Information and communication (J) and utilities (D) where the skill ratio exceeds one, digitalisation and automation might have also contributed importantly to the good productivity performance (Figure 8). In the group of activities where productivity increased and employment decreased, the positive productivity developments could be explained by the replacement effect of technological improvement (digitalisation and automation) as the skilled ratio increase substantially and in particular in the financial sector (K) which had the second highest skills ratio in 2022.

In the third group of activities where productivity decreased and employment increased, the effect of digitalization seems to be ambiguous or not clear as employment increased while the improvement in skills did not prevent the decrease in productivity or it was overshadowed by the labour-intensive nature of the service activities.

Following the same approach to manufacturing activities, the impact of digital change on the employment is assessed trough the interaction of productivity and employment in a longer period (2005-2022). Based on the interaction between these two variables of industries performance, they can be classified in two groups. One group composed by the industries where productivity and employment increased and where technological improvement might have played a complementary role on employment. The second group includes the industries where productivity increased but employment decreased, suggesting that technological improvement might had contributed to displacement of

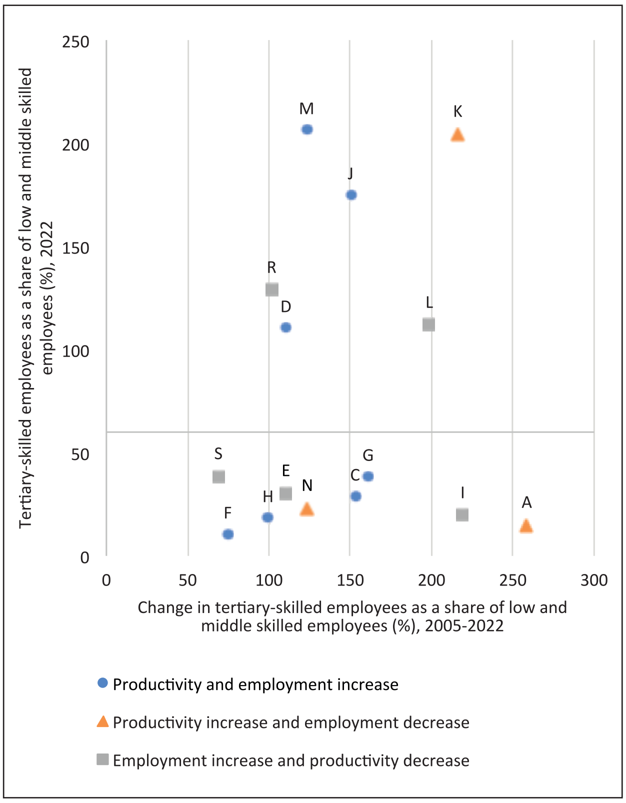
[5] A agriculture, forestry and fishing; C manufacturing; D Electricity, gas, steam and air conditioning supply; E water supply, sewerage, waste management and remediation activities; F Construction; G Wholesale and retail trade, repair of motor vehicles and motorcycles; H transportation and storage; I Accommodation and food service activities; J Information and communication; K Financial and insurance activities; L Real estate activities; M Professional, scientific and technical activities; N Administrative and support service activities; O Public administration and defense, compulsory social security; P Education human health and social work activities; R Arts, entertainment and recreation; S Other service activities.

employment. In 6 out of 14 industries, employment and productivity increased and in 8 industries productivity increased but not employment (Figure 10).

Further exploring the role that digitalisation and automation might have played on employment and differentiating manufacturing industries by the degree of technological complexity, it seems that in the case of low-technological industries it contributed to employment substitution (Figure 10). In the case of medium-high and medium-low tech industries, with the major exception of manufacturing of other types of transport equipment where employment decreased, technological improvement seems to have been complementary to employment creation. In the case of high-tech industries, it played two roles. It complemented employment in the case of manufacturing of pharmaceutical products where the increase in employment was the biggest. And it substituted employment in manufacturing of ICT products where the largest increase in productivity took place. It looks like, that the displacement impact of digitalisation on employment was the biggest that industry.

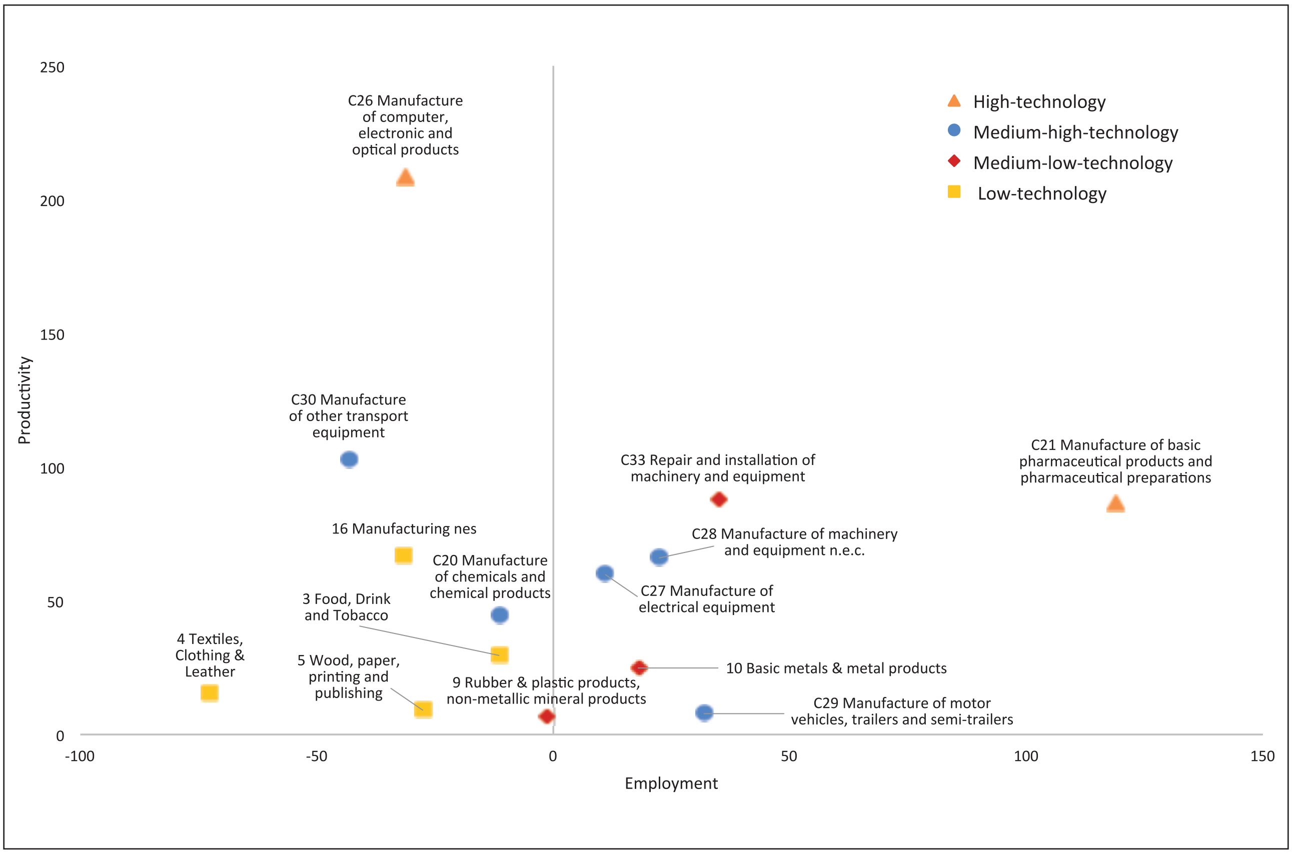
The role that skills improvement might have played in the interaction between employment and productivity in manufacturing industries can be assessed through the change in the skills ratio (2005-2022) and its level in 2022.

Figure 9



Source: SORS. Own calculation.

Figure 10: Change 2005-2022, percentage points



Source: SORS. Own calculation.

The data suggest that skills improvement, as measured by the increase in the skill ratio, was larger in industries where productivity increased, and employment decreased than in those industries where both productivity and employment increased (Figure 11). Looking at the impact of technological improvement trough the dynamics of skill enhancement suggests that the labour substitution effect of technological improvement prevailed in those industries where employment decreased whereas, in the industries where both productivity and employment increased technological improvement might have had complementary role leading to job creation.

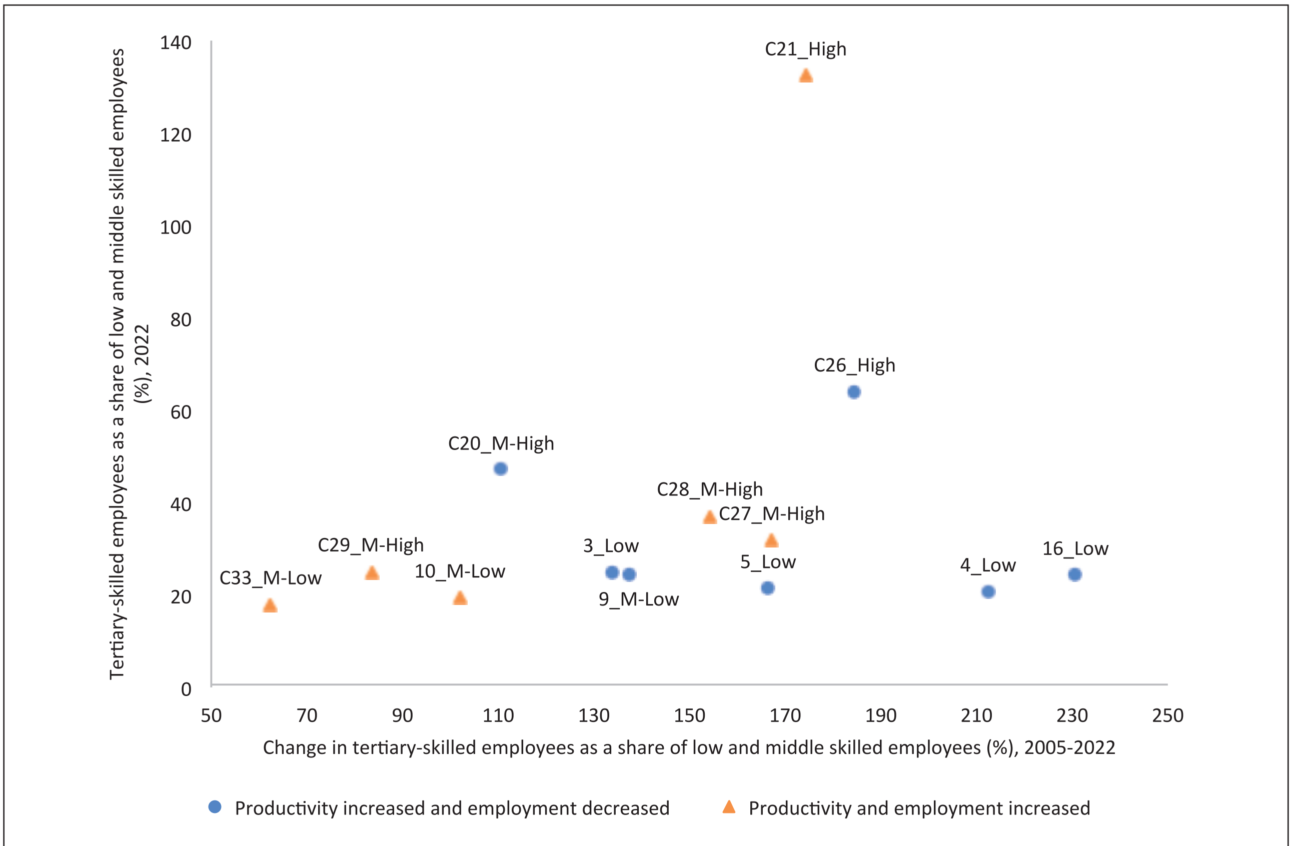
Overall, the increase in the ratio in all industries suggests that technological progress was biased towards high-skilled labour. Notwithstanding the overall increase in the ratio over 2005-2022, the ratio in 2022 in most industries remained below 50%.[6] The exception are the two industries classified as high-tech. In the case of Manufacture of basic pharmaceutical products and pharmaceutical preparations (C21) the ratio in 2022 exceeds 100% and in Manufacture of computer, electronic and optical products (C26) the ratio was 64%.

[6] While the skill ratio in manufacturing activity is relatively low compared to those in other activities, it has increased over the period 2005-2022

While the above assessment of the impact of digitalization and automation on employment is indirect and through productivity and skill dynamics, it seems broadly consistent with that of Borowiecki et. al., (2023), that use changes to ICT intensity as instrumental variable to estimate causal effects of digitalization, with a sampling bias towards manufacturing as well as medium-sized and large firms. Their results show that firms that invested more in ICT also employed more workers. In Figures 8 and 10 there are activities and industries where technological innovation imbedded on productivity growth led to higher employment. Nevertheless, Figures 8 and 9 also show that there are industries and activities where productivity increased but employment decreased indicating a prevailing substitution effect of technological improvement on employment. Both results taken together for those industries where the substitution effect on labour is predominant beg the questions of whether and what type of ICT investment would result in offsetting the observed substitution impact on employment.

Borowiecki et. al., (2023) besides pointing out to the positive role of investment in ICT on demand for labour, particularly high skilled labour, indicate that digitalisation does not increase wages which hampers job reallocation. This suggests that the incentives for ICT skill building are low.

Figure 11



Source: SORS. Own calculation.

This phenomenon might be related to the interaction of the overall productivity level and tax and benefit system resulting in a relative compressed disposable income profiles (MOLFASeO 2022). The issue at stake is how to strike a balance between innovation and social cohesion particularly in view of the potential impact of Gen AI on overall competitiveness and funding resources for financing the welfare state.

The potential impact of GenAI on the labour market

The analysis presented above captures the impact of automation and programable artificial intelligence on mainly routine task on employment whose complementary and substitution effects differs according to industry and, which seems to have bias towards high-skilled labour. For example, Borowiecki et.al., (2023) in their analysis of the effect of digitalization on job creation indicate that it benefited high skilled workers the most. Looking forward, the issue is whether GenAI, that has the property to create autonomously new content, will change this finding or belief. According to Cazzaniaga et.al., (2024) advanced algorithms can augment or replace high-skilled roles perceived as immune to technological innovation. Furthermore, empirical studies focused on US suggest that high-skilled workers, could be substantially replaced by AI (Eloundou et.al., 2023). According to Mckinsey (2023), automation in the US will continue affecting work activities involving, expertise, interaction with people and creativity. Their estimate until 2030 for the US economy is that automation could take over tasks accounting for 21.5 percent of the hours worked. Accounting for the impact of GenAI, the effect would increase up to 29.5 percent.

Assessing the potential impact of GenAI on employment is a complex task given the uncertainty of its effect on either complementing or replacing labour that depends on factors beyond the technology. Defining complementarity and operationalizing it for impact assessment is not trivial particularly in the context of the use of generative AI. Cazziniaga et.al., (2024) in defining complementarity for assessing the impact of GenAI on the labour force consider wider social, ethical, and physical context of occupations together with the skill level. Based on complementarity and skill level they built an index suggesting the degree of shielding from AI job displacement or AI job complementarity. According to that interaction they categorized occupations in three groups: "high exposure, high complementarity"; "high exposure, low complementarity"; and "low exposure". The degree of exposure and complementarity of the labour market to GenAI for a given country depends on the composition of the labour force in terms of occupational groups. For advanced countries they find that about 60 percent of jobs are exposed to AI. Of these, about half might be negatively affected by AI ("high exposure, low complementarity"), while the rest could benefit from productivity increase ("high exposure, high complementarity"). Their analysis is static and does not consider the effects of the ongoing integration of AI and robotics. Following Cazziniaga et.al., (2024), based on their assessment of AI occupational exposure and complementarity (i.e., complementarity-adjusted AI occupational exposure) and respective distributions' parameters (group median, dispersion and skewness) of individual occupations within each major occupational group (ISCO-08 classification) it is possible to determine their broad exposure in decreasing order as follows: Clerical support workers; Professionals; Technicians; Service and sales workers; Craft and related trade workers; Elementary occupations; Managers and; Skilled agricultural workers. Using this approach for assessing the exposure of Slovenia's labour market to GenAI would require applying the classification of exposure to individual occupations that are included in major occupational groups, which is a task beyond this article. Nevertheless, an insight on the future potential exposure of major occupational groups to GenAI for Slovenia's labour force can be obtained based on the structure of major occupational groups (2022), their past dynamics as discussed above and the rank of exposure of major occupational group's following Cazziniaga et.al., (2024). Figure 11 indicates that in Slovenia in the period 2010-2022, with the exception of the occupational groups of Professionals, Service and sales workers and Plant machine operators, the labour share of the rest of the occupational groups decreased. Looking forward, the risk of displacement due to GenAI could spread to the groups of professionals, service and sales workers. It could accelerate for the group of Clerical support services and continue for that of Technicians. While complementarity can reduce potential displacement of labour, the absence of the required skills to cope with GenAI would not shield working places or could result in widening the productivity gap against countries investing in new digital technologies. To mitigate such risks, besides fostering innovation, adoption and adaptation to AI, it will be necessary to place specific attention to older workers who tend to adapt more slowly to new technologies. This is particularly important taking into account demographic projections for Slovenia indicating that between 2022 and 2037 the share of prime-age population (25-54 years) is going to decrease by 4.4 p.p., while that of population aged 55-64 years will increase by 1 p.p.

Future labour market needs and the impact of AI

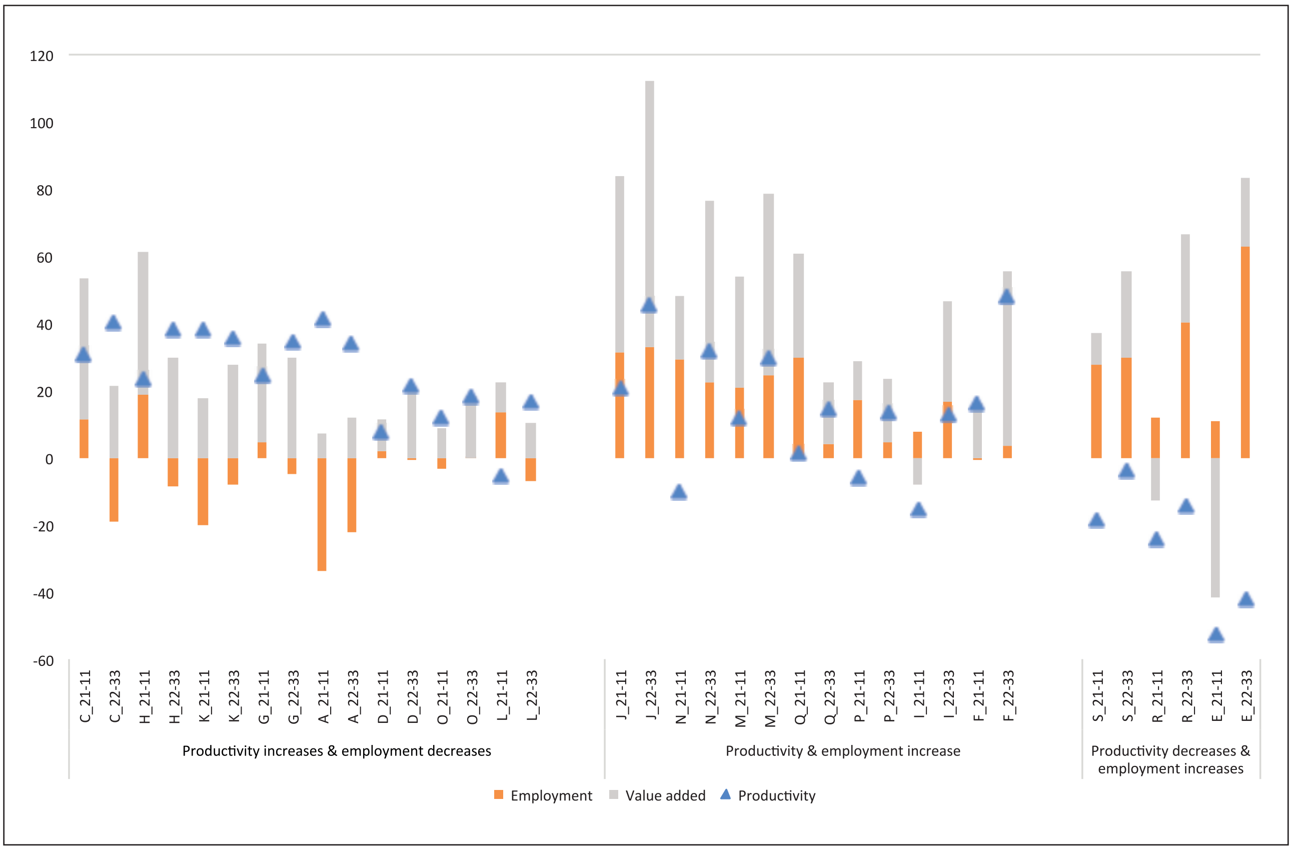
A view on the future labour market developments up to 2037 can be obtained from the long-term forecast of labour market of the Ministry of Labour, Family, Social Affairs and Equal Opportunities (MOLFSAeO 2024). That forecast takes into account the impact of ageing of population and imbedded trends of digitalization and automation and green transition on the future of the labour market. While the forecast does not touch on the impact of GenAI, it can serve as a basis to assess how the ongoing transformative developments could accentuate or alter identified trends in the labour market. The forecast indicates that, at the level of the economy, additional jobs will be created only until the year 2027. In the subsequent years most of the new job openings will be of associated with labour replacement needs (i.e., to replace individuals withdrawing from the labour market due to retirement).

Based on the information from the forecast, future employment developments associated with those of productivity can be identified. Accordingly, employment dynamics at the level of economic activity can be classified into three groups. The first group of activities in which productivity increases and employment decreases; the second group in which productivity and employment increase, and the third group in which productivity decreases and employment increases (Figure 12). The first group includes tradable activities (Manufacturing (C); Transportation and storage (H); Financial and insurance activities (K); Wholesale and retail trade (G); Real estate activities (L)); utilities (D); the government sector (O) in narrow sense, and Agriculture (A).

The second group includes mostly professional services including education (P) and health (Q) and construction (F). The fastest employment-growing sectors within this group are traded services as follows: Information and communications (J); Professional, scientific, and technical activities (M), and Administrative and support service activities (N). The third group of activities includes the overall fastest growing employment activities of Water supply, sewerage, waste management and remediation activities (E) which are also related to the green transition.

Looking at the future of labour as measured by job openings by occupation until 2037 based on the data of the forecast (MOLFSAeO 2024) indicates that the composition of the future labour demand will differ from the prevailing occupational structure in the year 2022 (Figure 13). Job openings for Professionals (38% of job total openings) will exceed their labour share in 2022 (23%). Apart from

Figure 12: Change in growth of productivity and its drivers period 2011-2021 and 2022-2033



Source: SORS and MOLFSAeO (2024). Own calculation.

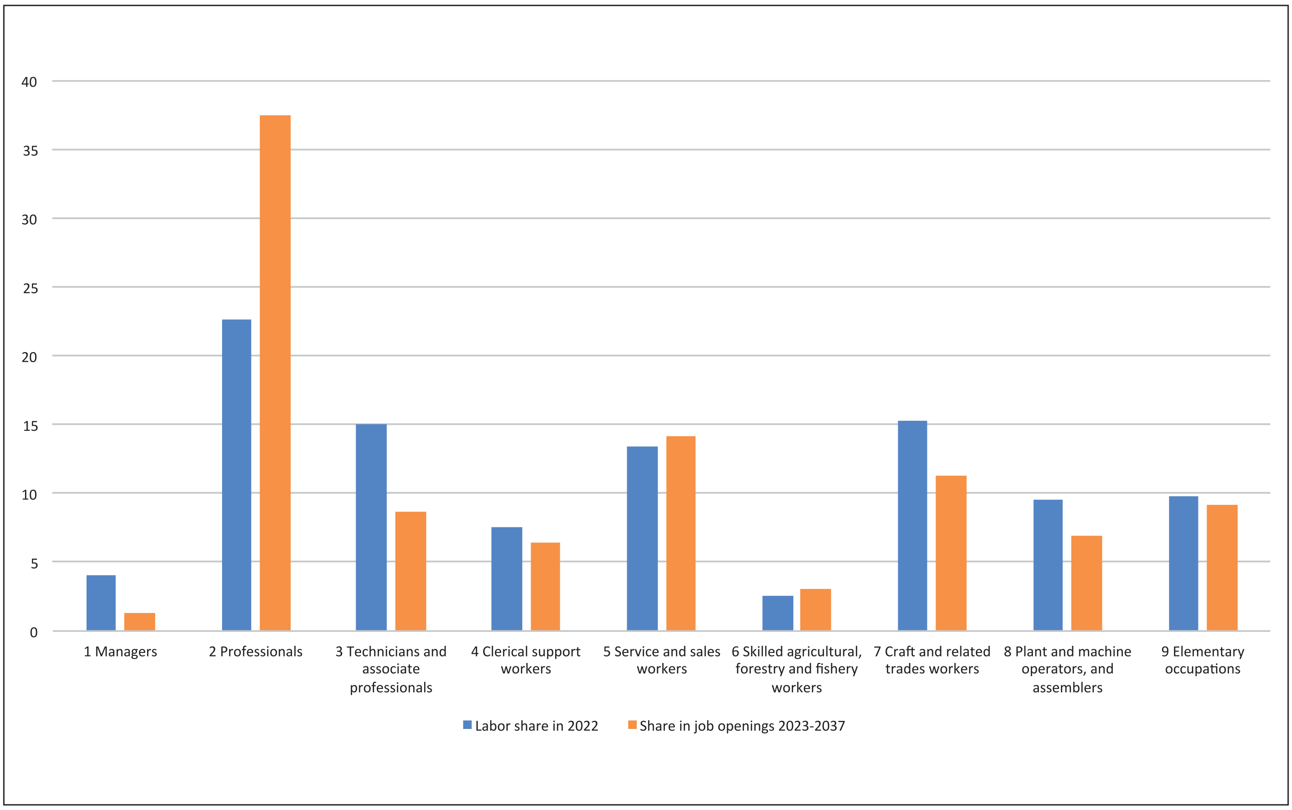
Service and sales workers, Elementary occupations and Skilled agricultural workers, where job openings will roughly correspond to their labour share in 2022, in the rest of occupations job openings will be smaller. In particular this will be the case for technicians and craft related workers (Figure 13).

Looking at the composition of future labour demand in terms of job openings (Figure 14) and differentiating according to their nature into economic expansion/contraction and replacement of workers due to retirement can provide additional insight on the potential effect of digitalization and automatization. The bulk of new job openings associated with expansion demand will be in the group of professional occupations until the year 2037 (Figure 15). Substantially smaller and only up to the year 2027 expansion demand will also result in new job creation in the following groups of occupations: Service and sale; Craft and related trade; and Elementary occupations. For the rest of occupations and, in particular for Technicians and Managers, there will not be new job creation, but reduction of existing ones throughout the whole period. This suggests that digitalization and automation will continue affecting significantly these two groups of occupations, and to lower extent, the rest of occupations whose respective labour shares have been decreasing until now (Figure 5). A similar assessment of the future replacement demand by group of occupations indicates that its composition resembles that of the current structure of occupations (Figure 16). Thus, the effect of automation and digitalization on employment is likely to be reflected primarily in the occupation's composition of the contracting demand where job places will decrease and created only in Professional and Service and sales eventually in smaller replacement needs in the same occupations where expansion demand falls.

Without pretending to assess the impact of GenAI on the scenario depicted above, an idea of its potential effect on the future of employment by occupations as just described can be drawn by taking into account the exposure and displacement risk profile of occupations discussed before (Cazziniaga et.al., (2024),). GenAI by modifying the labour exposure of high skilled labour force, could alter the envisaged demand composition for occupations. It could reduce the creation of new job openings for Professional and Service and sale workers (Figure 15) and accelerate the reduction of replacement demand for the rest of occupations in particular for Managers, Technicians and Clerical and support workers (Figure 16).

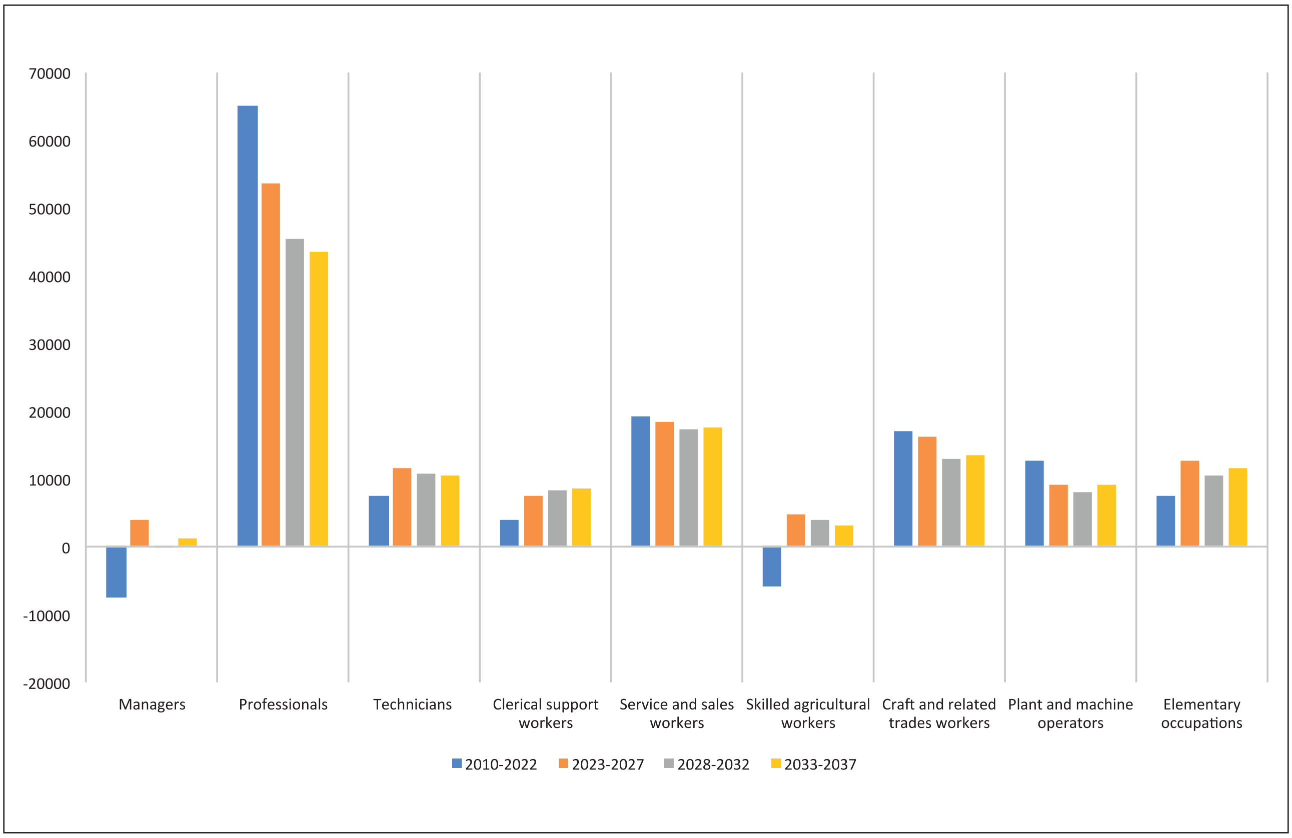
The impact of AI including GenAI on the labour market is uncertain. It has been unfolding on the background

Figure 13: Labor share in 2022 and in job openings 2023-2037



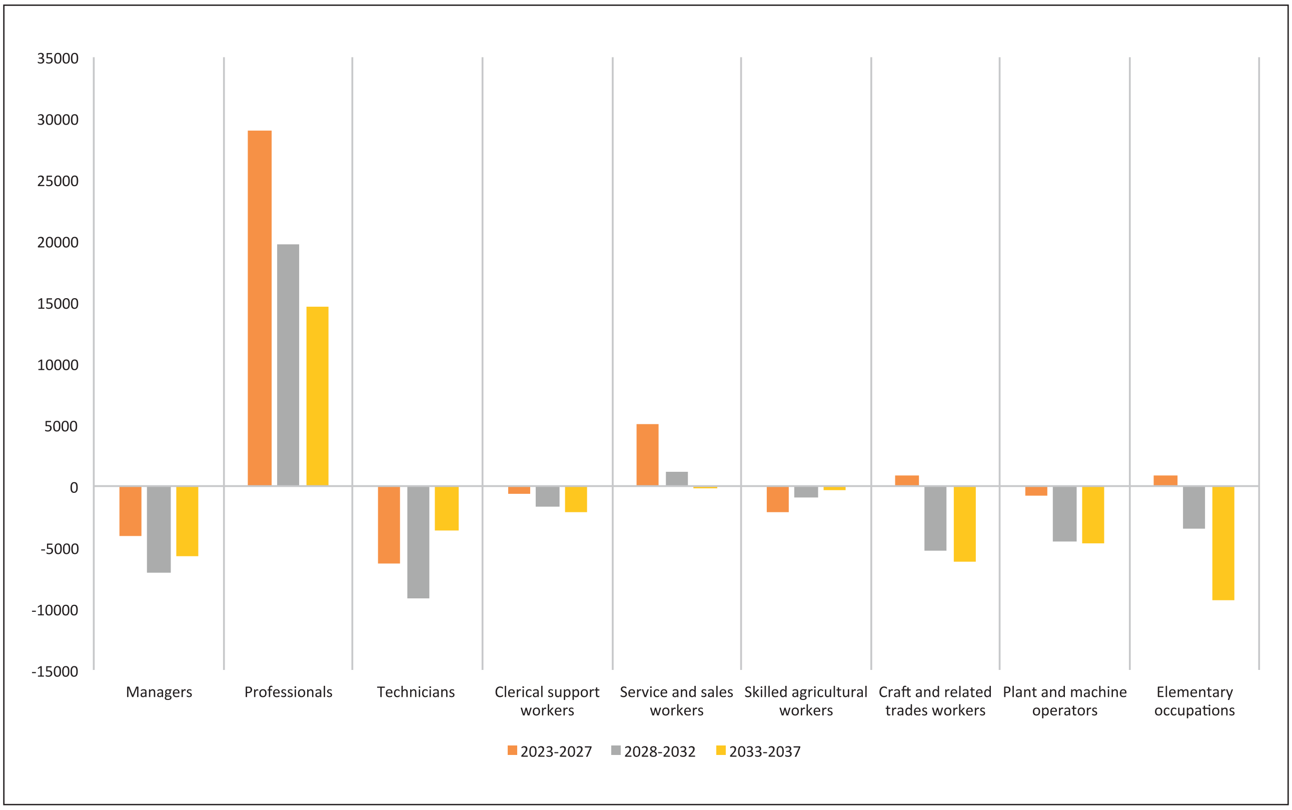
Source: SORS and MOLFSAeO (2024). Own calculation.

Figure 14: Job openings



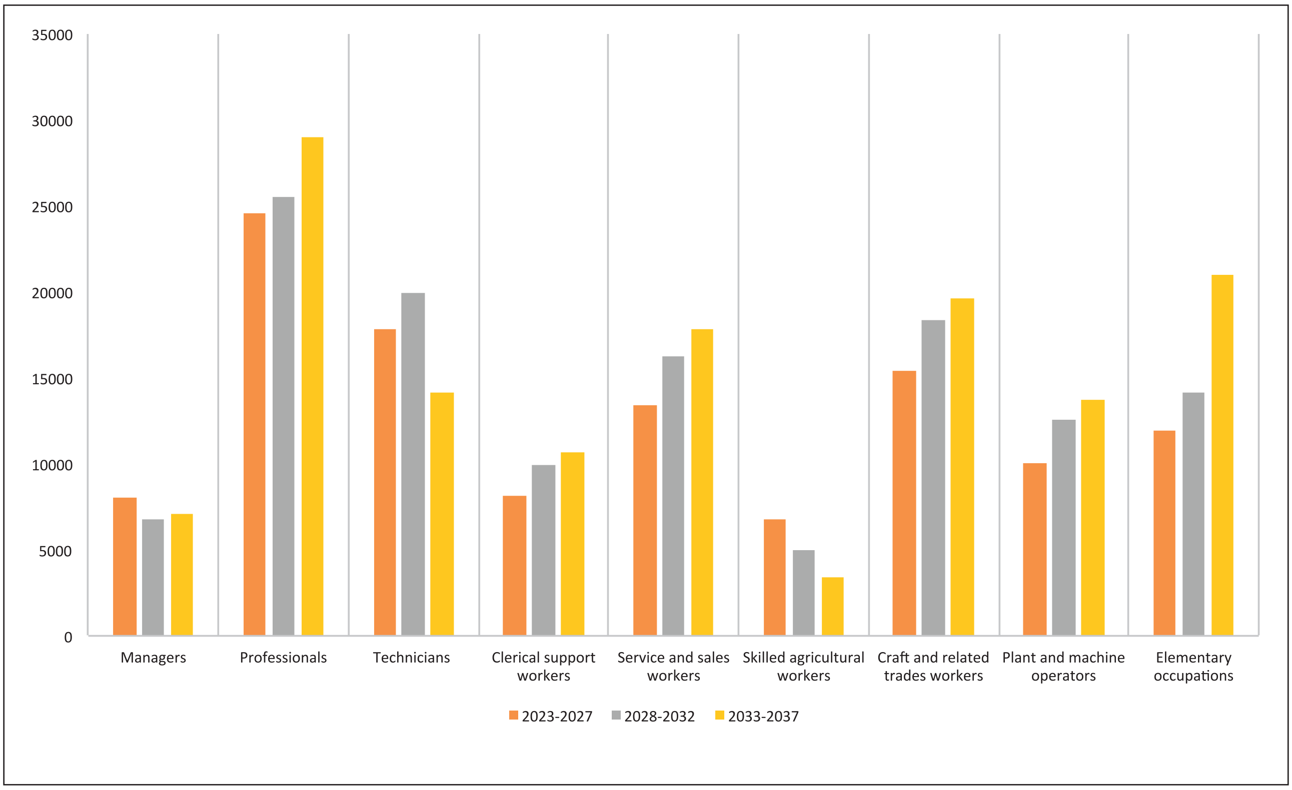
Source: MOLFSAeO (2024). Own calculation.

Figure 15: New or lost working places due to expansion or contaction in demand



Source: MOLFSAeO (2024). Own calculation.

Figure 16: Replacement demand



Source: MOLFSAeO (2024). Own calculation.

where the demographic developments are affecting the labour force as shown in high labour shortages. So far, the displacement impact of AI mostly programable and of automation on employment seems to have been cushioned or compatible with: labour upskilling; transition between occupation; labour shortages and early exit to retirement. The issue is whether the effect of GenAI on the labour market will be more disruptive in scope and the extent to which such impact will be cushioned in particularly by the envisaged labour shortages across most occupations. Nevertheless, beyond, the potential displacement impact on employment, particularly on older workers due to their challenges to adapt to new technologies, mobility and reemployment, GenAI could have important disruptive effects on productivity and sectors among countries. GenAI could boost or hinder competitiveness and affect welfare states of societies. Such risks require clear mitigation strategies consisting of fostering integration (adoption and adaption) and innovation to digital technologies. Such strategies should be mindful of the extra premium that GenAI places on the relevant skills which in the context of wage compression and high tax wedge in Slovenia could hinder capacity for AI adoption and innovation.

References

Acemoglu, D. and P. Restrepo (2018), "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment", American Economic Review, Vol. 108/6.

Acemoglu, D. and P. Restrepo (2020), "Robots and Jobs: Evidence from US Labour Markets", Journal of Political Economy, Vol. 128/6.

Borowiecki, M., Høj, J., and Miho, A (2023), "Digitalisation and the Labour Market: Worker-Level Evidence from Slovenia", https://www.oecd-ilibrary.org/economics/covid-19-and-productivity-enhancing-digitalisation-firm-level-evidence-from-slovenia_5f7e9340-en

Cazzaniga, M., Jaumotte, F., Li, Longji., Melina, G., Panton, A., Pizzinelli, C., Rockall, E., and Tavares, M (2024), "Gen-AI: Artificial Intelligence and the Future of Work." IMF Staff Discussion Note SDN2024/001, International Monetary Fund, Washington, DC.

Gregory, T., A. Salomons and U. Zierahn (2021), "Racing With or Against the Machine? Evidence on the Role of Trade in Europe", Journal of the European Economic Association.

Eloundou, T., Manning, S., Mishkin, P., and Rock, D (2023), "GPTs are GPTs: An Early Look at the Labour Market Impact Potential of Large Language Models." arXiv.org working paper.

McKinsey Global Institute (2023), "Generative AI and the future of work in America"

Ministrstvo za delo, družino, socialne zadeve in enake možnosti (2022), "Letno poročilo: Interakcija med davčnim sistemom in sistemom socialnih transferjev na razpoložljivi dohodek" https://www.gov.si/novice/2022-05-31-letno-porocilo-interakcija-med-davcnim-sistemom-in-sistemom-socialnih-transferjev-na-razpolozljivi-dohodek/

Ministrstvo za delo, družino, socialne zadeve in enake možnosti (2024), "Analiza razmer na trgu dela in rezultati srednje in dolgoročnih napovedi potreb trga dela do leta 2037", https://www.gov.si/ assets/ministrstva/MDDSZ/Analiza-razmer-na-trgu-dela-in-rezultati-srednje-in-dolgorocnih-napovedi-potreb-trga-dela-do-leta-2037-003.pdf

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Exposure of Slovenian economy and banking system to environmental degradation

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Macroeconomic and financial stability is becoming increasingly affected by intensifying environmental degradation, spanning both the climate change and nature depletion. In this study, we show that roughly 70% of Slovenian non-financial firms crucially depend on at least one or more ecosystem services, which are increasingly under threat by climate change and economic activity by itself. Moreover, given the intrinsic interconnectedness between the economy and the banking system, climate and nature-related risk is gaining relevance for financial stability, which is confirmed in this study by the constructed composite indicator of environmental risk.

JEL E01, G21, Q54

1. Introduction

In recent years, we have witnessed an increased frequency of extreme weather events alongside the intensified nature degradation, which has adversely affected economies and financial systems around the world. In this study, we examine the vulnerability of Slovenian economy and the banking system to environmental degradation. To do so, we explore to what extent economic activity depends on services that nature provides and are subject to depletion as a consequence of climate change, non-sustainable management of nature and land use, and economic activity itself. Moreover, given the connection between the real economy and the banking system, the corporate vulnerability to environmental degradation inevitably poses risks to financial stability, which is in this study examined through the lens of composite environmental physical risk indicator. We show that more than 70% of non-financial corporations (NFCs) in Slovenia critically depend on at least one ecosystem service. While the result is comparable to other euro area countries, Slovenian economy exhibits disproportionally large indirect dependency on ecosystem services through counterparts in the supply chain. The result reflects a high degree of global value chain integration by sectors with the largest dependency on ecosystem services, for example

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manufacturing and agriculture. On the side of physical risk mitigation, the most relevant ecosystem services supporting Slovenian economy are related to soil erosion stabilisation, flood and climate control, while in terms of resource availability water sources are particularly important. Considering the interconnectedness between dependency on nature and effect of economic activity on its degradation, we find that the impact of the Slovenian economy on environment, measured in terms of greenhouse gas (GHG) emissions and land use per output, is relatively limited and comparably lower than the median country in the euro area.

The dependency of the Slovenian economy on nature carries implications for financial stability in case environmental degradation affects performances of firms. To assess the exposure of the banking system to the environmental physical risks, construct a **composite risk indicator** that takes into account six different environmental hazards and the structure of the banking system portfolio. The results show that the physical risk increases with the severity of the chosen climate scenario as well as over time. While we already observe a slight increase in the physical risk in the current period, there is a substantial increase in the composite risk indicator in the next 20 years, mainly due to extreme heat and temperature related factors.

The structure of the study is as follows. In section 2, we discuss the relationship between an economy and the ecosystems. In section 3, we then extend the discussion with tying the banking system to climate related physical risks. In section 4, we conclude.

2. Interconnectedness between economy and the ecosystem

Recognising the dependency of the economy on ecosystem services plays a crucial role in evaluating exposure to physical risks associated with nature degradation. In particular, from the economic theory perspective, the natural capital can be perceived as one of the production inputs, alongside labour and other capital, and is thereby directly affecting production capacity of non-financial corporations and potential output of the overall economy. Moreover, to the extent that the dependency of production on ecosystem services also implies impact of firms on the nature's depletion, it also indicates economy's exposure to transition risks. Namely, given that terrestrial and marine ecosystems represent nature's capacity to absorb excessive carbon emissions (Rockström, et al., 2021), their preservation is pivotal to pursuing climate-related objectives. Consequently, firms and economies with higher dependencies on ecosystem are not only more exposed to physical risks but they are also more susceptible to regulatory and institutional polices associated with pursuing climate goals.

To quantify dependency of Slovenian economy on ecosystem services, we rely on the methodological framework laid out in Boldrini et al, 2023. In line with the seminal paper, denoted herewith ECB2023, we distinguish between direct dependency and indirect dependency, where the latter relates to exposure of non-financial corporations via their counterparts in the supply chains. The derivation of direct dependency is extracted from the ENCORE dataset[1], which assigns dependency scores to specific economic sectors in relation to 21 different ecosystem services. The direct dependency is complemented with the indirect exposure through global supply chains. The indirect dependency score is derived using EXIOBASE[2], which encapsulates environmentally-extended international supply-and-use (SUT) and input-output (IO) tables. The total dependency score (DS) for particular economy is then given by:

$$DS_{tot} = DS_{direct} + (1 - DS_{direct}) * DS_{indirect} \qquad (1)$$

Where DS_{direct} and $DS_{indirect}$ are quantitative measures taking values between 0, no dependency, and 1, very high dependency. The product in the aggregation attempts to minimise double counting, whereby in the case of very large direct dependency the impact through supply chains is minimised. We follow the convention in ECB2023, where high dependency is considered at the threshold value of 0.7, indicating severe impairment to production process in case of reduced ability to access the relevant ecosystem service.

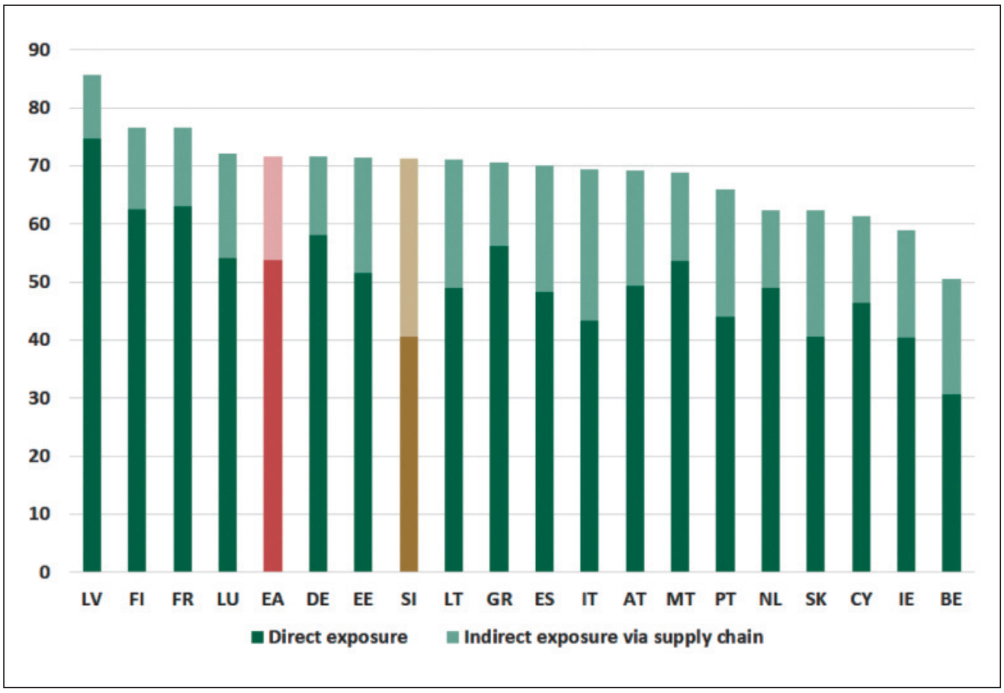
In case of Slovenia, the critical dependence on at least one ecosystem service, i.e. dependency score exhibiting the 0.7 threshold, is exhibited by roughly 70% of non-financial corporations as shown in Figure 1. While the total dependency score in Slovenia is comparable to the euro area average it disproportionally reflects the indirect exposure via supply chains, which stands the highest among the euro area countries (30% of firms). On the other hand, the share of firms exhibiting critically high direct dependency is fairly limited, 40%, with Belgium being the only country with lower direct exposure.

The above average indirect exposure to nature depletion could reflect a relatively strong concentration of dependency within manufacturing and agricultural sectors. In general, these sectors exhibit highest dependency on ecosystem services (Figure 2), while at the same time they are highly integrated into international supply chains. This is particularly the case in Slovenia, where import content of

[1] https://www.encorenature.org/en

[2] https://www.exiobase.eu/

Figure 1: Share of NFCs with high exposure to at least one ecosystem service (in %)

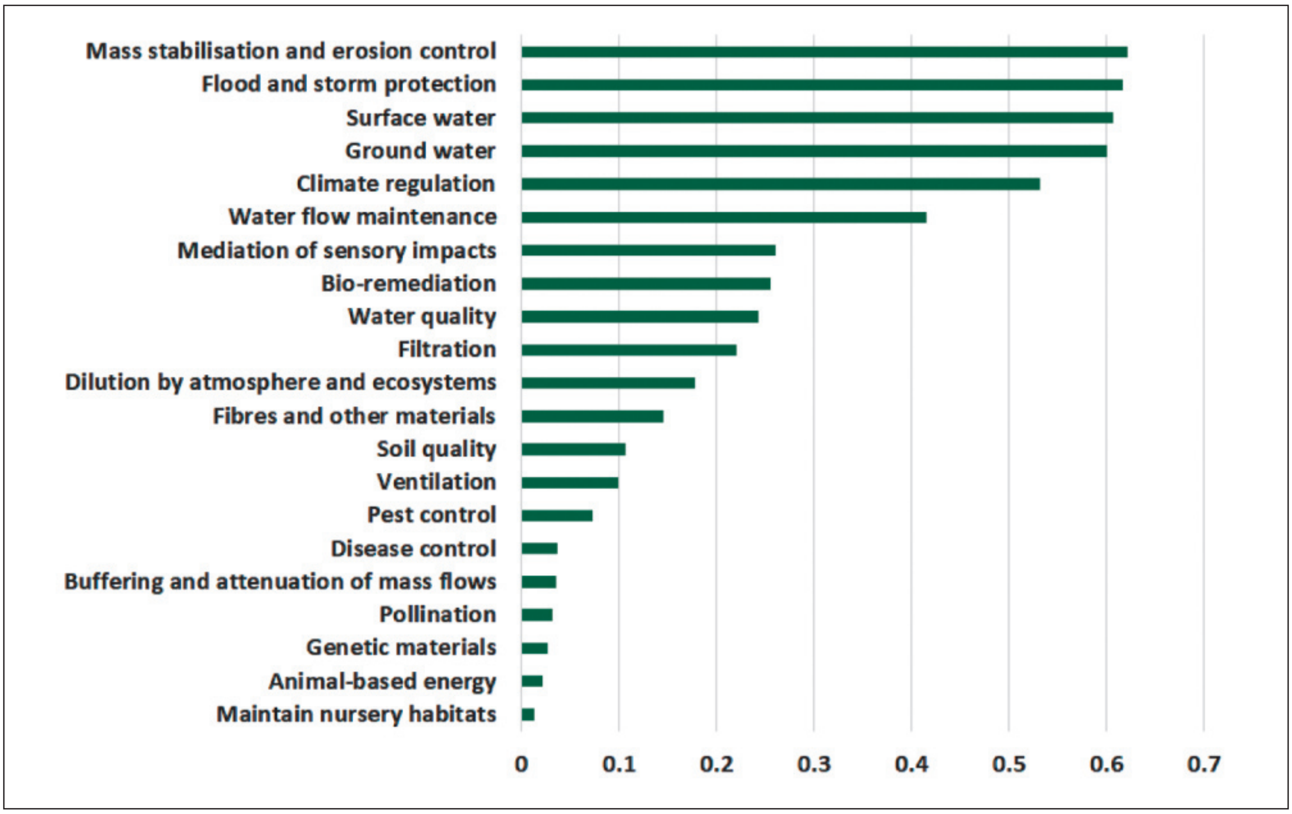


Source: Encore, Exiobase, Boldrini et al 2023
Note: Share of non-financial corporations with dependency score for at least one ecosystem service exceeding threshold value of 0.7.

Figure 2: Dependency on ecosystem services per economic sectors
x-axis: ecosystem services, y-axis: economic activity (NACE sections), value: direct dependency (from 0 to 1))

Source: Encore, Boldrini et al (2023)
Note: Dependency scores by NACE sectors extracted from the Encore database.

Figure 3: Relative importance of ecosystem services for Slovenian economy

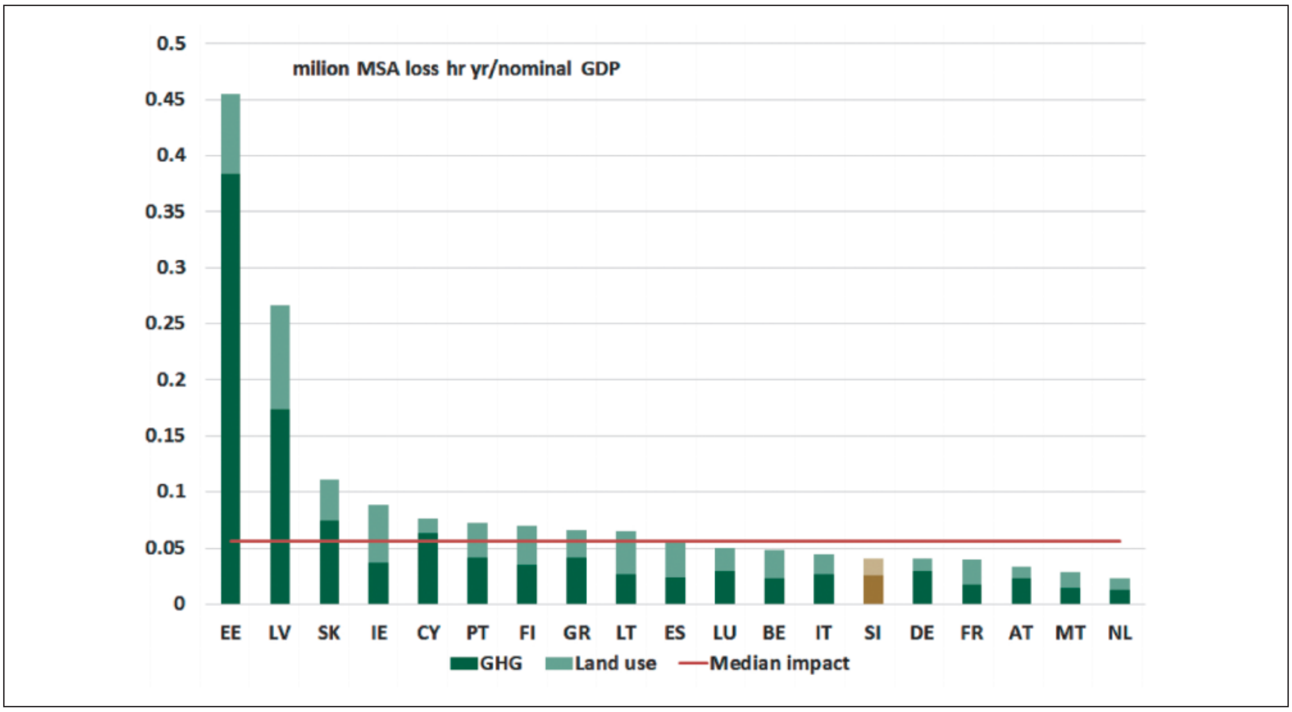


Source: Encore, Exiobase, Boldrini et al (2023)
Note: Figure 3 shows average dependency scores of non-financial corporations in Slovenia per individual ecosystem services.

production in the respective sectors stands at roughly 70% and 50%.[3] Moreover, the manufacturing sector represents a comparably larger part of the Slovenian economy as the corresponding share of value added in GDP stands roughly 5 percentage points above the one in the euro area.[4]
Most relevant ecosystem services supporting Slovenian economy relate to **provisioning services** (surface and ground water sources) and **regulating services** (mass and soil erosion stabilisation, flood control, and climate control and mitigation), as shown on Figure 3. The regulating services are closely related to control and mitigation against physical climate hazards, while provisioning services to direct resource availability. In this context, forests and other vegetation ensuring climate control and prevention against avalanches and floods play a particularly important role. An example of the impact of devastating floods was in Slovenia manifested last year with the direct damages estimated at replacement costs amounting to roughly EUR3bn or 5% of GDP.[5] In the context of flood risks, the analysis conducted by Pavlič (2023) shows that 5.6% of value added and 6.1% of total employment in Slovenia is directly exposed to the impact of floods with magnitude consistent with 100-year recurring rate. The estimates masks substantial regional and sectoral heterogeneity, whereby particularly smaller regions, highly dependent on manufacturing activity, exhibit highest exposure with value added and employment at risks exceeding 12% respectively.
While dependency on ecosystem services emulates exposure to physical risks, the view needs to be complemented with the impact that economic activity has on the nature. This is important both in the context of understanding to what extent the activity of firms is endogenously affecting nature-related production resources as well as in the context of susceptibility of firms to transition risks, stemming from regulation aimed at preservation of nature. The impact on nature and biodiversity is in the analysis of Ceglar et al. (2023) considered through green-house-gas emissions (causing climate change) and unsustainable land-use. Additional pressures on biodiversity, such as overexploitation of natural resources, pollution, nitrogen deposition and hunting, are not considered in this study, which leads to underestimation of the real impact on biodiversity. In terms of impact per nominal output, measured as million mean species abundance (MSA)-loss-ha-year/nominal GDP,

[3] The import content of particular sectors is computed using input-output tables, following the approach of (Radovan, 2022).
[4] See Manufacturing, value added (% of GDP) | Data (worldbank.org).
[5] Sprejet program odprave posledic škode v sektorju ribištva in akvakulture zaradi poplav | GOV.SI

Figure 4: Environmental footprint of euro area economies per output produced

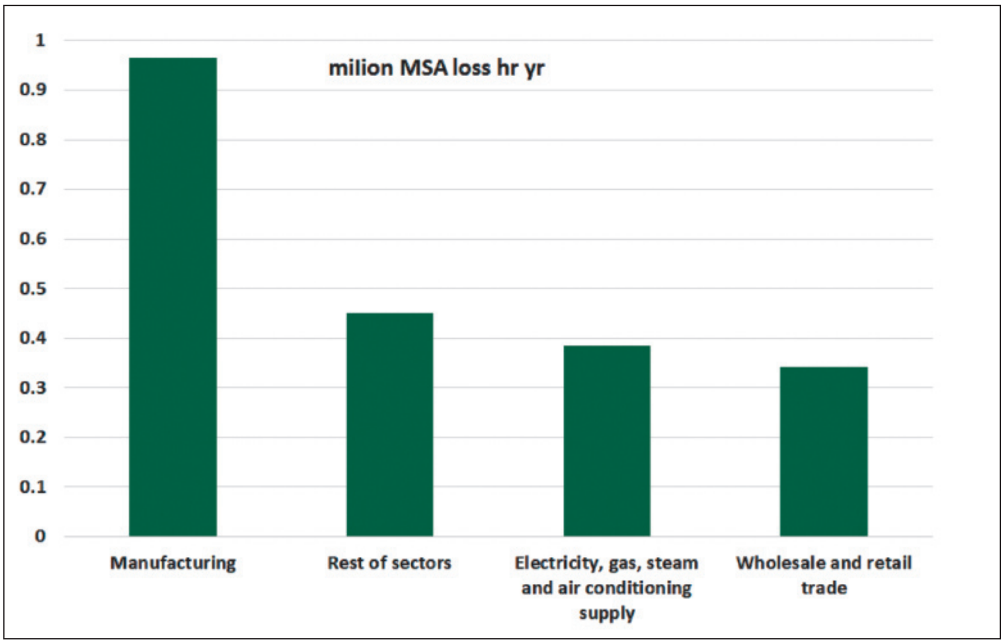


Source: AnaCredit, Exiobase, Ceglar et al (2023)
Note: The mean species abundance (MSA) losses are computed taking into account the GHG emissions and the area of land used in the production weighted by country nominal GDP for the reference year 2021.

Slovenia falls within the euro area countries with below median impact on nature, Figure 4. Focusing on particular activities, Figure 5 shows that sectors that degrade nature the most are often those that heavily depend on ecosystem services. For example, manufacturing sector is the sector that on the one hand exhibits high dependency on ecosystem services and at the same time produces the greatest adverse impact on the nature.

The activity of firms inherently depends on financing, an important part of which is in the Slovenian economy provided by the banking system. In this context, interconnectedness between economy and ecosystem renders implications for financial stability. While in the context of real economic activity, nature and ecosystems services are of particular importance given their role in production function, the environmental physical risks may provide a more wholesome

Figure 5: Sectors with greatest impact on nature



Source: AnaCredit, Exiobase, Ceglar et al (2023)
Note: The MSA losses are computed taking into account the GHG emissions and the area of land used in the production weighted by the country nominal GDP for the reference year 2019.

view in case of the financial system. The exposure of the Slovenian banking sector to environmental physical risks is explored in the next section.

3. Exposure of banking system to environmental physical risks

Climate and nature change will increase the likelihood of extreme weather events, which consequently prompts the increase of physical risks to take place. This can directly and indirectly result in physical damages that can have a significant impact on the financial system throughout. Policy makers started developing physical risk indicators that take into account climate change risks.[6] These physical risks indicators help us to analyse more effectively how these risks may affect firms' performance, what would be the effect on the financial systems and thus monetary policy and price stability.
For the purpose of this analysis we construct **climate risk score indicators** for physical risk based on environmental data sourced from the Environmental Agency of the Republic of Slovenia. The indicators have been defined at the municipality level and include data for six hazards, of which two are chronic and four acute risk hazards, following the NGFS (Network for greening the financial system) definition of environmental physical risk.[7] Chronic risk is defined as risk emanating from gradual change in precipitation or temperatures, while the acute risks stem from extreme heat, floods, windstorms and droughts.[8] The risk indicators for the specific hazard have been constructed based on the standardised deviation of the specific variable relative to the reference period 1981-2010, across three time periods and three RCP (Representative concentration pathways) scenarios designed by the IPCC (International Panel for Climate Change), for all hazards, except floods.[9] The three RCP scenarios included in this analysis are the RCP 2.6, RCP 4.5 and RCP 8.5 scenarios which foresee different socioeconomic pathways with GHG (Greenhouse gas) emission paths which correspond to a temperature increase of 1 ºC, approximately 2 ºC and 4 ºC by 2100 respectively.[10] Thus, the RCP 8.5 scenario is the most severe scenario in terms of temperature increases. The flood risk indicator has been constructed on the basis of deviation of the share of the municipality area exposed to any type of flood relative to the national average of the share across municipalities. The indicators are currently defined at the municipality level. The indicator construction is subject to change pending on alternative definitions of the hazards, different statistical methods in the aggregation or standardisation of the data and/or higher granularity, e.g. at the cadastre parcel level for NFCs.
To evaluate the exposure of the Slovenian banking system we construct a composite risk indicator aggregated across all six hazards, also taking into account the structure of the banking system NFC portfolio. The composite risk indicator (CRI) for municipality i is thus defined as the sum of the individual hazard risk scores (RS) for the municipality across all hazards h, while the banking composite risk indicator is defined as the weighted sum of the municipality risk scores, weighted by the share of NFC exposures in that municipality in the total NFC exposures of the banking system.[11]

$$CRI_i = \sum_{h=1}^{6} RS_h$$

$$BCRI = \sum_{i=1}^{212} CRI_i * w_i$$

where the weight for municipality is defined as follows:

$$w_i = \frac{Exposures\_NFC_i}{Exposures\_NFC\_system}$$

The composite risk indicators for each hazard are calculated for a historical reference period (1981-2010) and three 30-year time periods extending until 2100, across the three RCP scenarios with different levels of temperature increases. The following chart shows the banking system composite risk indicator for the NFC portfolio, assuming no changes in the bank portfolio structure over time.
The results show that the physical risk increases with the severity of a scenario and through time, with an increase in physical risk observable already in the current period (Figure 6). While the composite risk indicator is the highest

6 To better understand the effects of climate change, surveys could be of use for policy making as well. For example, in August 2023, Slovenia was hit by floods. According to the Bank of Slovenia's Survey on access to finance for businesses (Banka Slovenije, 2024), 20% of firms report that they were affected by the floods. A share of 11% of firms were directly affected. Those firms, which reported that they were affected by the floods, 20% of them reported substantial damages to their businesses. To cover the damages and losses, 62% of surveyed firms reported that they will finance from own resources, 13% of firms count on the help of the government, 6% of firms will take bank loans, while other firms will utilise other resources. 63% of the affected firms will not apply for a moratorium, either because they do not have a banking loan or they will manage to cover the losses and damages without moratoria.

7 https://www.ngfs.net/en/ngfs-climate-scenarios-phase-iv-november-2023

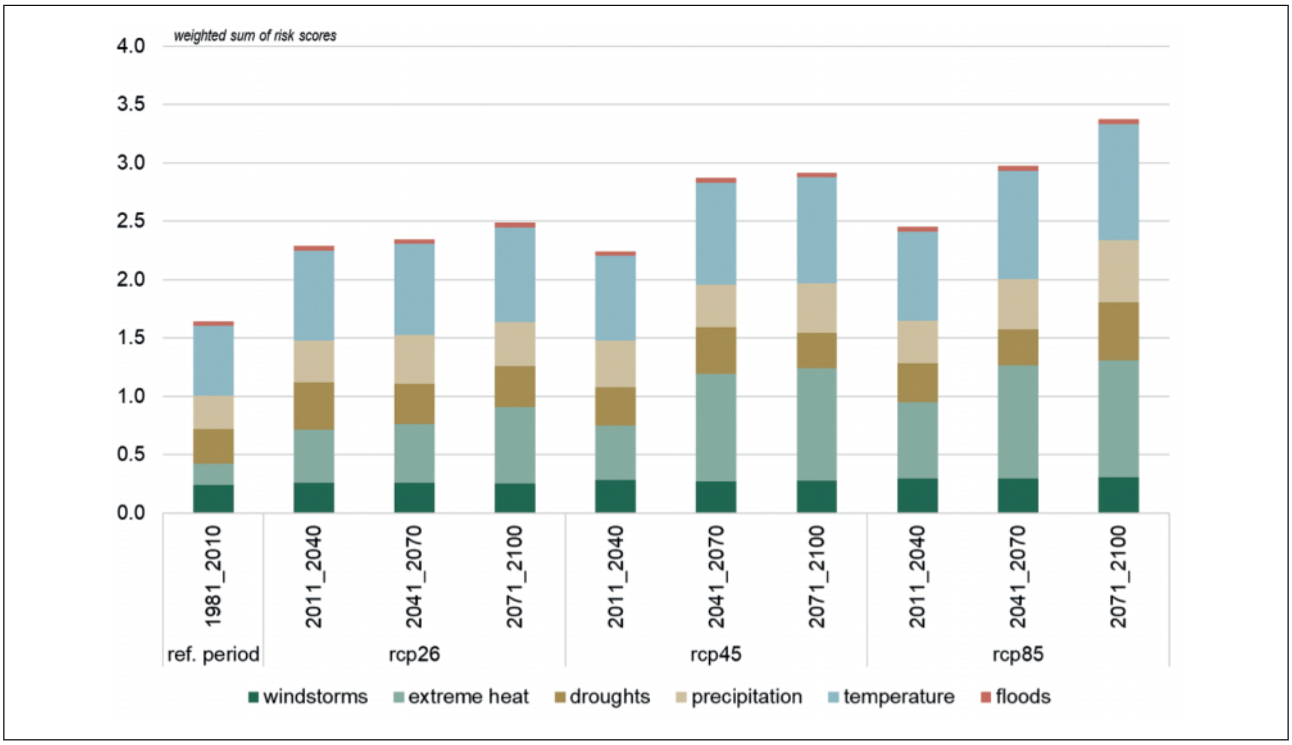
8 Extreme heat is defined in terms of number of days with tropical nights, defined as days when the night temperature does not decrease below 20 ºC. Droughts are defined in terms of the number of days when the soil water deficit index exceeds 60, windstorms are defined in terms of maximum windspeed gusts, floods are defined in terms of the frequency of floods ranging from very rare (catastrophic) to frequent floods. The flood maps have been revised following the catastrophic floods of August 2023 in Slovenia.

9 The min-max method on a scale 0-1 was used to standardise the risk scores.

10 https://meteo.arso.gov.si/uploads/probase/www/climate/text/sl/publications/povzetek-podnebnih-sprememb-temp-pad.pdf

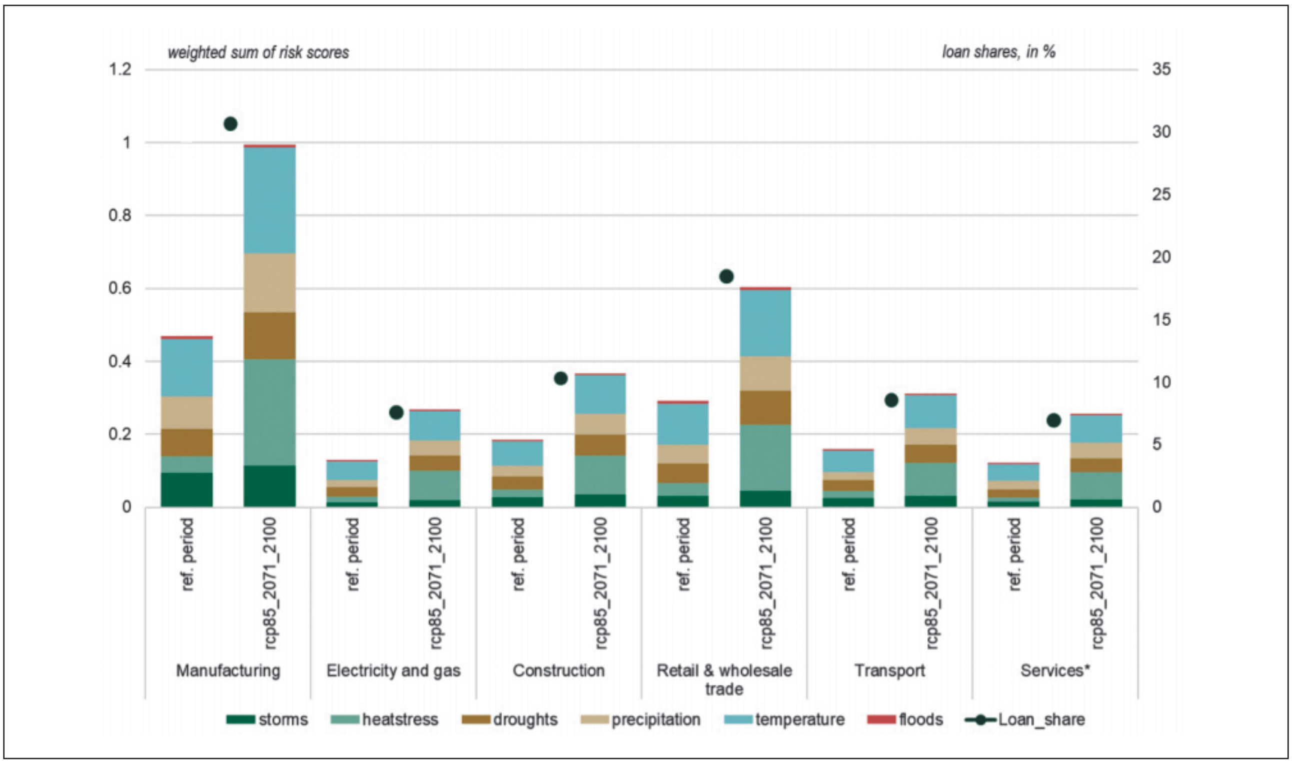
11 The cut-off date for calculating the weights is 31.12.2023.

Figure 6: Banking composite risk indicator for the NFC portfolio across scenarios and time



Note: Rcp26, rcp44 and rcp88 denote climate scenarios corresponding to a temperature increase of 1 ºC, approximately 2 ºC and 4 ºC by 2100 respectively. The left-hand side axis represents the weighted sum of risk scores. The units are per se dimensionless but have good representative indicative and relativity power showing the differences across time, scenarios, and type of risk exposure.

Figure 7: Composite risk indicator across two periods and loan share of selected economic activities



Note: The chart shows a comparison of the composite risk indicator in the reference period and the RCP 8.5 scenario for the 2071-2100 period. The loan shares (rhs) of selected economic activities are calculated using data as of 31.12.2023. Services denotes that the chart shows the value of the climate risk indicator and loan shares for professional, scientific and technical activities only. The left-hand side axis represents the weighted sum of risk scores. The units are per se dimensionless but have good representative indicative and relativity power showing the differences across time, scenarios and type of risk exposure.*

for the RCP 8.5 scenario at the end of the 21st century, there is a substantial increase in the composite indicator already in the 2011-2040 period. The composite risk indicator increases by 105% in the RCP 8.5 scenario in the 2071-2100 period relative to the reference period, with the greatest relative change observable for the risk score from extreme heat and precipitation. The change observed in the current period (2011-2040) is also non-negligible, with the composite risk indicator increasing by 39.5% in the RCP 2.6, 36.6% in the RCP 4.5 and 49.4% in the RCP 8.5 scenario. Moreover, the greatest contribution to the composite risk indicator in the reference period comes from chronic risk in general, specifically temperatures, droughts, and precipitation, while the greatest contribution in the 2011-2040 period across scenarios (in particular scenarios RCP 4.5 and RCP 8.5) comes from acute risk (of which extreme heat and droughts are the most pronounced). This marks a change in the drivers of climate risk, which reveals the increasing importance of acute risks already in the current period and in general going forward until 2100.

The colour shading reflects relative size of estimated composite risk indicator across hazards and activities. The exposure analysis also reveals that physical risk is likely to be concentrated in few sectors (Figure 7), specifically manufacturing, construction, electricity and gas, retail and wholesale trade, transport, and some services activities (professional, scientific and technical activities). In fact, these sectors account for over 80% of the composite risk indicator, the majority concentrated in manufacturing activities, particularly in energy-intensive activities. This may lead to risk amplification via higher transition risks and interactions between physical and transition risks.

While the risks are concentrated in these sectors, as shown in the heatmap (Table 1), the risk indicator increases across all sectors with the severity of the climate scenario and the length of the scenario horizon (risks are highest towards the end of the century). The greatest relative change on average across scenarios and periods though can be observed in the mining, electricity and gas and ICT (Information and communications) sectors.

The main message from this exposure analysis is that the banking system is exposed to physical risks, which are set to increase significantly, also when taking the bank portfolio structure into account. Moreover, risks are concentrated in few sectors, which may lead to risk amplification and interaction with existing transition risks, particularly so in the energy-intensive activities. Some part of climate risk increase is unavoidable, as there is an increase in the composite risk indicator already in the current period, though

Table 1: Heatmap of risk indicators in the reference period across hazards and activities

Econ. activity	Windstorms	Extreme heat	Droughts	Precipitation	Temperatures	Floods
Agriculture, forestry & fishing						
Mining & quarrying						
Manufacturing						
Electricity & gas						
Water supply & sewerage						
Construction						
Wholesale & retail trade						
Transportation & storage						
Accommodation & food service						
Information & communication						
Finance & insurance						
Real estate activities						
Professional, scientific & technical activities						
Administration & support						
Public administration & defence, social security						
Education						
Human health & social work						
Arts, entertainment & recreation						
Other service activities						

Source: Own calculations based on environmental data from National Environmental

limiting the amount of carbon emissions going forward will likely contribute to a significant decrease in overall risk, as measured by the composite risk indicator.
The results confirm the necessity of acting (swiftly) to reduce emissions globally. It should be mentioned that the analysis only focuses on the NFC sector and can be extended to include the household sector portfolio. The exposure of the NFC portfolio could also be modelled at a more granular level. In addition, the exercise is based on a static balance sheet assumption, i.e. considering no changes in the bank portfolio structure. The exposure analysis is a preliminary assessment of the exposure of the banking system to physical risks based on six hazards indicators which have been defined statistically. The risk assessment may change significantly depending on dynamic changes in the bank portfolio or considering alternative definitions of the composite risk indicator.[12]

4. Conclusion

This study examines vulnerability of Slovenian economy and banking system to environmental degradation**.** We find that more than 70% of Slovenian non-financial firms crucially depend on at least on or more ecosystem services. Given the structure of Slovenian economy and its high integration into global value chains, a large part of the assessed dependency reflects an indirect exposure through counterparts in the supply chains. Considering the high interconnectedness between real economy and the banking system, high direct and indirect dependency of firms on nature intensifies risks for financial stability, stemming from local and global environmental degradation. The intensified exposure to physical risk is confirmed by the composite risk indicator presented in this study, which is expected to be exacerbated even further according to the available scenarios.
Thus, addressing the highlighted vulnerabilities will require extensive investment in both, adaptive and transformative technologies in the future. The investment in the adaptive technologies is particularly relevant in the context of the current economic model and the structure of dependency of Slovenian economy on nature that was presented in this study. Nevertheless, to ensure a sustainable growth of productivity of the Slovenian economy on the basis of reduced energy dependency and resilience to global supply shocks, investment in transformative technologies will play a crucial role.
This study provides an initial step towards mapping the most material hazards coming from environmental degradation for the economy and in turn the banking sector. Integrated assessment of climate change and nature degradation will be necessary in the future to more accurately capture the implications for Slovenian economy, with special focus on supply chain dependency. Assessment of compound shocks from climate change and nature degradation, including biodiversity loss, will require collaborative efforts in a multidisciplinary environment between economists and financial experts, environmental and climate scientists, and insurance experts. According to the NGFS conceptual framework on nature degradation and implication for financial risk assessment (NGFS, 2023), three stage approach is recommended in this process: (i) mapping of the most material risks for economy, (ii) development of forward-looking scenarios and estimation of economic consequences, and (iii) integration into financial toolboxes (such as stress test).

[12] E.g.: median vs. maximum projections of the climate variables, alternative definitions of the particular hazards, different aggregation methods.

References

Banka Slovenije. (2024, Februar). *Raziskava o dostopnosti finančnih virov za podjetja*. Rezultati anket, Banka Slovenije. Pridobljeno iz: https://bankaslovenije.blob.core.windows.net/publication-files/raziskava_o_dostopnosti_financnih_virov_februar-2024.pdf

Boldrini, S., Ceglar, A., Lelli, C., Parisi, L., & Heemskerk, I. (2023, November). Living in a world of disappearing nature: physical risk and the implications for financial stability. *European Central Bank: Occasional Paper Series, No 333*.

Ceglar, A., Boldrini, S., Lelli, C., Parisi, L., & Heemskerk, I. (December 2023). *The impact of the euro area economy and banks on biodiversity*. Pridobljeno iz ECB Occasional papers: https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op335~79fbc42228.en.pdf?e0811f3c6688da05df37d40aa78a84b9

Pavlič, D. (2023, December). *Assessment of the Slovenian Economy's Exposure Using Flood Maps*. Retrieved from Banka Slovenije Short Economic and Financial Analyses: https://bankaslovenije.blob.core.windows.net/publication-files/kefa_pavlic_final.pdf

Radovan, J. (2022, April). *An import-adjusted approach to quantify the contributions to real GDP growth in Slovenia*. Retrieved from Banka Slovneije Discussion Papers: https://bankaslovenije.blob.core.windows.net/publication-files/pa_4_2022.pdf

Rockström, J., Beringer, T., Hole, D., Griscom, B., Mascia, M. B., Folke, C., & Creutzig, F. (2021, Septeber 15). We need biosphere stewardship that protects carbon sinks and builds resilience. *Proceedings of the National Academy of Sciences of the United States of America, Vol. 118*.

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Integrating artificial intelligence for proactive and reactive credit management strategies

*Boštjan Kožuh**

Artificial intelligence (AI) is revolutionising the banking sector, impacting various aspects such as credit decisioning, risk management, and customer service. The integration of AI into credit approvals marks a shift toward more dynamic and efficient processes, allowing banks to transition from traditional reactive methods to proactive service models. The article highlights the advancements in generative AI and the capabilities of sophisticated models like GPT. It also explores the reasons banks are adopting AI, driven by evolving customer expectations and technological advancements, and the strategic, operational, and technological changes needed for effective AI integration. Additionally, it addresses ethical considerations and the importance of compliance to ensure responsible use of AI.

JEL C45, G21

1. Introduction

Banks operate in a complex environment with a delicate balance of business objectives, which include increasing sales of products, managing and reducing risk exposure, reducing customer attrition, enhancing profitability, and ensuring compliance with regulatory standards. In addressing these multifaceted challenges, artificial intelligence (AI) has proven to be an invaluable asset. AI's influence extends across numerous banking functions, but its transformative impact on credit approvals may be among the most significant.

AI is not new to the banking industry; its applications have expanded alongside advancements in technology and evolving customer expectations. Today, AI extends beyond routine task automation to encompass decision-making and predictive analytics across numerous banking functions, like fraud detection, customer service, marketing, investment strategies, and operational efficiencies. The recent developments in generative AI, capable of creating new content and exploiting qualitative and less structured data, have introduced a potential for a new level of innovation.

AI-driven credit decisioning can increase revenue while lowering costs (SAS, 2015). Sharper identification of risky customers enables banks to increase approval rates without increasing credit risk. What is more, by automating as much of the lending journey as possible, banks can reduce the costs

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of support functions and strengthen each customer's experience with faster loan approval and disbursement of funds, fewer requests for documentation, and credit offers precisely tailored to meet customer needs (Agarwal et al., 2021).

2. What is artificial intelligence?

Artificial intelligence is technology that enables computers and machines to simulate human intelligence and problem-solving capabilities (IBM, n.d.), such as understanding language, recognising patterns, solving problems, and making decisions. Its application spans numerous industries, including banking where it revolutionises operations from risk assessment to customer interactions.

AI is often described as a "suitcase word" (Minski, 2006), reflecting its usage to encompass a variety of concepts and technologies rather than one precise concept. It is therefore not surprising that we encounter many different classifications of AI–by domain (key area), by capability (narrow vs. general), by approach (generative vs. discriminative), etc.

3. Generative AI

While Generative AI (GenAI) has been around for some time, the most recent surge in this field was sparked by major advancements in large language models (LLMs), most notably with the launch of ChatGPT by OpenAI in November 2022. Today's models are not only capable of producing text that closely mirrors human writing, but they also excel in understanding text, extracting information, and performing various other language-related tasks. Trained on a broad spectrum of data, these models are now becoming increasingly multimodal, allowing them to process and generate not just text but also images, audio, video, and other types of data.

The success and versatility of ChatGPT have not only demonstrated the practical applications of large language models in sectors like banking but have also led to an increase in interest and investment across various industries. The potential of GenAI in banking is significant, with projections indicating an annual opportunity worth between $200 billion to $340 billion, representing 9 to 15 percent of operating profits (Chui et al., 2023). This impact is primarily expected to derive from increased productivity across banking segments, especially in corporate and retail sectors. The technology's integration is already enhancing customer service, agent productivity, software development, and more through various applications such as content generation, process automation, and advanced data analytics.

Table 1: Classification of AI by domain

	What is it?	Examples in banking
Machine Learning (ML)	ML is focusing on the idea that systems can learn from data, identify patterns, and make decisions with minimal human intervention. It is essential for applications requiring data-driven predictions or decisions.	Credit scoring, anomaly detection
Natural Language Processing (NLP)	NLP enables computers to process and understand human language.	Customer service chatbots, text generation
Robotics	Robotics deals with the ability of robots to perform tasks that were traditionally done by humans.	ATM maintenance, Robotic process automation
Computer Vision	Computer vision focuses on processing and interpretation of visual information from the surrounding world.	Identity verification, queue management

Table 2: Classification of AI by approach

	Approach	Examples in banking
Discriminative AI	Discriminative AI focuses on tasks of predicting a label or outcome based on given input data. It does that by learning how to tell different types of data apart and then using the learning to predict values, classify items, recognise speech etc.	Probability of default, customer classification
Generative AI	Generative AI is designed to understand and mimic the patterns of data it learns from. It then creates new content that looks like the original examples, like text, images, video and others	Creating a summary of an annual report, crafting personalised messages

3.1 Generative AI success factors

The successful scaling of GenAI in banking requires a multifaceted approach, as its transformative potential will not present itself without strategic and operational changes. Some essential dimensions for effectively scaling generative AI include (Chui et al., 2023; Smith et al., 2024; Riemer et al., 2023):

- **Strategic roadmap:** Banks must define a clear vision and strategic alignment for GenAI, securing senior leadership commitment and setting precise business goals that effectively integrate GenAI in business processes.
- **Talent:** Rapid advancements in GenAI necessitate a focus on talent development, including training existing staff and recruiting new specialists with necessary business and technical AI skills.
- **Operating model:** An adaptable operating model is crucial, characterised by flexibility and scalability to accommodate GenAI technologies while aligning with business objectives.
- **Technology:** Decisions around building, buying, or partnering for technology solutions are critical. Banks need to balance innovation with practical risk management and integration into existing systems.
- **Data:** Quality data management is essential, especially for handling unstructured data, which is vital for GenAI applications. Banks should enhance their capabilities to process and utilise this data effectively.
- **Risk and controls:** Implementing robust risk management and control frameworks is necessary to address the unique challenges posed by GenAI, including regulatory compliance and ethical considerations.
- **Adoption and change management:** Effective change management strategies must be employed to ensure that GenAI tools are adopted across the organisation. This involves fostering an understanding of GenAI benefits and addressing any resistance to its integration.

Together, these dimensions provide a comprehensive framework for banks to navigate the complexities of implementing and scaling GenAI, ensuring they can harness its full potential as well as managing associated risks.

4. AI adoption in banking

The banking sector is increasingly embracing the transformative potential of AI, marking a significant shift in how the sector operates. For example, Deutsche Bank is aggressively experimenting with AI capabilities to reimagine the bank and planning to increase its AI employee base by more than double (Chan, 2023). Similarly, JPMorgan Chase bets on using AI and is actively configuring its environment and capabilities to also enable use cases leveraging GPT-4 and other open-source generative AI models (Dignan, 2023).

These examples represent just a small selection, as nearly every bank has begun to rapidly embrace AI, driven by a combination of internal and external factors, including technological advances and their growing importance, alongside changing customer expectations and behaviours.

4.1 Shifting customer expectations and technological progress

The shift in customer expectations stands as a pivotal catalyst for the adoption of AI. Today's banking customers, influenced by rapid advancements in technology and digital services across other sectors, expect not only convenience and speed but also personalised and proactive service. The ubiquity of smartphones and the rise of digital-only banks have further accentuated these expectations, compelling traditional banks to adopt AI-driven approaches to remain competitive (McKinsey & Company, 2019).

4.2 Evolution of information-seeking behaviours

The way people seek and consume information is changing, significantly influencing the fast adoption of AI in banking. Generative AI tools such as ChatGPT are becoming the new go-to for 70% of consumers when it comes to seeking product or service recommendations (Capgemini, 2023), replacing traditional search methods and in-person interactions. This forces companies to rethink their online content optimization approaches (Kožuh, 2024) as well as invest in AI-driven chatbots and virtual assistants to deliver instant responses and 24/7 support (Beck, 2024).

4.3 The rapid progress of AI capabilities

The rapid advancement of AI technology is also a major driving force behind its adoption in banking. As AI models and algorithms continue to evolve and improve, we need to think of today's AI as the least capable AI we will ever use. Innovations in areas like text understanding and processing, deep learning, reasoning, autonomous agents, and others have already allowed banks to start solving problems that were previously deemed too complex for automated systems (Suleyman and Bhaskar, 2023) and they will only become more sophisticated, capable, and integral to operations in the future.

4.4 The increasing value of AI across all business areas

Another strong motivator for adopting AI in the banking sector is the recognition of its significant benefits across dif-

ferent business areas, largely propelled by the advent of generative AI. Thanks to its inherent ability to learn, advance and create, it will be a driving force for continuous reinvention across banks over the next few decades (Smith et al., 2024).
AI's ability to enhance decision-making and operational efficiencies extends beyond customer-facing functions to include back-office operations, risk management, compliance, and even human resources. The broad applicability of AI allows banks to reduce costs, mitigate risks, and streamline processes in a way that was not possible with traditional automation technologies.

5. Two approaches to product sales

Banks employ artificial intelligence to enhance the efficiency and effectiveness of their product sales strategies. Two distinct methods, the reactive and proactive approaches, illustrate how AI can be leveraged to meet and anticipate customer needs.

5.1 Reactive approach

This method involves the bank responding to customer-initiated interactions. AI tools are deployed to automate and optimise the handling of customer inquiries and applications. For example, LLM-driven chatbots provide real-time assistance, guiding customers through application processes or addressing their concerns, thereby streamlining customer service operations (Beck, 2024). The reactive approach focuses on efficiency, primarily engaging customers when they reach out to the bank, ensuring that their immediate needs are met promptly and effectively.

5.2 Proactive approach

Conversely, the proactive approach utilises AI to analyze customer data and predict financial needs before the customer explicitly expresses them. By employing predictive analytics, banks can identify patterns and signals in customer behaviour and transaction data, enabling them to offer tailored financial products proactively. For instance, a bank might analyse spending trends to offer pre-emptive loan approvals when a customer's behaviour suggests a potential need, such as upcoming large purchases or investments (SAS, 2015). This approach not only serves the customer's latent needs but also enhances engagement by providing personalised solutions that reflect an understanding of the customer's financial lifecycle.

5.3 Balancing reactive and proactive strategies

By integrating these approaches, banks can effectively meet both the current and future needs of their customers. Using AI to blend data-driven insights with prompt service delivery enables banks to offer a well-rounded customer experience that combines immediate support with tailored, forward-looking services. Moreover, this integration should be strategically aligned with the bank's objectives to maximise profits and minimise risks. Properly utilising AI to manage these strategies allows banks to optimise resource use, control risk exposure, and improve financial products without sacrificing service quality or unnecessarily increasing risk.

6. Simplified (traditional) process of credit approval with AI

The traditional credit acquisition process in banking is notably lengthy and labour-intensive (Smith et al., 2024), often constrained by fixed conditions and overly restrictive practices. This conventional approach not only dampens customer satisfaction due to prolonged waiting periods and inflexible service options but also affects employee morale as it involves repetitive and manual tasks (Chui et al. 2023). Recognising these challenges, the primary goal in modernising this process through AI is to significantly enhance the speed and efficiency of each step without escalating the associated risks.

6.1 Credit application

In the initial stage, AI streamlines the way applicant data is processed. Through automated analysis of submitted documentation like financial statements and identity verification, AI can expedite the initial data gathering. With a generative AI approach banks can efficiently extract and process data from a vast amount of structured and unstructured information, reducing the dependency on manual data entry and speeding up the preliminary creditworthiness evaluation.
For instance, AI can analyse documents to swiftly generate a company profile, highlighting financial health, growth drivers, and business projections based on prevailing industry data, thus enhancing the accuracy and speed of the credit application review.

6.2 Risk analysis

At the risk analysis stage, AI systems utilise predictive analytics to perform a deep dive into the applicant's financial behaviour. With the rise of generative AI banks increasingly integrate both structured and unstructured data to provide a holistic view of an applicant's creditworthiness. This includes analysing credit scores, spending patterns, income reliability, and even simulating future financial scenarios and total household income to accurately assess the risk associated with a potential borrower (SAS, 2015). "Know-your-customer" (KYC) models, which continually learn from new data, are an example of this approach. These models can dynamically adjust to new financial behaviours and trends, ensuring that the risk analysis is both current and predictive.

6.3 Offer creation

Following a thorough risk analysis, AI assists in crafting personalised loan offers. By leveraging data on the applicant's financial status and preferences, AI algorithms can determine the optimal loan terms, amounts, and conditions that meet both the client's needs and the bank's risk criteria (Biz2x, 2023). This ensures that each offer is tailored to maximise the likelihood of acceptance while optimising the bank's financial products portfolio.

6.4 Documentation and disbursement

AI further simplifies the documentation and disbursement stages. It can prepare and customise loan agreements to conform to both regulatory requirements as well as personal circumstances and loan specifics. Once the loan is approved, automated process facilitates the quick and accurate disbursement of funds, thus minimising delays (Ramasheuski, and Babrovich, n.d.).

6.5 Customer support and repayment monitoring

The role of AI extends into the post-disbursement phase through proactive customer support and repayment monitoring. AI-driven systems monitor repayment patterns and can predict potential defaults before they occur, allowing pre-emptive corrective actions.
AI-powered chatbots also provide round-the-clock support, answering queries and resolving issues, thereby maintaining a high level of customer satisfaction and identifying new business opportunities. Predictive models alert bank officers to potential late payments, facilitating early intervention strategies such as payment reminders or restructuring options (Biswas et al., 2020).

7. Proactive approach

The banking sector is undergoing a paradigm shift from a reactive service model to a more proactive, anticipatory approach. This shift enables banks to not only respond to customer needs as they arise but also to anticipate these needs and address them pre-emptively (Sydle, 2024). The proactive approach focuses on identifying opportunities to offer services and products that enhance customer satisfaction and bank profitability, while maintaining acceptable levels of risk.

7.1 Identifying opportunities with AI

The use of artificial intelligence in the proactive approach involves complex data analysis and predictive modelling to identify and target customers who might benefit from specific banking services. AI algorithms analyse vast amounts of data, including transaction histories, customer interactions, and broader economic indicators, to identify patterns that suggest customers' future needs or capacity to accept new banking products (SAS, 2015).
For instance, AI can predict when a customer might need a larger credit line based on their spending patterns and upcoming expenditures. Similarly, AI systems can suggest refinancing options to a customer when interest rates drop, if the system predicts that the customer would benefit from and qualify for such an offer.

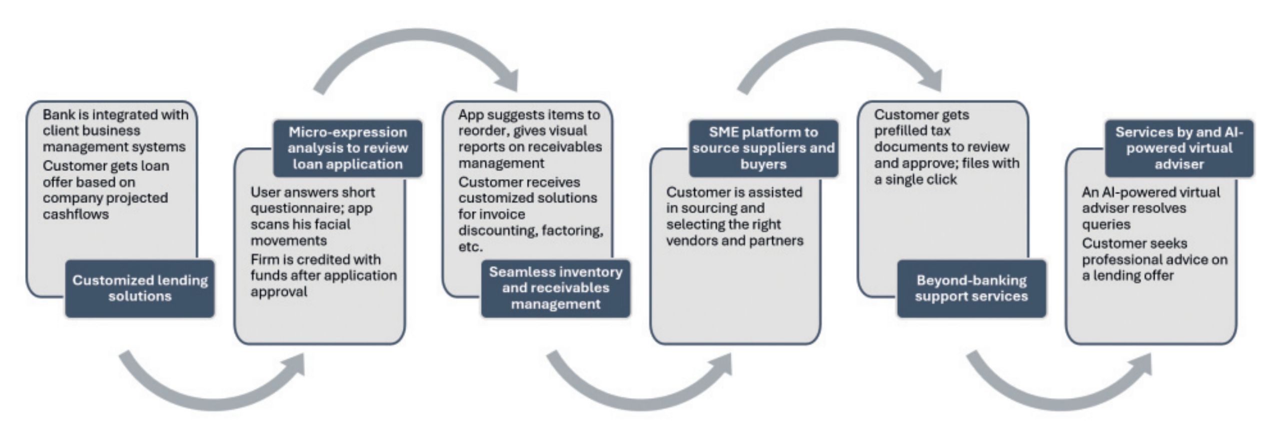
7.2 Optimising product offers

Another crucial aspect of the proactive approach is the optimization of the range and features of products offered to customers. AI-driven systems analyse customer data to determine the most attractive product mix and pricing strategies that maximise both acceptance rates and profitability. This optimisation considers not only the potential profit from each customer but also integrates risk assessments to ensure that offers are made within acceptable risk thresholds.
For example, AI models can dynamically adjust credit card limits or mortgage terms based on real-time analysis of customer financial health and market conditions, existing campaigns, customers' life events and others; thus, they are ensuring that offers are both attractive to customers and aligned with the bank's risk management strategies (PWC, 2023)

7.3 Timing and personalisation of offers

The effectiveness of the proactive approach also depends on the timing of the offers. AI systems leverage 'next best offer' (NBO) algorithms that determine the optimal time to present a specific offer to a customer, thereby enhancing the likelihood of acceptance. These AI systems can trigger offers based on specific customer actions, such as a high-value transaction or a change in the customer's financial status (Biswas et al., 2020) and deliver them in real-time.
Personalisation extends beyond the timing and type of the offer to the communication channels used. AI helps in determining the best channels—whether mobile, online, ATM screens, or direct communication—to reach customers effectively, considering their preferences and behaviours.

Figure 1: Example of AI transformed lending process for small- or medium-size enterprise customer (interpretation Biswas et al., 2020).



8. Responsible use of artificial intelligence

As AI becomes more embedded in the banking sector, it is crucial to acknowledge the responsibilities that come with its use. Banks are built on trust, making the ethical and responsible deployment of AI not only a regulatory necessity but also a fundamental aspect of preserving public confidence and supporting sustainable business practices.

8.1 The ethical imperatives of AI in banking

AI systems in banking must adhere to ethical standards that prevent biases, protect privacy, and ensure inclusivity. Given that AI systems are often trained on historical data, there is a risk that these systems may perpetuate or even exacerbate existing biases if not carefully monitored and adjusted. For example, if a loan approval AI model is trained on past data that contains biased human decisions, it may continue to make unfair decisions against certain demographics (Mehrabi et al., 2021). To counteract this, banks must implement robust de-biasing techniques and continually update AI training datasets to reflect a fair and equitable view of society.

Transparency and explainability are another critical aspect of ethical AI deployment. The decision-making processes of AI systems—especially those involving customer interactions and credit approvals—should be transparent enough that they can be explained in understandable terms to customers and regulators. This is particularly important in scenarios where AI decisions affect the financial health of individuals or enterprises (de Lange et al., 2022).

8.2 Operational integrity and overreliance on AI

The operational integrity of AI systems must be guaranteed to ensure they perform reliably under various conditions without causing unexpected harm due to errors or vulnerabilities. It is crucial to balance AI-driven automation with human oversight to mitigate the risk of overreliance on technology and the danger of employee de-skilling (Allmer, 2022), which could lead to failures in critical decision-making processes. Ensuring that human bankers are in the loop and able to override AI decisions when necessary is vital for maintaining both operational safety and customer trust.

8.3 Privacy and data security

AI systems typically require substantial data inputs to function optimally. This requirement raises significant privacy concerns, particularly regarding the collection, storage, and processing of personal and sensitive financial data. Banks must adhere strictly to data protection laws, such as GDPR. Furthermore, the principles of data minimisation and purpose limitation must be upheld to ensure that data collection is not only lawful but ethically justified (OECD, 2021).

8.4 Regulatory compliance and AI robustness

The dynamic regulatory landscape in which banks operate also dictates the adoption of AI systems that are able to maintain their accuracy, reliability, and performance in various financial applications, even in the face of changing market conditions or unexpected events. Additionally, they need to be not only compliant with current laws but are adaptable to potential regulatory changes. The robustness of AI models, therefore, becomes a priority, requiring continuous monitoring and updates to align with evolving regulatory and market conditions (OECD, 2021).

8.5 Ethical considerations and societal impact

Finally, the broad use of AI in banking raises several societal concerns. The potential for AI to impact significant life decisions, such as creditworthiness and eligibility for banking services, requires a cautious approach. Banks must consider the societal impacts of their AI systems, ensuring they contribute positively to societal welfare and do not exacerbate social inequalities.

9. Conclusion

The integration of AI in banking is not merely a technological upgrade but a strategic imperative that necessitates comprehensive organizational adaptation. Banks that effectively harness the capabilities of AI, even in critical areas like credit approvals, can expect to see substantial improvements in productivity and profitability across various segments. However, this requires a balanced approach that includes developing AI talent and AI technology stack, ensuring ethical usage and data governance, managing risks, and maintaining regulatory compliance. As AI continues to evolve, its responsible and strategic implementation will be crucial for banks to fulfil their potential in delivering innovative services and securing a competitive edge in the financial sector.

References

- Agarwal, A. et al., 2021. AI-powered decision making for the bank of the future. McKinsey and Company.
- Allmer, J. (2022). Deskilling as an effect of AI, 7.6.2022, https://www.diva-portal.org/smash/get/diva2:1684401/ATTACHMENT01.pdf
- Beck, S. (2024). How artificial intelligence is reshaping banking. Forbes, 23.2.2024, https://www.forbes.com/sites/forbestechcouncil/2024/02/23/how-artificial-intelligence-is-reshaping-banking
- Biswas, S. et al. (2020). AI-bank of the future: Can banks meet the AI challenge?, McKinsey & Company.
- Biz2x. (2023). How Generative AI Will Impact Business Lending. Biz2x, 27.6.2023, https://www.biz2x.com/blog/how-generative-ai-will-impact-business-lending/
- Capgemini. (2023). Why consumers love generative AI. Capgemini, 16.6.2023, https://prod.ucwe.capgemini.com/wp-content/uploads/2023/05/Final-Web-Version-Report-Creative-Gen-AI.pdf
- Chan, B. (2023). Deutsche Bank wants to transform its business with generative AI. The German bank's tech chief lays out its strategy as it hires hundreds. Business Insider, 14.9.2023, https://www.businessinsider.com/deutsche-bank-to-launch-generative-ai-tools-hire-hundreds-engineers-2023-9
- Chui, M. et al. (2023). The economic potential of generative AI. McKinsey & Company.
- de Lange et al., 2022. Explainable AI for credit assessment in banks. Journal of Risk and Financial Management, 15(12), p. 556, https://doi.org/10.3390/jrfm15120556.
- Dignan, L. (2023). Digital Transformation, AI and Data Strategy Sets Up Generative AI - Customer Story. JPMorgan Chase. Constellation Insights, 5.7.2023, https://www.constellationr.com/system/files/uploads/user-23065/Insights%20Template_JPMorgan.pdf
- IBM. (n.d.). What is Artificial Intelligence (AI)? https://www.ibm.com/topics/artificial-intelligence
- Kožuh, B. (2024). Convince ChatGPT to prioritize your online content over competitors – a step-by-step framework for Generative AI Search Optimization (GAISO). 10.2.2024, https://bit.ly/gaiso
- McKinsey & Company. (2019). The future of personalization—and how to get ready for it.
- Mehrabi, N. et al., 2021. A survey on bias and fairness in machine learning. ACM Computing Surveys (CSUR), 54(6), pp. 1-35.
- Minski, M. (2006). The Emotion Machine: Commonsense Thinking, Artificial Intelligence, and the Future of the Human Mind. Simon & Schuster
- OECD (2021), Artificial Intelligence, Machine Learning and Big Data in Finance: Opportunities, Challenges, and Implications for Policy Makers, https://www.oecd.org/finance/financial-markets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf.
- PWC, (2023). AI in banking: The new digital customer experience, PWC, 25.6.2024, https://www.pwc.com/m1/en/media-centre/articles/reimagining-banking-and-customer-experience.html
- Ramasheuski, A., Babrovich, N. (n.d.). ScienceSoft. https://www.scnsoft.com/lending/loan-automation (accessed: 4.4.2024)
- Riemer, S. et al., 2023. A GenAI Roadmap for FIs. BCG, 13.11.2023, https://www.bcg.com/publications/2023/a-genai-roadmap-for-fis.
- Russell, S.J. and Norvig, P., 2009. Artificial Intelligence: A Modern Approach, 3rd ed. Pearson.
- SAS. (2015). Credit limit optimization - Sales improvement strategy. Internal documentation.
- Smith K., Abbot M., Centonze M. (2024). https://www.accenture.com/content/dam/accenture/final/accenture-com/document-2/Accenture-Age-AI-Banking-New-Reality.pdf
- Smith, K., Abbot, M., Centonze, M. (2024). The Age of AI: Banking's New Reality. Accenture, https://www.accenture.com/content/dam/accenture/final/accenture-com/document-2/Accenture-Age-AI-Banking-New-Reality.pdf.
- Suleyman, M. and Bhaskar, M. (2023). The Coming Wave. Bodley Head.
- Sydle. (2024). From Reactive To Proactive Bank: 10 Tips To Better Serve Your Clients. Sydle, 4.3.2024, https://www.sydle.com/blog/proactive-bank.

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The Model Risk: A Savior or a Scapegoat?

*Matej DraščEk and Alja Sosič Hribar**

In today's swiftly evolving and unpredictable global landscape, banks face the formidable challenge of navigating through an increasingly complex mix of business, societal, and regulatory pressures. The rapid pace of technological advancements, coupled with the intricate interconnections of global markets, has exposed existing financial institutions to heightened vulnerabilities. In particular, banks are compelled to confront an environment riddled with uncertainty and volatility, as market dynamics and regulatory frameworks undergo abrupt and often unforeseen shifts. This volatile environment mandates a re-evaluation of conventional strategies, compelling banks to embrace adaptability and resilience in their operations.

JEL D81, G21, G24

Amidst societal, demographic, technological, economic, regulatory geopolitical, etc. flux, the ability of banks to remain flexible, making well-informed decisions and managing risks effectively, becomes paramount. It necessitates a balanced approach that marries flexibility with a conservative stance towards risk-taking, ensuring that prudence is not sacrificed. The dependence on predictive models, which serve as the cornerstone for risk management and decision-making processes, has underscored the criticality of model risk. As these models predominantly rely on historical data, the rapidity of change renders past data and assumptions increasingly obsolete, thereby amplifying the susceptibility of models to inaccuracies in forecasting future events.

The increasing emphasis on model risk, often integrated within the broader spectrum of operational risks in several banks, demands a shift. It requires that risk management strategies not only derive insights from historical data and trends, but also incorporate a significant degree of professional judgement. This approach acknowledges the inherent limitations of models, recognising that while professional judgement is susceptible to flaws, it introduces an indispensable layer of adaptability and critical thinking. Consequently, in an era marked by rapid changes and uncertainties, the capacity to blend data-driven insights

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with expert judgement becomes a crucial asset, enabling financial institutions to navigate the complexities of the modern business landscape with greater efficacy and resilience. In the forthcoming article, we explore the evolving landscape of risk management, spotlighting the emergence of new risk paradigms such as VUCA (Volatility, Uncertainty, Complexity, and Ambiguity), BANI (Brittle, Anxious, Nonlinear, and Incomprehensible), polycrisis, and permacrisis. These concepts, rapidly becoming integral to the lexicon of risk management professionals, underscore the heightened complexity and interconnectedness of contemporary global events.

We emphasise the critical need for raising awareness among risk management professionals about the growing significance of model risk in an era defined by rapid technological advances and unpredictable global dynamics. The discussion extends to the indispensable role of professional judgment, advocating for its integration alongside model-based approaches. This dual-focus approach acknowledges the limitations inherent in relying solely on historical data and predictive models, which may not fully capture the ethos of future uncertainties and complexities.

When VUCA became BANI

Originally the VUCA concept was developed by the U.S. military to conceptualise the war environment after the Cold War as volatile (V), uncertain (U), complex (C) and ambiguous (A). The concept was adopted in the business world to articulate uncertainties faced by organisations (Bennett & Lemoine, 2014). With digitalisation and technology advancements, a more modern definition was needed to describe these challenges.

The term BANI is an evolution of VUCA, as the latter did not fully capture the complexities of contemporary challenges. BANI offers a more comprehensive understanding of today's environment by describing it as brittle, anxious, nonlinear and incomprehensible (Jensen, 1999). The main difference between BANI and VUCA is that VUCA primarily emphasises the dynamic and uncertain nature of the environment such as market volatility and geopolitical instability, while BANI focuses on the fragility of existing systems and the responses of individuals and organizations to change (Jensen, 1999). This shift represented a fundamental change in how banks saw and handled the challenges of the contemporary world.

However, the current situation we found ourselves in has evolved beyond the conventional framework of VUCA or BANI. The world is in a unique situation, where banks as well as individuals are experiencing high levels of anxiety due to uncertainty and rapid change, while multiple crisis happening simultaneously. Climate change, political uncertainty, spread of diseases, scarcity of natural resources and cybersecurity are just some of the issues banks are currently facing. These crises are not isolated events, but rather interconnected parts of a larger system that is fundamentally vulnerable.

The rise of polycrisis and permacrisis

The term "polycrisis" aptly captures the intricate interconnectedness and overwhelming nature of the multiple crisis' banks face. It is a term that was introduced in the Global Risk Report 2023 by the World Economic Forum and sums the COVID-19 pandemic, war in Ukraine, fluctuating energy prices, cyber insecurity and high cost of living which are closely connected and interact with one another.) Actually, the combined impact of multiple crises on humanity and the world is far greater than the sum of those crisis would produce in isolation (German, 2023). The simultaneous occurrence of multiple crisis also makes it difficult to predict events or scenarios for which banks must prepare. The term polycrisis is not solely used to describe the current circumstances. Tooze (2022) examines history to trace the roots of this complex phenomenon. He highlights events such as the Greek debt crisis, Russia's initial aggression against Ukraine, the Brexit referendum and the refugee crisis in Syria, to be early indicators of the interconnected crises that eventually evolved into the multifaceted polycrisis banks currently face. Further, the current polycrisis is just the continuance of 2008 world financial crisis, which was indeed about mortgage-backed securities, however it coincided with Putin's first aggression against Georgia. Over time, global crises have become increasingly interconnected and complex, with each new crisis building upon and complicating the challenges of the past. There is no way of reversing a polycrsis, however, it is possible to learn how to adapt to it through improvisation, innovation, reform, and crisis management (Whiting & Park, 2023). The latter implies that the situation can only be managed, not resolved, which makes the matter permanent. The permanency of the situation coined the term »permacrisis« (Smith, 2022).

Permacrisis describes an extended period of instability and insecurity, especially one resulting from a series of catastrophic events. In permacrisis the challenges show no signs of abating, rather accelerating (Brown et al., 2023). The concept of permacrisis also suggests that any acceleration of difficult situations only risks an even worse result. Therefore, it can be concluded that there are no simple and straightforward solutions to the challenges of this complexity. This is what we call a wicked problem.

When simple solutions are not enough

A wicked problem has no clear solution as solving one of its aspects may reveal or create a new, even more complex problem. Furthermore, every wicked problem is unique, can be considered a symptom of another problem, they have no stopping point, can't be tested, and have no definitive answers, only better or worse (Rittel, 1972).
Every solution to the wicked problem is thus a one-shot chance, there is no trial and error which is why every implemented solution bares consequences. When it comes to environmental questions or political questions that greatly affect almost every bank in the market, finding a solution that will solve the problem for most of those involved is crucial (Rittel & Webber, 1973).
Rapid technological advancements and interconnected global markets have made existing systems vulnerable. Banks especially must deal with uncertainty and anxiety, as market dynamics and regulations change abruptly. This forces them to re-evaluate their traditional strategies to risk management and models and adapt to new realities. As a result, banks need to be more flexible and adaptable in making decisions but making also conservative and prudent approach to managing risks and building up models. This involves the integration of professional judgement with strict mathematical models to establish the risk management that will suffice the need of prudent yet flexible risk management in banks.

The rise of model risk in banks

In the complex and ever-evolving landscape of modern banking, the reliance on financial risk measurement and valuation models has become indispensable. These models, intricate by nature, are tasked with the heavy lifting of pricing, risk assessment, and strategic decision-making (Nilsen & Aven, 2003). However, this reliance is double-edged. While models offer a sense of control and predictability, they also introduce a significant source of risk—model risk. This risk, stemming from potential errors in model design, implementation, or application, can lead to substantial financial losses if not adequately addressed.
Model risk manifests when the financial models employed to predict market trends, assess risks, or value instruments fail to perform as expected. This failure can arise from various sources, including incorrect model specifications, application errors, and implementation risks. Such discrepancies might originate from overlooking essential risk factors, employing outdated models, or inaccuracies in model parameter calibration and programming. Given the critical role these models play in banks' decision-making processes, the stakes of mitigating model risk are exceedingly high.
Mitigating model risk requires a comprehensive strategy encompassing awareness, regular evaluation, and calibration of models, simplicity in model choice, and rigorous back-testing and stress-testing. Ignoring even small, unexplained problems can lead to significant issues, highlighting the necessity of quantifying model risk and ensuring that senior managers thoroughly understand model assumptions. Moreover, a multidisciplinary approach to model building and an independent risk oversight function are essential for a comprehensive review and monitoring of models (Rasmussen, 1997; Jones, 2023).

How to address the model risk?

At the organisational level, mitigating model risk demands concerted efforts from all levels in the bank. This collaborative approach signifies the importance of an appropriate organizational structure that effectively minimizes such risks. From individual practitioners to senior management, the collective engagement in recognising, assessing, and addressing model risk is pivotal.
The COVID-19 pandemic has starkly highlighted the vulnerabilities in the banking sector's reliance on traditional models (Shabir et. al., 2023). As these models faltered in the face of unprecedented market conditions, the urgent need for revisions and strategic adjustments became apparent. The pandemic challenged the sector with unforeseen difficulties, necessitating a re-evaluation of longstanding assumptions and the integration of novel, high-frequency data for recalibration. The widespread impact of model failures across banking operations — from risk assessment to liquidity management — underscores the pressing need for strategies that enhance model resilience both immediately and in the long term.
Addressing these challenges necessitates a dual-phase approach (Laurent et. al., 2020). Initially, short-term crisis management focuses on immediate model adjustments to ensure business continuity. Following this, a long-term strategy aims at fortifying model-risk management frameworks to improve resilience and adaptability. This strategy involves establishing dedicated task forces and applying agile methodologies for a swift and effective review of model-risk management practices.
However, the journey towards effective model risk mitigation is fraught with potential pitfalls. Rapid and uncoordinated mitigation actions risk exacerbating the problem, leading to model failure and inconsistent decision-making. It's crucial not only to manage crises efficiently in the short term but also to ensure that short-term fixes do not evolve into long-term issues. By advancing model-risk management practices, banks can elevate these frameworks from mere

control functions to strategic partners in decision-making. This transformation enables banks to navigate through current crises and brace for future uncertainties with greater confidence and effectiveness (Jones, 2023).

The flux of artificial intelligence in model risk

The integration of Artificial Intelligence (AI) in the banking sector and its models exemplifies a contemporary revolution that raises both immense potential and notable challenges. On one hand, AI's capability to refine and expedite the loan approval process and its models demonstrates its utility in enhancing operational efficiency within banks. This technological advancement promises to redefine traditional practices, making them more agile and customer-centric (Bueno et. al., 2024). On the other hand, historical instances of discriminatory practices, such as the "redlining" phenomenon observed in the 1930s Chicago – where loan approvals were unjustly influenced by racial demographics – serve as a stark reminder of the potential for AI systems and its models to perpetuate and even amplify existing biases if not properly checked (Hale, 2021). The adoption of blockchain technology, for instance, could serve as a means to safeguard data integrity and transparency in models, ensuring that the decision-making processes powered by AI are built on a foundation of trust and verifiability. Furthermore, the formation of development teams that embody diversity in thought, experience, and background is advocated as a crucial step towards creating models that are more reflective of the society they serve and less prone to inheriting historical biases (Addula et. al., 2024)

Illustrative of AI's potential to positively transform the banking sector and its models are case studies of fintech startups that have leveraged AI's sophisticated analysis to extend credit to demographics traditionally underserved by conventional banking systems (Sadok, Sakka & El Maknouzi, 2022). These examples underline the nuanced understanding of creditworthiness that AI can bring to the models in banks, highlighting its capacity to foster financial inclusion. By carefully navigating the complexities and ethical considerations inherent in AI adoption in models, the banking sector can harness its potential to not only streamline operations but also to act as a force for good, ensuring that technological advancements contribute to a more inclusive and equitable financial ecosystem.

The need of professional judgement into model risks

In our daily lives, the biases we adopt enable us to function more efficiently, streamlining decision-making processes and enhancing our capacity to manage routine tasks. However, this reliance on cognitive shortcuts also increases our vulnerability to overlooking significant risks and making oversimplified judgments (Davis, Hogan & Hart, 2023). Particularly in the realm of model risk management, where predictions about the future – a realm inherently fraught with uncertainty – are paramount, it becomes crucial to meticulously control for biases. This ensures that the models we rely on are not inadvertently skewed by the very prejudices that are pervasive in human cognition.

Professional judgment in risk management plays a pivotal role in the strategic decision-making process of organisations across various sectors. It involves the application of experienced insights, analytical skills, and informed intuition to evaluate potential risks, determine their impact, and prioritise actions accordingly. This nuanced approach enables managers to go beyond purely quantitative analysis, incorporating a qualitative understanding of the risk landscape. The challenge emerges when the inherent biases within predictive models are intricately linked with professional judgment, leading to a critical misinterpretation. This misinterpretation often results in an overreliance on qualitative data, which could significantly amplify the risks associated with model predictions. Recently it has been underscored the superior predictive capabilities of professional judgment, particularly when it is derived from extensive work experience, over purely model-based forecasts (Warner, Fortin & Melkonian, 2024). This revelation underscores the indispensable need to integrate professional judgment into the modelling process to enhance the accuracy and reliability of predictions.

However, it is paramount to acknowledge the inherent risks associated with incorporating professional judgment into predictive models. While the expertise and insight provided by seasoned professionals can be invaluable, there is also a potential for subjective bias that could skew model outcomes. Striking a balanced approach is essential; neither extreme reliance on quantitative models nor exclusive dependence on professional judgment is advisable. Achieving this equilibrium necessitates a structured framework within which professional judgment is not only solicited but also meticulously documented. Establishing a transparent audit trail is crucial, as it ensures accountability and facilitates the retrospective analysis of decision-making processes. This is particularly relevant in high-stakes environments such as banking, where decisions influenced by even a single individual's judgment could have profound implications. Integrating professional judgment into predictive models is thus not merely an option but a necessity to bridge the gap between quantitative data and real-world complexities.

Is a model risk a scapegoat of the banks?

The narrative of model risk as a scapegoat for financial instability reflects a broader discourse on the complexities and unpredictability of financial markets. Yet, it also offers an opportunity for introspection and improvement. Banks, by delving into the essence of model risk, can unveil the layers of assumptions, methodologies, and expectations that underpin their operational frameworks. This exploration is not merely an exercise in risk management but a strategic endeavour to harness the full potential of financial models while acknowledging and mitigating their inherent limitations.

As the banking sector continues to evolve, so too must the approaches to managing model risk. The advent of advanced technologies and methodologies offers new avenues for enhancing the accuracy, reliability, and resilience of financial models, combining this with professional judgement. Machine learning algorithms, big data analytics, and blockchain technologies, among others, present opportunities to address the multifaceted challenges of model risk. By integrating these innovations with the professional judgement, banks can improve their predictive capabilities, refine risk assessments, and bolster their strategic decision-making processes.

In conclusion, model risk serves as a critical reminder of the inherent uncertainties within the banking sector. By acknowledging and addressing this risk, banks can navigate the complex landscape of modern finance with greater foresight and stability. Through a concerted effort spanning awareness, evaluation, simplicity, and continuous innovation, the financial sector can transform model risk from a potential liability into a catalyst for growth and resilience. Model risk with its complexities highlights the importance of inclusion of new technologies and artificial intelligence with professional judgement as only this presents the path forward for banks seeking to thrive in an ever-changing global market.

References:

- Addula, S. R., Meduri, K., Nadella, G. S., & Gonaygunta, H. (2024). AI and Blockchain in Finance: Opportunities and Challenges for the Banking Sector. International Journal of Advanced Research in Computer and Communication Engineering. Retrieved from: https://www.researchgate.net/ profile/Karthik-Meduri/publication/378635286_AI_and_ Blockchain_in_ Finance_Opportunities_and_Challenges_for_the_Banking_Sector/ links/65e401f7c3b52a117006dec1/AI-and-Blockchain-in-Finance-Opportunities-and-Challenges-for-the-Banking-Sector.pdf
- Bennett, N., & Lemoine, G. J. (2014). Leading in a VUCA world. MIT Sloan Management Review, 56(1), 21-28.
- Brown, G., El-Erian, M., Spence, M., Lidow, R. (2023). Permacrisis: A Plan to Fix a Fractured World. Simon & Schuster UK Ltd.
- Bueno, L. A., Sigahi, T. F., Rampasso, I. S., Leal Filho, W., & Anholon, R. (2024). Impacts of digitization on operational efficiency in the banking sector: Thematic analysis and research agenda proposal. International Journal of Information Management Data Insights, 4(1), 100230.
- Davis, D., Hogan, A., & Hart, D. (2023). Myths of Trauma Memory: On the Oversimplification of Effects of Attention Narrowing Under Stress. Frontiers in Psychology, 15, 1294730.
- de Godoy, M. F., & Ribas Filho, D. (2021). Facing the BANI world. International Journal of Nutrology, 14(2), 33-33.
- Dymski, G. A. (1997). Why does race matter in housing and credit markets? Current research and future directions. Race, markets, and social outcomes, 157-189.
- German, V. (2023). Del VUCA a la Policrisis: Nueva forma de abordar las crisis. Retrieved from: https://drjenespanol.com/articulos/del-vuca-a-la-policrisis-nueva-forma-de-abordar-las-crisis/
- Hale, K. (2021). A.I. Bias Caused 80% Of Black Mortgage Applicants To Be Denied. Retrieved from: https://www.forbes.com/sites/korihale/2021/09/02/ai-bias-caused-80-of-black-mortgage-applicants-to-be-denied/
- Jensen, R. (1999). "The Dream Society: How the Coming Shift from Information to Imagination Will Transform Your Business." McGraw-Hill.
- Jones, S. (2023). A literature survey of corporate failure prediction models. Journal of Accounting Literature, 45(2), 364-405.
- Lawrence, M., Janzwood, S., and Homer-Dixon, T (2022). What Is a Global Polycrisis? Version 2.0. Discussion Paper 2022-4., Cascade institute
- Marie-Paule Laurent, Olivier Plantefève, Maribel Tejada, and Frédéric van Weyenbergh. 2020. Banking models after COVID-19: Taking model-risk management to the next level. Retrieved from: https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/banking-models-after-covid-19-taking-model-risk-management-to-the-next-level
- Nilsen, T., & Aven, T. (2003). Models and model uncertainty in the context of risk analysis. Reliability Engineering & System Safety, 79(3), 309-317.
- Rasmussen, J. (1997). Risk management in a dynamic society: a modelling problem. Safety science, 27(2-3), 183-213.
- Rittel, H. (1972). "On the Planning Crisis: Systems Analysis of the 'First and Second Generations". Bedriftskonomen. Nr. 8.
- Rittel, H., Webber, M. (1973), »Dilemmas in a General Thery of Planning«. Springer, Vol. 4, No. 2, pp. 155-169. Accessed: 09/02/2011.
- Sadok, H., Sakka, F., & El Maknouzi, M. E. H. (2022). Artificial intelligence and bank credit analysis: A review. Cogent Economics & Finance, 10(1), 2023262.
- Shabir, M., Jiang, P., Wang, W., & I ık, Ö. (2023). COVID-19 pandemic impact on banking sector: A cross-country analysis. Journal of Multinational Financial Management, 67, 100784.
- Smith, J. (2022). Permacrisis: What it means and why it's word of the year for 2022. The Conversation. Retrieved from: https://theconversation.com/permacrisis-what-it-means-and-why-its-word-of-the-year-for-2022-194306
- Tooze, A. (2022). Welcome to the world of the polycrisis. Retrieved from:https://www.ft.com/content/498398e7-11b1-494b-9cd3-6d669dc3de33
- Warner, C. H., Fortin, M., & Melkonian, T. (2024). When are we more ethical? A review and categorization of the factors influencing dual-process ethical decision-making. Journal of Business Ethics, 189(4), 843-882.
- Whiting, K., & Park, H. (2023, March 7). This is why 'polycrisis' is a useful way of looking at the world right now. World Economic Forum. Retrieved from: https://www.weforum.org/agenda/2023/03/polycrisis-adam-tooze-historian-explains/

UDK 004.8

The Future of AI – From Learning to Understanding

*Sašo Dolenc**

The article provides a comprehensive overview of the latest developments in artificial intelligence (AI), framing the AI revolution as a transformative period comparable to the advent of the internet. It delves into the complexities and challenges that researchers encounter in dissecting the mechanisms through which AI executes cognitively demanding tasks. Key topics covered include the concept of generalisation within AI systems, the backpropagation algorithm, and the dynamics of unsupervised learning. The article further explores how large-scale AI models manage to "understand" content through a process of data compression and concept generation, suggesting that AI models create a conceptual world within its mathematical space. The discussion culminates in an examination of the forthcoming horizon for AI: the capability to autonomously conceptualise and categorise unprocessed data, independent of human guidance.

JEL O33

Over the past few years, the field of artificial intelligence (AI) has made remarkable progress. The advancements in the capabilities of AI tools are truly astonishing. Today, we can communicate with computers using our everyday language, and machines have mastered complex tasks that were once believed to be the exclusive domain of humans. The progress in improving the quality of smart devices has surprised even veteran experts in the field.

The essence of the AI revolution

AI technological revolution can be compared to the emergence of the internet a few decades ago, but at that time technological innovations such as email, remote file access and the World Wide Web were introduced much more slowly into everyday life. The power and utility of new AI tools such as chatGPT and various image generation systems is truly fascinating, and their easy accessibility has quickly led to mass adoption.

With the new smart language systems, we can talk to articles and books, ask them all sorts of questions, seek further clarification, and do many things we could not do with texts before. We can also conduct market analysis, draft a wide range of communications, reply to emails, summarise the content of meetings and many other similar time-consuming tasks. Nor is it a barrier to new technologies if

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the text we want to read is only available in a language we do not understand. The smart tools make it easy to discuss its content in English, even if the source text is in Arabic, Chinese or any of the many languages already supported by the new systems.

The proliferation of languages already covered by new AI tools has made human knowledge even more accessible to people around the globe. Researchers are now working to develop language models that support all the world's languages for which sufficient digitised resources are available as a prerequisite for the implementation of machine learning.

What scientists don't yet understand about AI

These technological advances are accompanied by claims that even scientists developing new AI tools do not have a good understanding of why there is such a leap in the capabilities and usefulness of this type of technology right now. Researchers are, of course, very familiar with the workings of the devices and programs that power smart tools. They also understand that in addition to understanding the theory, to effectively perform machine learning of AI models, they need a lot of computing power, which is not cheap. However, it is quite another thing for experts to be able to explain how AI actually performs the tasks that we believe require some kind of a thought process.

The frequent remark that large language models such as chatGPT can only statistically predict the most likely next word in sequence ignores the very essence of the revolution we are witnessing in the field of artificial intelligence. By learning to predict letters or words in a text, the neural network can also be taught many other tasks.

Large neural networks can extract patterns from the mass of data they learn from, allowing them to perform many complex tasks, which is a remarkable achievement. In a way, this is similar to the phenomenon where systematic training in long-distance running would prepare an athlete to be equally successful in other sports. The result is strange and perhaps surprising, but it is an important element of the recent AI revolution.

How do machines perform tasks that require thinking?

Large language models of artificial intelligence, capable of running smart services such as chatGPT, are based on large neural networks. These are huge mathematical equations where, during the learning process, parameters are gradually adjusted so that the models are then able to calculate a meaningful answer to a given question. However, as with the connections between neurons in the human brain, it is not immediately clear how the structure of the connections between neurons translates into the calculated answers to questions in artificial neural networks. Large-scale AI models operate on a black box principle, where input data passes through the complex connections of a large neural network, which can include billions of parameters or weights, but the way these parameters integrate with each other to produce specific results is not obvious. Understanding the "black box" problem, which concerns the performance of large-scale AI language models and functioning of the human brain, is one of the great scientific puzzles of our time. This challenge is not only important for building and managing even more powerful AI models in the future, but also represents one of the fundamental questions in AI research.

The key problem is not, of course, a lack of understanding of the mathematical principles that underpin how AI models work. The central problem lies in a deeper question: how is it possible that huge mathematical equations can so efficiently perform tasks such as answering questions, generating text, translating between languages, creating images and other similar activities that, until recently, only humans could do well?

The phenomenon of generalisation in AI

A fundamental element of machine learning is the phenomenon of generalisation. It represents the basic way AI models can learn to "understand" something, not just learn it by heart. Generalisation in machine learning is the ability of a model to efficiently and correctly predict or explain new, previously unknown data that comes from the same general population as the training data. In essence, it is the capacity of the model to apply the learnt knowledge from the training set to data that it has not seen during training, which is crucial for its practical applicability.

Models can learn to perform tasks such as translating sentences from one language into another by training on a set of already translated examples. However, they can generalise their knowledge and learn to perform similar tasks on examples they have not seen before. Models not only remember patterns they have already seen, but also independently develop rules during the learning process that enable them to apply these patterns to new examples. In particular, large language models such as GPT-4 have a surprising capacity for generalisation.

When we train an AI model, we want it to learn patterns that are generally valid for the problem we are trying to solve, but we do not want it to overfit to the specifics of the training dataset. If we overfit the model to the training data, it will perform excellently on the training data, but its performance on the new data will be much worse, because it has learned the specific details of the training set rather than developing an "understanding" of the general patterns.

The invention of the artificial neuron and training algorithm

The remarkable technological revolution in artificial intelligence that we have witnessed in recent years is the result of years of research, which has recently reached an important peak. Scientists have long wondered what makes the human brain intelligent, and many years ago concluded that the ability to think is most likely related to the number of neurons and how they are organised.

That is why, in the middle of the 20th century, researchers began to investigate how the workings of the neurons in the brain could be mimicked by mathematical models. This approach led to the invention of the artificial neuron, which is nothing more than a mathematical formula that attempts to emulate the functioning of a biological neuron. Many interconnected artificial neurons then form a neural network, which is also just a mathematical equation with many parameters.

The next major step in developing artificial neural networks was the discovery of a method by which artificial neurons can be trained. The backpropagation algorithm allows neural networks to learn from data or tasks that have already been solved. Simply put, the neural network calculates its prediction of the outcome and compares it to the actual outcome of the task, then calculates how much each neuron contributed to the error. In the next step, it corrects the parameter settings of each neuron so that the overall prediction error is reduced. If the process is repeated many times, the neural network parameter settings are gradually changed in such a way that the neural network becomes better and better at predicting the correct results.

The unsupervised learning process

Supervised machine learning means that we know in advance what we want the neural network to learn. For such learning, we need a large number of solved tasks on which to train the neural network. But unsupervised machine learning is a much more interesting approach, because we train the neural network to be as good as possible at a particular task, such as predicting the next word in a text, while at the same time it learns many other tasks that we have not trained it to do.

The unsupervised learning process of neural networks can also be seen as a process of discovering hidden structures in the data. We do not instruct a machine what to learn, but by teaching it to predict the next word, we enable it to systematically "read" texts and learn their content.

In 2017, OpenAI researchers taught a neural network to predict the next letter in a collection of 82 million reviews written by customers on Amazon for different products. An important result of this machine learning was that by training the neural network to predict the next character in texts, it learned not only this skill, but also a number of other skills for which it was not directly trained.

For example, they found that one of the neurons in the neural network became particularly sensitive to the mood of a particular text. In most cases, if the neuron was active, the rating was positive, but if it was inactive, the rating was negative. They also found that by switching this neuron on and off, they could directly control the sentiment of the newly generated reviews.

The experiment showed that learning to predict letters or words in a text can also teach the neural network many other tasks over time. In a way, this is similar to the phenomenon that systematic training in long-distance running would train an athlete for other sports. The result is unusual and perhaps surprising, but it is an important element of the recent AI revolution.

Knowledge as the by-product of guessing

Over the next few years, when much larger neural networks were trained on a very large set of texts, it turned out that although the neural network only learns to predict the next word in a sequence of words, it somehow learns to "understand" the content of those texts. Of course, this "understanding" is not the same as in the human brain, but even in an artificial neural network, structures are formed that somehow correspond to the ideas, or a very condensed form of the notation, of the mass of information contained in the texts.

If the learning process is performed correctly, the neural network automatically extracts key ideas from the dataset during the learning process. These ideas are then stored in the neural network, which is a rather compressed record given the large amount of source data. The trick is that the neural networks we use for generative models have a much smaller number of parameters than the amount of data we train them on, so the models need to discover and effectively internalise the essence of the data to be able to regenerate it. By compressing it into a shorter record, they can extract key patterns from the data that enable understanding and prediction, which is certainly an impressive achievement.

The frequent observation that large language models such as chatGPT can only statistically predict the most likely next word in a sequence misses the point of the revolution we are witnessing in the field of artificial intelligence. Learning to predict the next word should be understood as a reading process, the by-product of which is the "knowledge" of the content that the neural network is reading.

Data compression and concept generation

The essence of unsupervised learning, where we optimise a neural network for one task while it learns something else that we are actually interested in, can also be thought of as a form of data compression. The complexity of a dataset can be defined as the shortest possible instruction to reproduce that data. While the machine is learning to predict the next word in the text, it manages to significantly reduce the size of the recording of the essence of this data, by managing to store it in the parameter settings or weights of the neural network.

Through generalisation and other similar processes, large AI language models perform a kind of compression of the knowledge they learn from. They condense large amounts of available information through generalisation into a well-structured compact form that takes up much less disk space than the original data. Although it is just a matter of setting parameters in a huge mathematical equation, this process of machine learning can also be seen as a kind of formation of concepts that otherwise form the basis of thought. Although during the learning process the neural network only tries to correctly predict the next word in the large corpus of texts we are training it with, it also creates a kind of conceptual world that remains hidden in its parameters or weights after the learning process is complete. Artificial intelligence does not learn "by memorising", but rather generalises and organises data by developing slightly differently constructed "concepts". In doing so, it creates structures in the hidden (latent) mathematical space of the neural network. It could also be described as a kind of virtual world of ideas, as Plato imagined long ago when he tried to understand how people think and learn.

The next frontier for artificial intelligence

Artificial intelligence currently learns from textual data that contains ideas already organised and articulated through concepts. The conceptualisation, carried out by humans, is thus pre-established. AI synthesises and structures the pre-existing conceptual frameworks found in its training corpus into the mathematical latent space of a neural network.

The next significant breakthrough for AI will be its ability to conceptually structure and thus understand information that has not yet been conceptually processed or organised. This involves deriving insights from raw, unprocessed "sensory" data. This capability is partially demonstrated by AI systems powering autonomous vehicles, which interpret the road vehicle surroundings to ensure safe navigation and decision-making in traffic. However, even in this scenario, the categorisation of data is predetermined.

The potential for AI to devise different, novel, and alternative categorisations of the world opens up a vast array of intriguing and significant philosophical questions and dilemmas. The advancement towards AI that can independently conceptualise and categorise raw data without human intervention will mark a profound shift in our understanding of cognition and the nature of intelligence itself. This evolution challenges us to reconsider the boundaries of AI capabilities and its role in expanding the horizons of human knowledge and perception.

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Bank customers' perception of Artificial Intelligence services and products: The case of neobanks

*Timotej Jagrič, Aljaž Herman and Aleksandra Amon**

The purpose of this study is to determine the factors that stimulate higher acceptance of Artificial Intelligence (AI) in banking products and services, allowing banks to implement them and seize their advantages more intensively. The logistic regression was employed on a sample of neobanking users in Slovenia. We found that demographic and safety/risk factors, as well as the characteristics of banks users exhibit statistically significant impact on the perception of AI in the banking sector. For the Slovenian market, we find smaller aversion towards AI-based solutions. The identified factors can help banks stimulate higher acceptance of AI-based products and services, so they can implement them to a greater extent and create added value.

JEL G2, G21, G23

1. Introduction

Artificial Intelligence (AI) has importantly evolved over the years, representing a transformative force across various industries. From the basic rule-based systems to the machine learning algorithms, AI has progressed, enabling systems to autonomously learn and adapt. In this study, we explore the development of AI as it pertains to the banking sector. The banking sector represents one of the most systemically important sectors in the global economy (Amon and Jagrič, 2023). Through analysing the development of AI within the banking sector, we strive to understand how banking customers currently perceive AI services and which factors can impact customers' perception of the AI-based solutions. Our aim is to identify the determinants of this perception, which will enable banks to communicate with their users in a targeted manner and contribute to higher acceptance of AI-based solutions amongst users. Our study's findings will provide a tool for traditional banks to improve the customers' perception of AI in banking products and services, which will enable them to incorporate AI-based solutions more intensively and exploit the benefits arising from AI.

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The focus of the research work at the Institute of Finance and Artificial Intelligence is on exploiting the opportunities arising from new technologies such as AI. Combined with data analytics and financial expertise, we provide valuable insight into financial markets. One of our research interests is the dynamic banking sector. This paper is a part of our ongoing research into new entrants in the banking sector, neobanks, and new dimensions in this sector deriving from new technologies such as AI.
As AI continues to evolve, its implications for the banking sector become increasingly pertinent. The integration of AI into traditional banking institutions has had far-reaching implications. AI technologies have streamlined processes, improved risk management, and introduced personalised services, enhancing the overall efficiency of financial operations. McKinsey's Annual Global Banking Review found that AI has progressed to new levels and will have even more prominent role. This will likely cause prevalence of tech-fuelled competition, which will be important performance differentiator amongst banking institutions. Based on their findings, taking the opportunities from new technologies such as AI is the number one priority McKinsey advises for banking institutions (Bhattacharyya et al., 2023). Because of that, banks should encourage AI acceptance amongst their customers. The purpose of this study is to identify the factors that can help banks with increasing that acceptance.

We can see that our study is set within the context of the historical and contemporary influence of AI in the banking industry. It is very important for banks to be aware of the determinants of AI's acceptance, which we aim to identify in this study, because higher willingness of clients to use AI solutions means that banks can use AI solutions more intensively. AI solutions exhibits great potential in banking sector; it could improve banks' efficiency in processes, strategies and customers (Fares et al., 2023). AI will significantly improve risk management by better detection of threats (Rahman et al., 2023; Shambira, 2020; Subudhi, 2019), reduce operational costs (Ashta & Herrmann, 2021; Shambira, 2020; Subudhi, 2019), improve customers' satisfaction (Al-Araj et al., 2022; Omoge et al., 2022; Shambira, 2020; Tulcanaza-Prieto et al., 2023) with enabling new, innovative products and increase banks' competitiveness (Dwivedi et al., 2021), especially towards new AI-based entrants neobanks (Hopkinson et al., 2019; Temelkov, 2020). Moreover, Table 1 summarises key present and potential implications of AI based on the findings of global surveys of banks.

A significant case of AI integration in the banking industry is represented by neobanks (Monis and Pai, 2023; Sardar and Anjaria, 2023). McKinsey also states that fintech institutions in the banking sector were amongst the strongest performers in the previous years (Bhattacharyya et al.,

Table 1: Banking institutions' perception of AI implications in the banking sector

Area in the banking sector	AI implications
Customer relationship management (CRM), products and services	According to the study by Finextra and Opentext (2018), AI in customer service and retention will have the largest impact on the value chain. In WEF's study (2020), 64% anticipate implementation of AI to generate new revenue with new products, customer service and client acquisition in the next two years. McKinsey also suggests banks to exploit AI to better their customer service, products and services (Bhattacharyya, 2023).
Security and risk management	Fraud prevention and anti-money laundering were perceived amongst top three most likely areas to be transformed by AI in the next five years. Also, fraud and risk reduction were found to be the most likely business outcomes of AI implementation (Finextra and Opentext, 2018b). WEF found 64% expect AI implementation in risk management in the next two years. Also, they have found risk management to be the area with the highest current AI implementation rate, adopted by 56% (WEF, 2020b). Fraud detection was the area where AI is used the most, according to a study by The Economist (2022), with 57.6% participants using it heavily. Risk assessment ranked fourth with 48.3% using it heavily. McKinsey also found potential for improved technological risk management with the implementation of AI (Bhattacharyya, 2023).
Operations	Compliance was found to be second most likely area to be transformed by AI in the next five years (Finextra and Opentext, 2018b). 64% in WEF's study expect AI implementation in process automation and new products and processes. 52% have already implemented AI for new AI-enabled products and processes (WEF, 2020b). In 2022 study, 53.7% were already using AI heavily in optimising IT operations (The Economist, 2022). McKinsey also sees the potential in processes and platforms automation (Bhattacharyya, 2023).
General usage	In a 2018 study of financial services providers, 45% reported they have already implemented AI technologies (Finextra and Opentext, 2018b). In 2020 study of global financial sector, increasing adoption of AI in this sector was found. 77% anticipated AI to possess high or very high overall significance for their business in the next two years (WEF, 2020b). In 2022 study, 50,2% were already using AI heavily in digital marketing (The Economist, 2022). In the UK, the usage of machine learning in the financial sector is increasing continuously. 72% already reported using or developing machine learning applications (Bank of England, 2022).

Source: Authors' analysis.

2023). Neobanks, a product of the digital revolution, are financial institutions that operate exclusively online, without traditional physical branches. They have gradually evolved from the conventional banking model, simultaneously with the evolution of fintech (Amon et al., 2023). Unlike traditional banks, neobanks streamline their operations and offer wide scope of banking services, such as savings, payments, and loans, through innovative mobile applications and web platforms (Amon and Jagrič, 2022). While the research into crucial drivers for their rapid and successful development is still ongoing, some significant factors of their demand have already been found, such as the number of ATMs in the area, rural population and market return (Jagrič and Amon, 2023). Jagrič et al. (2021) have also found significant external factors that contribute towards the establishment of neobanks in a particular area. Namely, favourable tax policies, high economic freedom, developed technological infrastructure and developed technological financial markets.

Neobanking institutions leverage cutting-edge technology, including AI, to provide agile, customer-centric solutions. Neobanks have been rapidly gaining traction globally in recent years, challenging conventional banking models by offering convenience, lower fees, and enhanced user experiences. Despite their rising popularity, neobanks vary in prevalence across different regions, with some markets experiencing a more significant rate of adoption than others. There is also an important question of sufficient regulation, considering different nature of their business model compared to traditional banking one, as well as new and increasing risks they bring to financial markets.

Because of this swiftly increasing and varying significance of the neobanking business model, we focus this research on the perception of banking and neobanking users in Slovenia. With the econometric analysis, we analyse the effects of various demographic and behavioural characteristics on the bank customers' perception of AI. With this multifaceted approach, we aim to contribute important insight into the dynamic landscape of AI and new banking business models such as neobanks, shedding light on the intricate interplay between customer perceptions, characteristics, demographic factors, and the integration of AI in financial services. This comprehensive study seeks to provide a nuanced understanding of the complex dynamics shaping the intersection of AI and banking, offering valuable insights for industry stakeholders, consumers, and researchers alike.

2. Literature review

Several studies have already been conducted on the connection between AI and the banking industry.

Rahman et al. (2023) studied the significance and issues in acceptance of AI in the Malaysian banking industry, as well as significant determinants for banking customers' adoption of AI through 302 in-depth interviews conducted by banking sector's professionals. The authors found AI to be crucial driver in detecting frauds and managing risks. They identified flawed regulation, data security and privacy, as well as lack of informational-technological infrastructure and skilled employees as main issues now for AI adoption in the banking sector.

Payne et al. (2018) collected data from 218 digital natives. By using multivariate regression and multiple regression, they analysed differential effects of various technological and non-technological factors on the usage of mobile banking and AI-based mobile banking services. Factors such as attitude towards AI, perceived trust, perceived security, the need for service and quality of service were used. Consistent with the previous studies, they have found the concept of relative advantage to have the most effect on the usage of mobile banking, however, not on AI-based mobile banking. This indicates more complexity in customers' perception of AI-based banking services and indicates the need for future research, as we will conduct in this study.

Noreen et al. (2023) studied the acceptance of AI in banking in Asian countries from the customers' perspective. The authors analysed 799 questionnaires and found that factors such as perceived usefulness, subjective norms, awareness, and knowledge of AI have a significant positive relationship with the intention to accept AI in their banking services. As could be expected, perceived risk shows significant negative relationship with intention to adopt AI in one's banking services.

Fares et al. (2023) used a systematic literature review approach, a thematic and content analysis of 44 articles. Based on that, they found a significant role of AI in three areas of the banking industry: customers, processes, and strategies. Moreover, the authors found the need for future research into the adoption of AI, which is the aim of our study.

Lazo and Ebardo (2023) also used the method of a systematic literature review for 35 studies with the aim of studying the barriers and drivers in the adoption of AI in the banking sector. They focused on all major stakeholders' perspective, including banks, their customers, service providers and the regulators. From the banking customers' point of view, the authors found the main factors in AI

adoption in the banking industry include trustworthiness, understanding and familiarity, as well as security and positive feedback of others. However, they found trust and security issues, unavailability, unreliability, and technology downtime to deter banking customers in the other direction, negatively affecting the adoption of AI in banking.
Subudhi (2019) studies banking and AI relationship in India. The author found recent rapid advancements in the field of AI to be significantly influencing traditional banking models, both in positive and negative way. The study found positive effects like reduction of operational risk due to employees' errors, lower costs, scalability, and improvements in data analytics. However, they also found increasing risks, highlighting the cybersecurity risk. This is consistent with findings of previous studies such as Jagrič et al. (2021). Concluding on their research, Subudhi (2019) found that AI in banking bring many opportunities that will have positive effect on banks' customers, as well as employees.
Shambira (2020) studied the adoption of AI in Zimbabwe banking industry, from the perspective of banking institutions. By surveying over 120 bank employees, he found the drivers of AI adoption in the banking sector to be customer satisfaction, better risk management and cost reduction. He also found the barriers to AI adoption in banking, namely lack of knowledge on AI, lack of resources, ethical, privacy and security challenges.
Lee and Chen (2022) also studied the intention of consumers to adopt AI in the banking industry, focusing on the anthropomorphic and intelligent aspects. They developed a research model using a convenience nonprobability sampling approach on 451 survey responses, based on Stimulus-organism-response (SOR) theory. Two AI feature construct as stimuli were included, perceived intelligence and anthropomorphism. The model analysed how intelligence and anthropomorphism influence perceived cost, risk, trust, and other factors of adopting AI-based mobile banking applications. Their results show that intelligence and anthropomorphism increase banking customers' willingness to adopt mobile banking applications through task-technology-fit and trust. Interestingly, both intelligence and anthropomorphism were found to have insignificant effects on perceived, while higher levels of anthropomorphism increase banking customers' perceived cost.

3. Database

Data was gathered via online survey of individuals based in Slovenia during research conducted by Lavrič and Jagrič (2023). Surveying took place on 1ka, an online surveying platform, between 22 March and 7 June 2023. 553 responses were collected, of which 547 were complete and 6 partially complete. In this analysis, we focused on participants that usea neobank or use neobank and a traditional bank. 306 such responses were included in the model.
The survey questionnaire was comprised of 31 questions, divided into three main categories: demographics, characteristics of banking customers and neobanking experience.
The second category included question regarding customers' perception of AI, which represents our dependent variable. This question stated, "I am bothered by the fact that most of neobanking services are conducted by AI". Participants had to rate their agreement with this statement on Likert scale from 1 to 5, where 1 meant "I completely disagree with this statement" and 5 meant "I completely agree with this statement". We have transformed the categorical dependent variable into binary variable exhibiting value 1 where participants rated their agreement to the statement with 3, 4 and 5; and value 0, where participants rated their agreement with 1 and 2.
The responses to the rest of survey questions represent the explanatory variables in our analysis. The explanatory variables included were the following. From the first category; gender, age, education level, employment and marital status, average monthly income, and statistical region of residence. In the second category: type of bank used (traditional bank, neobank or both), number of banks used, most used payment method, way of conducting banking services (physical branch, online banking, or both), informing on bank's stability, main reason for choosing a bank, trust in traditional banks and neobanks. In the third category, explanatory variables are the following: way of learning about neobanks (by friends, colleagues, work, etc.), year of beginning to use a neobank, the purpose of using a neobank, the reason to start using a neobank, the neobank used (N26, Revolut, etc.), type of neobanking account, perception on misuse of personal data, advantages and disadvantages of neobanks, satisfaction with neobanks' speed of transfers and payments, perception of money security, level of provisions and frequency of scams in neobanks.

4. Methodology

Given the dataset characteristics, logistic regression methodology is the best fit for our analysis. It is a widely used method with binary outcome variable, suitable for various types of distributions (Hosmer and Lemeshow, 2000). Its main advantage is not assuming a normal distribution of the dependent variable, however, in the situation with non-linear relationships, its accuracy decreases (Ong et al., 2005).

Logistic regression can be applied with tobit, logit or probit models. Because our dataset consists of binary variables, which are not normally distributed, the binary logit model is the best fit. Moreover, binary logit model is particularly appropriate in modelling a probability model for qualitative binary dependent variables (Gujarati and Porter, 2009), such as ours. The binary logit model is structured as follows (Gujarati and Porter, 2009):

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i = \text{ß}_1 + \text{ß}_n X_i \ldots \text{ß}_n X_n$$

where L is the logarithm of the odds ratio, also known as the logit value, and $Pi/(1\text{-}P1=)$ is the odds ratio.
We applied maximum likelihood estimator, because it is a consistent estimator, distributing normally in large samples with asymptotic estimated standard errors (Gujarati and Porter, 2009; Stock and Watson, 2003).

5. Results
In this section, we provide a comprehensive analysis of the outcomes derived from our binary logistic regression model, specifically tailored for the identification of individuals impacted by the integration of artificial intelligence within neobanking environments.
Even with a relatively small number of observations where individuals express a negative opinion on AI in neobanking (13.4%), we managed to gain valuable insights. Our finalised model, shown in Table 2, comprises eleven statistically significant explanatory variables, belonging to three distinct groups of factors – demographic, bank users' characteristics, and safety/risk factors.
In assessing the goodness of fit for our logistic regression model, we calculated both McFadden's R-squared values and its adjusted measure Nagelkerke's pseudo R-squared that's even more accurate in some cases, such as ours.
The model achieved a McFadden R-squared of 0.31 and a Nagelkerke R-squared of 0.397, indicating a moderate

Table 2: Binary logistic regression model

Variable	Coefficient	p-value	Groups of factors	Influence level	
CONSTANT	-3.921	0.062			Low
AGE _30_50	0.402	0.004	Demographic factors	Min influence through possible customer selection	
EMPLOYMENT	1.923	0.017			
INCOME	-1.084	0.001			
BANKS_OVER_3	0.542	0.099	Bank users' characteristics	Mid influence by bank policy measures	Level of influence
PAY_ SMARTWATCH	-1.164	0.008			
START_USING	-0.793	0.004			
PURPOSE_LOAN	2.051	0.013			
PURPOSE_EXTRA_SERVICES	1.154	0.009			
REASON_OTHER	1.611	0.033			
DATA_MISUSE	0.740	0.004	Safety/risk factors	High influence	High
SCAM	0.673	0.001			

McFadden R-squared	0.310	Mean dependent var	0.134
Nagelkerke R-squared	0.397	S.E. of regression	0.290
Akaike info criterion	0.622	Sum squared resid	24.679
Schwarz criterion	0.768	Log likelihood	-83.181
Hannan-Quinn criter.	0.681	Deviance	166.363
Restr. deviance	241.064	Restr. log likelihood	-120.532
LR statistic	74.702	Avg. log likelihood	-0.272
Prob (LR statistic)	0.000	Total observations	306
H-L Statistic	70.169	Obs with Dep=0	265
Prob. Chi-Square (8)	0.5348	Obs with Dep=1	41

Source: Authors' analysis.

to strong level of explanatory power in capturing variation in individuals' preferences regarding AI integration in neobanking environments.

For additional confirmation we calculated the Hosmer-Lemeshow (H-L) statistic which assesses how well the predicted probabilities from the model match the observed outcomes. Here, the null hypothesis posits a perfect fit of the model to the data, indicating no discrepancy between observed and predicted outcomes across defined groups. Our obtained probability of Chi-Square statistic with 8 degrees of freedom of 53.48% significantly exceeds the conventional significance level of 5%. Consequently, we cannot reject the null hypothesis. Thus, we conclude that the model exhibits adequate fit, as there is insufficient evidence to suggest systematic differences between observed and predicted outcomes within the specified groups.

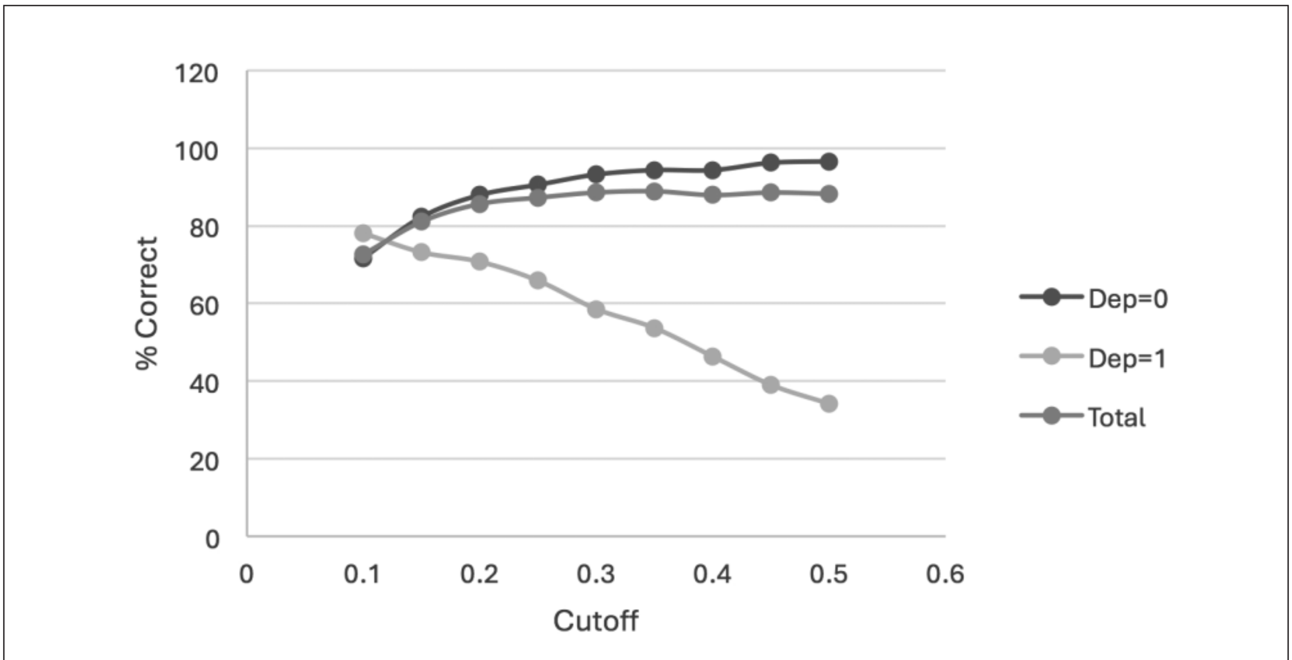
As the last step, we calculated the optimal cutoff value (Figure 1). In logistic regression modelling, the probabilities of category membership are estimated based on predictor variables. After fitting the model, predictions are made by comparing these probabilities to a chosen cutoff value. Observations with estimated probabilities above the cutoff are classified as one category, while those below are classified as the other. The selection of the cutoff influences the model's sensitivity and specificity, and adjusting it allows for balancing these performance measures. Our optimal cutoff value, determined to be 0.15, ensures that approximately 81.05% of total cases are correctly classified.

Interpreting the coefficients from our binary logit model, where 1 signifies a negative opinion about AI in neobanking and 0 indicates a positive opinion, reveals insightful patterns regarding individual group of factors.

Demographic factors such as age between 30 and 50, employment status (full-time, part-time and self-employed), and lower income levels are associated with a more negative opinion towards AI integration in neobanking. This suggests that older, employed individuals with lower incomes tend to hold a more negative view of AI integration in neobanking, possibly due to familiarity with traditional banking, scepticism towards new technologies, and concerns about accessibility and trust. Consistently, research from the Slovenian Statistical Office (SURS) into online financial service activities shows that the majority of individuals that conducted financial services via internet in the past three months in 2023, are between 35 and 44 years old (SURS, 2024b), also indicating a prevalent scepticism among older individuals. These findings are also consistent with previous findings such as Payne et al. (2018), Noreen et al. (2023) and Lazo and Ebardo (2023).

Regarding variables that describe bank users' characteristics, we find that those that started using a neobank earlier are less inclined towards a negative perception of AI in banking. Such individuals are most likely technological pioneers or technology is amongst their interests and skills. We can also assume that the decision of individuals who started using neobanks later was also influenced by the COVID-19 pandemic and other external factors, because of which their affinity towards neobanks is different.

Figure 1: Optimal cut-off value for our model.



Source: Authors' analysis.

Moreover, individuals who engage with multiple banks (3 or more) and do not prefer payments with their smartwatches tend to hold a more negative opinion towards AI-based solutions. The same is valid for individuals who use neobanks for taking a loan, accessing additional services not offered by traditional banks, and users with alternative reasons for neobanking usage – reasons other than accessibility, popularity, and low costs of running, transferring, and using a credit card. Those users tend to hold a negative opinion towards AI integration in neobanking. The negative belief of users with those characteristics could be due to concerns about the complexity of services, potential impacts on personalised experiences, and uncertainties regarding data privacy and security.

Regarding those reasons, variables that exemplify safety and risk considerations also play a significant role. Concerns regarding data misuse and scams are associated with a more negative opinion towards AI in neobanking.

Initially, the bank's influence on demographic factors is rather low. One possible method for attracting specific customer groups is by organizing personalised activities or events aimed at these particular demographics. Conversely, over the second group, encompassing the characteristics of bank users, the bank may have higher level of influence. Notably, the integration of novel technologies emerges as a significant determinant within this category. For instance, our analysis reveals a notably favourable perception among individuals utilising smartwatch-based payment methods towards the incorporation of artificial intelligence functionalities within neobanks. However, the most substantial level of influence that banks can have is over the third group, characterized by safety and risk-related attributes. It is within this domain that the potential to expand users' perception of integration of AI in neobanks is most asserted.

These findings also raise the question of whether such a perception is also present in other segments of the Slovenian market. The Slovenian Statistical Office (SURS) studied enterprises' perception of AI and found prevalently negative perception towards AI-based solutions. Out of all surveyed enterprises in 2023, 85,79% do not use AI and less than 7% have even considered the possibility of using it. The main reasons for not using it are high costs, lack of knowledge, incompatibility with current systems, unavailability of required data, privacy concerns, unclear legal liability and ethical concerns (SURS, 2024a). While more thorough study of the Slovenian enterprises' perception is required for representative comparison, our findings suggest more favourable perception of AI-based solutions amongst individuals than amongst enterprises, according to the SURS's findings.

6. Concluding remarks

To conclude, our results shed light on distinguishing patterns within various demographic and banking users' characteristics. The results show that specific demographic and safety/risk factors, as well as bank users' characteristics, can impact whether the users are more or less inclined towards AI-based banking products and services. Our findings are consistent not only with findings of the Slovenian Statistical Office, but also with other studies of AI perception in banking, despite being conducted in a much smaller, and because of that, peculiar market. This interesting result indicates that the perception towards AI services and products may be a common characteristic of banking users globally.

Furthermore, characteristics of bank users like engaging with multiple banks, usage of more technically advanced payment methods and the duration of using neobanks, also significantly influence negative perception of AI in the banking sector. Individuals that utilise neobanks for specific purposes also lean towards a negative perception of AI. These findings resonate with existing literature and raise concerns about service complexity, personalised experiences and data security that need to be further addressed given the increasing role of neobanks in the financial ecosystem. Safety and risk considerations, particularly concerns about data misuse and scams, were established to be significant factors contributing to a negative opinion towards AI perception. This also aligns with the broader perspective of Slovenian enterprises, as majority of them expressed reluctance toward AI-based solutions in their operations due to various reasons, including high costs, lack of knowledge, and data privacy risk. We are also conducting an international study that will test to which degree are these characteristics consistent with characteristics of other markets.

Our findings suggest that while demographic factors play a role, the impact of banking institutions on the perception of AI is also very significant. Increasing the level of positive perception towards AI-based solution in banking should be a priority. Our findings present a helpful tool for that. For instance, the integration of modern technologies, such as more technically advanced payment methods, present an opportunity to positively influence perceptions of AI in the banking sector. Moreover, a significant potential for expanding positive perception of AI in banking lies in addressing safety risks and emphasizing the significance of ensuring data security and privacy in the banking sector amongst many innovations.

References

Al-Araj, R., Haddad, H., Shehadeh, M., Hasan, E., & Nawaiseh, M. Y. (2022). The Effect of Artificial Intelligence on Service Quality and Customer Satisfaction in Jordanian Banking Sector. *WSEAS Transactions on Business and Economics*, *19*, 1929–1947. https://doi.org/10.37394/23207.2022.19.173

Amon, A., Bobek, S., Jagrič, T., & Sternad Zabukovšek, S. (2023). Analiza digitalne transformacije poslovnih modelov bank z modelom Canvas. *Bančni Vestnik*, *72*(1/2), 19–26. https://bv.zbs-giz.si/bancni-vestnik/e-arhiv/2023-1-2/analiza-digitalne-transformacije-poslovnih-modelov-bank-z-modelom-canvas

Amon, A., & Jagrič, T. (2022). Challenges and opportunities of a neobanking phenomenon : a case study of N26. In *Challenges of the financial institutions in the digital and green transformation of economic ecosystem* (pp. 49–67). Pearson.

Amon, A., & Jagrič, T. (2023). BLOCKCHAIN TECHNOLOGY IN BANKING AS A TOOL TOWARDS THE SDGs. *Strengthening Resilience by Sustainable Economy and Business - towards the SDGs, FEB International Scientific Conference 2023*.

Ashta, A., & Herrmann, H. (2021). Artificial intelligence and fintech: An overview of opportunities and risks for banking, investments, and microfinance. *Strategic Change*, *30*(3), 211–222. https://doi.org/10.1002/jsc.2404

Bank of England. (2022). *Machine learning in UK financial services*. https://www.bankofengland.co.uk/report/2022/machine-learning-in-uk-financial-services

Bhattacharyya, D. Dietz, M., Edlich, A., Höll, R., Mehta, A., Weintraub, B., Windhagen, E. (2023). *The Global Banking Annual Review 2023*.

Dwivedi, P., Alabdooli, J. I., & Dwivedi, R. (2021). Role of FinTech Adoption for Competitiveness and Performance of the Bank: A Study of Banking Industry in UAE. *International Journal of Global Business and Competitiveness*, *16*(2), 130–138. https://doi.org/10.1007/s42943-021-00033-9

Fares, O. H., Butt, I., & Lee, S. H. M. (2023). Utilization of artificial intelligence in the banking sector: a systematic literature review. *Journal of Financial Services Marketing*, *28*(4), 835–852. https://doi.org/10.1057/s41264-022-00176-7

Finextra and Opentext. (2018a). *AI in Financial Services: Next Steps to Realising the Potential*. https://www.opentext.com/file_source/OpenText/en_US/PDF/wp-ai-financial-services-next-steps-to-realising-the-potential-en.pdf

Finextra and Opentext. (2018b). *AI in Financial Services: Next Steps to Realising the Potential*.

Gujarati, D. N., & Porter, D. C. (2009). *Basic econometrics* (5th ed.). McGraw-Hill Irwin.

Hopkinson, G., Klarova, D., Turcan, R. V., & Gulieva, V. (2019). How Neobanks' Business Models challenge Traditional Banks. *International Business Centre at Aalborg University*, *August*, 3. https://www.researchgate.net/publication/335205599_How_neobanks'_business_models_challenge_traditional_banks

Hosmer, D. W., & Lemeshow, S. (2000). *Applied Logistic Regression*. John Wiley & Sons, Inc.

Jagrič, T., & Amon, A. (2023). Key factors of neobanking's occurrence. *Journal of Innovative Business and Management*. https://doi.org/10.32015/JIBM.2023.15.1.1

Jagrič, T., Fister, D., Amon, A., & Jagrič, V. (2021). Neobanks - eagles or pigeons of banking ecosystems? *Bančni Vestnik*, *70*(11), 50–57. https://bv.zbs-giz.si/bancni-vestnik/docs/default-source/special-issues-of-bancni-vestnik-in-english/bancni-vestnik-11-21-web2.pdf?sfvrsn=74e86c1_2

Lavrič, Š., & Jagrič, T. (2023). *Analiza poslovanja neobank*. Faculty of Economics and Business, University of Maribor.

Lazo, M. P., & Ebardo, R. A. (2023). Artificial Intelligence Adoption in the Banking Industry: Current State and Future Prospects. *JIM*, *11*(3), 54–74. https://doi.org/https://doi.org/10.24840/218 3-0606_011.003_0003

Lee, J. C., & Chen, X. (2022). Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: the intelligent and anthropomorphic perspectives. *International Journal of Bank Marketing*, *40*(4), 631–658. https://doi.org/10.1108/IJBM-08-2021-0394

Manser Payne, E., Peltier, J. W., & Barger, V. A. (2018). Mobile banking and AI-enabled mobile banking: The differential effects of technological and non-technological factors on digital natives' perceptions and behavior. *Journal of Research in Interactive Marketing*, *12*(3), 328–346. https://doi.org/10.1108/JRIM-07-2018-0087

Monis, E., & Pai, R. (2023). Neo Banks: A Paradigm Shift in Banking. *International Journal of Case Studies in Business, IT, and Education*, 318–332. https://doi.org/10.47992/ijcsbe.2581.6942.0275

Noreen, U., Shafique, A., Ahmed, Z., & Ashfaq, M. (2023). Banking 4.0: Artificial Intelligence (AI) in Banking Industry & Consumer's Perspective. *Sustainability (Switzerland)*, *15*(4). https://doi.org/10.3390/su15043682

Omoge, A. P., Gala, P., & Horky, A. (2022). Disruptive technology and AI in the banking industry of an emerging market. *International Journal of Bank Marketing*, *40*(6), 1217–1247. https://doi.org/10.1108/IJBM-09-2021-0403

Ong, C. S., Huang, J. J., & Tzeng, G. H. (2005). Building credit scoring models using genetic programming. *Expert Systems with Applications*, *29*(1), 41–47. https://doi.org/10.1016/j.eswa.2005.01.003

Rahman, M., Ming, T. H., Baigh, T. A., & Sarker, M. (2023). Adoption of artificial intelligence in banking services: an empirical analysis. *International Journal of Emerging Markets*, *18*(10), 4270–4300. https://doi.org/10.1108/IJOEM-06-2020-0724

Sardar, S., & Anjaria, K. (2023). the Future of Banking: How Neo Banks Are Changing the Industry. *International Journal of Management, Public Policy and Research*, 2(2), 32–41. https://doi.org/10.55829/ijmpr.v2i2.153

Shambira, L. (2020). Exploring the Adoption of Artificial Intelligence in the Zimbabwe Banking Sector. *European Journal of Social Sciences Studies*, *5*(6). https://doi.org/10.46827/ejsss.v5i6.942

Stock, J. H., & Watson, M. W. (2003). *Introduction to Econometrics*. Pearson.

Subudhi, S. (2019). Banking on Artificial Intelligence: Opportunities & Challenges for Banks in India. *International Journal of Research in Commerce, Economics & Management*, *9*(1041), 1–5. https://ijrcm.org.in/article_info.php?article_id=9049

SURS. (2024a). *Število podjetij po razlogih za neuporabo tehnologij umetne inteligence ob pretehtanju možnosti uporabe in velikostnem razredu, Slovenija, večletno*. SiStat Database. https://pxweb.stat.si/SiStatData/pxweb/sl/Data/Data/2984703S.px/table/tableViewLayout2/

SURS. (2024b). *Število posameznikov po izvedbi finančnih aktivnosti prek interneta v zadnjih 3 mesecih za zasebne namene, starostni skupini in spolu, Slovenija, letno*. SiStat Database. https://pxweb.stat.si/SiStatData/pxweb/sl/Data/-/2978605S.px/table/tableViewLayout2/

Temelkov, Z. (2020). *Overview of Neobanks Model and Its Implications for Traditional Banking*. 156–165. https://doi.org/10.46763/yfnts2031156t

The Economist Intelligence Unit Limited. (2022a). *Banking on a game-changer: AI in financial services*. https://impact.economist.com/perspectives/sites/default/files/aiinfinancialservices.pdf

The Economist Intelligence Unit Limited. (2022b). *Banking on a game-changer: AI in financial services*.

Tulcanaza-Prieto, A. B., Cortez-Ordoñez, A., & Lee, C. W. (2023). Influence of Customer Perception Factors on AI-Enabled Customer Experience in the Ecuadorian Banking Environment. *Sustainability (Switzerland)*, *15*(16). https://doi.org/10.3390/su151612441

WEF. (2020a). *Transforming Paradigms: A Global AI in Financial Services Survey*. World Economic Forum and Cambridge Centre for Alternative Finance, University of Cambridge. https://www3.weforum.org/docs/WEF_AI_in_Financial_Services_Survey.pdf

WEF. (2020b). *Transforming Paradigms: A Global AI in Financial Services Survey*. World Economic Forum and Cambridge Centre for Alternative Finance, University of Cambridge.

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AI-based business valuation solution for the banking industry

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In this paper, we present a novel and comprehensive methodology for business valuation. Valuation is a pivotal aspect of corporate finance, influencing decisions in areas like mergers and acquisitions, and portfolio management. However, the subjectivity and complexity of valuation methods highlight the need for innovative approaches. Our methodology leverages artificial intelligence, specifically advanced machine learning algorithms like Large Language Model Classifier (LLMC), to enhance the accuracy and depth of industry classification and business valuation processes. We demonstrate the effectiveness of our approach through a hierarchical framework that integrates industry classification insights from LLMC with a subsequent mechanism utilizing Neural Network Model based on Unsupervised Learning (NNMUL) to identify similar industry peers. Comparative analysis with traditional linear regression methods showcases the exceptional superiority of our AI-driven approach. Moreover, we outline ongoing research exploring the cyclical regularities of multipliers, aiming to provide deeper insights into factors influencing business valuations and economic cycles.

JEL C45, G21, G32

1. Introduction

The Institute of Finance and Artificial Intelligence is at the forefront of addressing complex challenges at the intersection of finance and cutting-edge technologies. Our institute specializes in leveraging artificial intelligence to solve intricate financial problems, offering innovative solutions that enhance decision-making processes. By combining advanced machine learning algorithms, data analytics, and financial expertise, we provide insights into market trends, risk management, and other financial metrics. One of our key focus areas is company valuation, where we pioneer new approaches to assess the worth of businesses. In this paper, we introduce a concept that we are developing, shedding light on a novel and comprehensive methodology for business.

Referred by Kulwizira Lukanima (2023), valuation is a pivotal topic in the business realm, crucial to areas like corporate finance, mergers and acquisitions, and portfolio management. While commonly mentioned, the nuances of valuation are often not well understood. Valuation methods vary, leading to different analysts assigning different values to the same entity, influenced by their chosen approach and the specific purpose of the valuation. Consequently, the perceived

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value of an asset differs based on the methodology applied. This diversity in valuation approaches underscores its complexity and subjective nature.

In the realm of scientific literature, Kazlauskiene & Christauskas (2008) wrote that value is identified as the most comprehensive and precise indicator of a business's condition, reflecting shifts in both its internal dynamics and the external environment. In the dynamic landscape characterised by the inevitability of risk and uncertainty in the enterprise's forecasting process, the business value is susceptible to significant fluctuations attributed to the changing landscape of various drivers. While risk and uncertainty prompt a forward-thinking approach, considering future scenarios and encompassing the full spectrum of value dimensions, the wide-ranging fluctuation of business value poses a challenge in arriving at a conclusive assessment. Given that business value is intricately tied to influencing drivers, there is a pressing need for an analysis of these drivers to comprehend their impact.

Wilimowska & Krzysztoszek (2013) continue that the dynamic shifts in the business environment and internal factors of a company exert a continuous influence on the drivers of the company's value. Traditional methods prove insufficient in adequately capturing the nuances of the valuation process. The utilisation of IT technologies, specifically neural network technologies, presents an avenue for enabling dynamic valuation of parameters. Value-based management necessitates tools capable of not only describing factors in a static sense but also accounting for their dynamic nature, thereby facilitating interactive valuation. Through the application of unconventional modelling methods tailored to these intricate processes, managers gain the capability to create, monitor, and exert control over the valuation process.

As well, corporate valuation is in a strong relationship with a bank industry. It is pivotal for banks for several reasons. First, accurate valuation aids in risk assessment, as highlighted by Koller et al. (2010), indicating how banks evaluate the risk associated with lending and investment decisions. Second, it is essential for regulatory compliance, as noted by Laux & Leuz (2010), which discusses the importance of valuation in adhering to regulatory requirements, particularly in the context of the financial crisis. Third, corporate valuation helps banks in portfolio management, as described by (Damodaran, 2001), where he emphasises its role in managing and balancing investment portfolios effectively.

2. Overview of the advanced methods for business valuation

Reis et al. (2020) mentioned that the forthcoming transformation of the business landscape through machine learning (ML) is widely anticipated. While several successful ML case studies have emerged, the mechanisms through which organisations can realise business value (BV) from ML remain largely unexplored.

Koklev (2023) has worked on the requirements for employing machine learning in business valuation. He came to the conclusion that incorporating statistical methods into mass valuation addresses the inherent limitations of the discounted cash flow (DCF) method, rendering it unsuitable for achieving an unbiased business valuation. By focusing on forecasting an estimation for the market capitalisation of the company rather than determining and interpreting parameters, machine learning (ML) methods prove to be well-suited for company valuation. ML techniques excel in simulating the intricate process of enterprise value creation, thanks to their capacity to capture complex, non-linear relationships between financial reporting data and market capitalisation. Moreover, existing methods for assessing the significance of indicators play a crucial role in resolving the black box problem, enabling the derivation of interpretable models.

In the paper Reis et al. (2020) propose a conceptual model grounded in the dynamic capabilities theory, aiming to unveil the fundamental drivers of ML-derived business value concerning both financial and strategic performance. The validity of their model was assessed through a survey involving 319 corporations. The results indicate that ML utilisation, big data analytics maturity, platform maturity, top management support, and process complexity are, to some extent, influential factors for ML BV. Additionally, platform maturity serves as a moderator, exerting a certain degree of influence between ML use and ML BV, as well as between big data analytics maturity and ML BV.

Wilimowska & Krzysztoszek (2013) describe the concept of deploying neural networks for company valuation. Based on the valuation method, researchers examine value drivers that impact assets, income, or both. They note that the mixed valuation method primarily considers two groups of drivers: asset and income. Describing a straightforward model of company value, they present the following relationship as:

$$V = F(V_A) + F(V_I) = F(x_1, x_2, \dots, x_n) + F(y_1, y_2, \dots, y_m),$$

where variables $x_1, x_2, \dots, x_n$, and $y_1, y_2, \dots, y_n$ represent value drivers, sequentially influencing the explained variables V_A and V_I, where V_A is determined as net assets value and V_I as discounted cash flows. To initiate the mixed valuation method, an initial forecast of assets value and income value must be conducted.

Another research was made, where (Dhochak, Pahal and Doliya, 2022) focused on a pre-money value of startups. They used a dataset comprising 757 Indian startup deals from January 2012 to December 2019 to construct a predictive model employing the artificial neural network (ANN) technique, a deep learning approach, for forecasting startup valuations. Besides the ANN-based model for the evaluation of startups, a comparative analysis is conducted with a linear classifier and linear regression. The findings suggest that the application of the ANN model can serve as a supplementary means for predicting pre-money valuation, potentially even as an alternative to traditional valuation models, depending on its adaptability and accuracy.

3. Inner workings of our AI solution

The ongoing digital transformation in the corporate landscape is opening doors for the implementation of artificial intelligence, particularly machine learning, within companies. It is evident that traditional methods of business valuation persist, with artificial intelligence poised to play a supportive role in the realms of data collection and preparation. Looking ahead, artificial intelligence is anticipated to play a substantial role in enhancing the process of company valuation (Holder, Gruenbichler and Grbenic, 2022).

Modelling by using AI typically involves searching for the function transformations from inputs to outputs. The significant advantage of AI lies in the automatic discovery of such transformations through an iterative process. Initially, the output error between the actual and desired values is large, but through the tuning (statistical learning) procedure, which backpropagates the error back to the model, it is reduced accordingly. The error signal thus serves as a self-correcting mechanism, further reducing the error (Kingma and Ba, 2017). This represents a case of supervised learning. Examples of supervised learning include traditional artificial multilayer perceptron neural networks, recurrent neural networks, and classic machine learning techniques. Ones are able to handle time series, sequences and voices (Hochreiter and Schmidhuber, 1997), others images, videos and graphs (Gu *et al.*, 2018). Common tasks addressed using supervised learning include classification and regression. Classification outputs probability classes, while regression predicts numbers, most often real-valued.

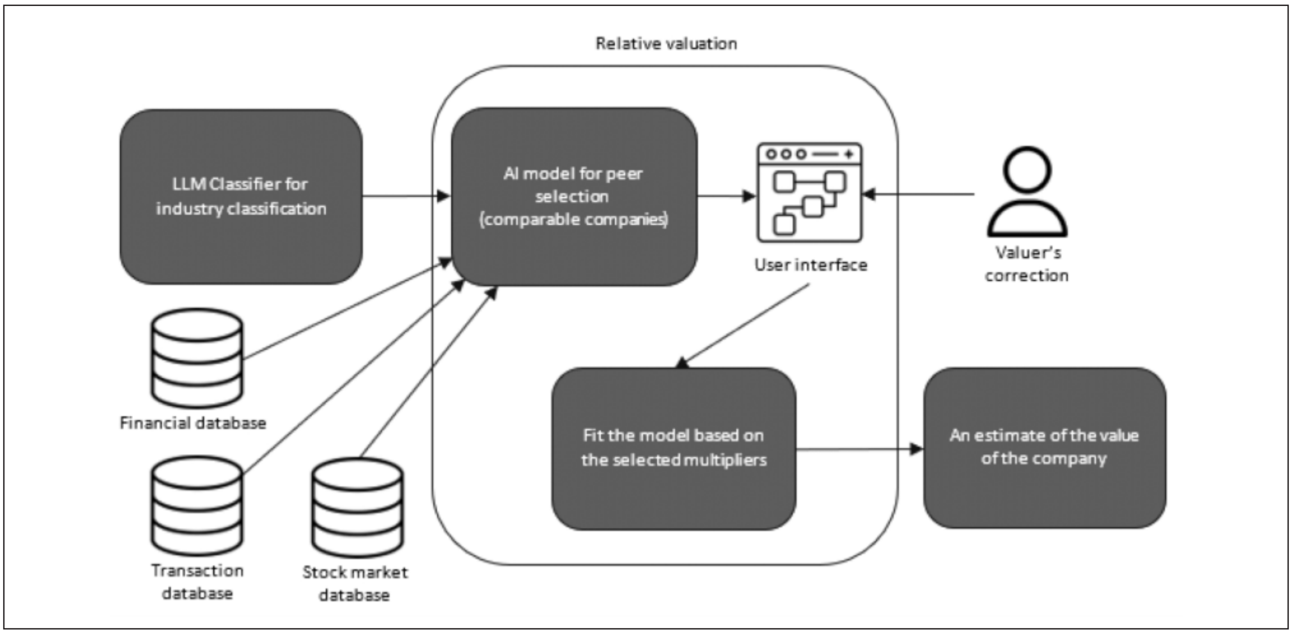
On the other hand, unsupervised learning methods also exist. Here, no optimal model (transformation) is searched for, and no error-correcting signal is calculated. Unsupervised learning is primarily used to search for similar patterns between data samples. Such a task is called clustering. Additionally, dimensionality reduction is a common task of unsupervised learning, where a high-dimensional domain is projected into a lower-dimensional domain. In practice, this means that maximal information is attempted to be preserved using fewer attributes.

Linear regression (LR) algorithm, either (1) famous Gaussian least squares or (2) maximum likelihood, often acts as a fundamental benchmark in statistical learning, especially due to its simplicity and robustness. It is low resource-intensive and offers many improvements and supplements, such as regularization techniques (Lasso, Ridge). It is also well transparent which means that functioning of the LR can be easily statistically checked and corrected for any non-desired deviations. AI-driven methods on the other hand are difficult to interpret and frequently impossible to understand, also due to their inherent complexity.

Feature selection (FS) algorithms are a kind of dimensionality reduction methods (Witten and Tibshirani, 2010). Typically, the AI-driven methods are able to do that by default, the LR on the other hand needs a separate treatment. Two distinctive FS methods have been applied prior to the LR. First FS used is the conventional F-test, which ranks features according to their importance. The higher the importance, the higher the chance that a given variable will be selected. First few most important variables are selected. The second FS algorithm utilized is the Neighborhood Component Analysis (NCA). Contrary to the F-test, the NCA is the non-parametric FS method. In general, two different NCA algorithms exist, one for classification, the other for regression (we have selected the latter one). NCA is an iterative method that during the optimization process maximises the likelihood criterion. Next, a number of most optimal variables, with respect to the graphical plot of importances, is selected manually.

In conjunction with the aforementioned advancements, our institute is actively developing a pioneering concept for business valuation – a hierarchical approach that strategically leverages artificial intelligence (Ill. 1). Hereinafter we describe the mechanisms that function internally to a system and are not outwardly visible. The initial phase involves the utilisation of a model for accurate business classification into industry categories. The output of this classification model serves as valuable input data for a subsequent model designed specifically for business valuation. This hierarchical framework capitalizes on the insights derived from the industry classification, enhancing the precision and depth of the business valuation model. The integration of these two models not only refines the evaluation process but also underscores the synergy between accurate indus-

Illustration 1 - Hierarchical concept for business valuation (conceptually upgraded diagram from (Jagrič and Herman, 2024)).



try classification and robust business valuation, ultimately contributing to a more comprehensive and nuanced approach to assessing company worth.

For our industry classification component, we used BERT that stands for Bidirectional Encoder Representations from Transformers (Devlin *et al.*, 2019), a state-of-the-art natural language processing model, that has revolutionized various text-based tasks with its ability to capture intricate linguistic patterns and contextual nuances. By adapting this powerful architecture to the domain of industry classification, we have achieved a dynamic and adaptive system capable of discerning subtle industry distinctions with remarkable accuracy.

The transformer architecture introduced by Vaswani et al. (2023), forms the foundation of our Large Language Model Classifier (LLMC), replacing traditional recurrent layers with self-attention mechanisms and feed-forward neural networks (FFNN). This design enhances parallel computation and efficient learning. LLMC leverages the transformer's attention mechanism to understand contextual relationships within text, employing an encoder-decoder structure. However, LLMC primarily focuses on language modelling and utilises only the encoder module to process input text, emphasising its ability to capture nuanced semantic information crucial for various natural language processing tasks.

Within each layer of the encoder, self-attention mechanisms enable LLMC to weigh the importance of different words in the input sequence, capturing dependencies and relationships across the entire text (Vaswani *et al.*, 2023). This mechanism enables LLMC to discern subtle semantic cues and contextual nuances, facilitating more nuanced and accurate industry classifications. Additionally, the feed-forward neural networks within each layer further refine the representations, capturing higher-order interactions and non-linearities within the data (Logeswaran and Lee, 2018).

The classification process begins with the input of textual data, in our case company descriptions. As its name already suggest, the model handles input data in bidirectional way – from left to right and right to left (Seo *et al.*, 2018). This input is tokenised and fed into the fine-tuned LLMC, which accurately encodes the textual information into high-dimensional representations, capturing both local and global contextual information (Devlin *et al.*, 2019).

The fine-tuned LLMC (Haidar and Bertholom, 2023) excels in this task due to its ability to understand the semantics of the input text and discern subtle semantic cues indicative of specific industries. Unlike traditional rule-based or shallow learning approaches, LLMC leverages deep contextual embeddings to uncover complex relationships and nuances within the data, resulting in more nuanced and accurate classifications (Garrido-Merchan, Gozalo-Brizuela and Gonzalez-Carvajal, 2023).

Moreover, our fine-tuned LLMC is adaptable and scalable, capable of accommodating new industry trends, emerging sectors, and evolving linguistic patterns. Through continuous learning and refinement, the model can stay up with the changes in the business landscape, ensuring that our industry classifications remain up-to-date and relevant. There is a

more detailed presentation of fine-tuned LLMC described in the paper by Jagrič and Herman (2024).
In the end, our LLMC shows a praiseworthy level of accuracy in classifying business descriptions for industry classification, with accuracy ranging from 83.5% to 92.6%. The distribution of accurate predictions is relatively balanced across classes, addressing the challenge of favouring certain classes. The variation in accuracy across classes reflects the complexity and distinctiveness of textual data in each category. Overall, the model demonstrates effective learning and generalisation capabilities across a range of industry classes, with high accuracy in certain classes and moderate to high accuracy in others which is shown in the paper written by Jagrič and Herman (2024).
Within the internal mechanisms of our system, which operates without external visibility, the outcomes generated by our LLMC for industry classification serve, besides other sources of data, as pivotal input data for our subsequent process utilising NNMUL which is the first step of our relative valuation model. This sophisticated technique is employed to discern the most closely related industry peers based on financial, transaction, and stock market data where the classifications provided by the LLMC model serves as added value.
To test the efficiency of unsupervised learning for finding most similar industry peers, we have employed a benchmark case study. The motivation of the case study was to select most comparable transactions for the given data sample and calculate their mean value of the five types of financial multipliers. As a benchmark, the LR method was utilized, considering FS method – variables that were selected by the F-test FS. As an AI-backed method, a NNMUL was utilised (Kohonen, 1995). Same information was given to both methods to make predictions and their results have been compared. The number of comparable transactions for the LR methods was set to be between , while the AI-driven selected the optimal number of comparable transactions by itself. The whole database consisted of almost 41,500 data samples. Experiments have been done in the MATLAB/Simulink platform. Certain percentage of these were devoted to training and validation, the rest of them were left for testing purposes. The calculated mean value of multiplier was then compared with the actual multiplier value, caring that none of the models were given any information about the multiplier values. A Euclidean distance was measured as an error indicator and a simple decision is taken upon, as stated by following equation:

$$\begin{cases} E(NNMUL^{est.}) < E(LR^{est.}) & NNMUL^{sup.} = NNMUL^{sup.} + 1 \\ otherwise & LR^{sup.} = LR^{sup.} + 1 \end{cases}$$

Here, the $E()$ represents the Euclidean distance calculation and $NNMUL^{est.}$, $LR^{est.}$ represent the estimated multiplier values from NNMUL and from LR. The decision to augment corresponding NNMUL or LR number of superior answers, i.e., $NNMUL^{sup.}$ and $LR^{sup.}$ by 1 is executed (initial value equal $NNMUL^{sup.}$=$LR^{sup.}$=0). Complete testing set is run through and fundamental statistics with indicators is run on such obtained results.
As mentioned, there were five different multipliers to be calculated by the (1) proposed algorithm and (2) the simple LR as a benchmark. Those multipliers were represented by ratios between (1) EPV (enterprise value) and sales, (2) EPV and EBITDA (earnings before interest, taxes, depreciation, and amortisation), (3) EPV and EBIT (earnings before interest and taxes), (4) EPV and total assets, and (5) EQV (earnings quality valuation) and EBT (earnings before taxes). The testing size (number of samples) due to the unavailability of some multipliers varied. Moreover, the results are based on out of sample data, i.e., data that was not used to train the model.
Based on the FS method where variables were selected by the F-test FS, $NNMUL^{sup.}$ method exhibits as a superior tool compared to $LR^{sup.}$. Only a very low percentage of individual company valuation values, such as 11-21%, are superior calculated by LR, including only F-test variables. In greater detail, those values calculated by NNMUL exceeded by a share of 89% for the multiplier (1), 83% for (2), 79% for (3), 89% for (4), and 84% for the multiplier (5).
In summary, we have employed a comparative analysis between the benchmark (linear regression) and an AI method. Superiority of the AI method was exceptional. There are certain tasks that AI can do much better compared to the classic, traditional methods. Some tasks are impossible to do with the classic methods. AI field is strongly evolving with number of applications drastically rising. However, one must not forget about the lack of transparency and interpretability of such models. Hence, especially for the risk-bearing applications, one must implement such methods with caution. It seems that the benefit of the AI, which is self-teaching, can quickly become a drawback if methods are not utilised properly.
Before the final step of our relative valuation model, we combined those selected multipliers from NNMUL with valuer's corrections. This ensures that our selected features and the expert's opinion are aligned in the selection of these multipliers, thus ensuring a higher level of accuracy. As the last part of the relative valuation model, we fitted the model based on those selected multipliers to get the final value of the enterprise.

4. Conclusion

Our solution for business valuation stands out for its innovative hierarchical approach, seamlessly integrating advanced artificial intelligence (AI) mechanisms to enhance accuracy and depth. At its core is the utilisation of LLMC, a cutting-edge natural language processing model renowned for its ability to capture intricate linguistic patterns and contextual nuances. Through LLMC's dynamic and adaptable framework, we ensure our industry classifications remain up-to-date and relevant, even in the face of evolving trends and linguistic patterns. This adaptability translates into exceptional accuracy, with our LLMC consistently achieving high accuracy levels ranging from 83.5% to 92.6% across 13 industry categories. The balanced distribution of accurate predictions underscores the robustness of our approach, avoiding biases towards specific industry classes and ensuring comprehensive coverage across diverse sectors.

Furthermore, our solution goes beyond mere classification by seamlessly integrating the outputs of our LLMC model into a subsequent mechanism using the Neural Network Model based on the Unsupervised Learning (NNMUL). This sophisticated integration adds value by efficiently identifying the most similar industry peers, enhancing the precision and depth of our business valuation process. A benchmark study comparing our AI-driven approach with traditional linear regression methods further highlights the exceptional superiority of our method, particularly in tasks where AI excels. However, we acknowledge the importance of caution in implementing AI methods, particularly in risk-bearing applications, due to their inherent lack of transparency and interpretability.

The possibilities of extensions to our current solution involves exploring avenues for further enhancing the sophistication and effectiveness of our approach to business valuation. One potential extension involves optimizing the number of industry classes and fine-tuning the LLMC model accordingly to improve the accuracy and depth of our industry classification and valuation processes. While LLMC has demonstrated effectiveness in capturing linguistic nuances, fine-tuning it for an optimal number of industry classes can further refine its added value towards an integrated solution. This approach leverages the flexibility of LLMC to adapt to the nuances of a tailored classification scheme, potentially yielding more precise industry classifications and consequently enhancing the quality of business valuations.

Furthermore, an extension of our solution could involve incorporating mechanisms for searching additional information that may have informative value for the evaluation process. While our current approach relies primarily on textual data provided by company descriptions and external data sources such as financial, transaction, and stock market data, our solution could benefit from incorporating various other sources of information to enrich the evaluation process. This includes competitor analysis, which provides benchmarks and insights into industry dynamics and competitive positioning, as well as macroeconomic indicators to understand broader economic trends impacting industries. Monitoring regulatory changes relevant to specific industries, analysing consumer behaviour data for market demand insights, and tracking technological advancements and disruptive trends within industries are also crucial.

We are currently conducting a study aimed at exploring and explaining the cyclical regularities of multipliers. This research seeks to uncover patterns and trends in the fluctuation of multipliers over time, shedding light on the cyclical nature of these metrics in various economic contexts. Through rigorous analysis and interpretation, we aim to deliver valuable perceptions into the underlying features driving these cyclical regularities, ultimately contributing to a deeper understanding of the dynamics influencing business valuations and economic cycles.

References

Damodaran, A. (2001) *The dark side of valuation: Valuing old tech, new tech, and new economy companies*. Available at: https://books.google.com/books?hl=sl&lr=&id=ddcjhQX9fX8C&oi=fnd&pg=PR15&dq=damodaran+2018+The+Dark+Side+of+Valuation&ots=hi0GyunIOB&sig=uasIl_Lq3Tuffy7ywjHOQ68UhLM.

Devlin, J. *et al.* (2019) 'BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding', p. 16. Available at: https://doi.org/https://doi.org/10.48550/arXiv.1810.04805.

Dhochak, M., Pahal, S. and Doliya, P. (2022) 'Predicting the Startup Valuation: A deep learning approach', *Venture Capital* [Preprint]. Available at: https://doi.org/10.1080/13691066.2022.2161968.

Garrido-Merchan, E.C., Gozalo-Brizuela, R. and Gonzalez-Carvajal, S. (2023) 'Comparing BERT against Traditional Machine Learning Models in Text Classification', *Journal of Computational and Cognitive Engineering* [Preprint]. Available at: https://doi.org/10.47852/bonviewjcce3202838.

Gu, J. *et al.* (2018) 'Recent advances in convolutional neural networks', *Pattern Recognition*, *77*, pp. 354–377. Available at: https://doi.org/10.1016/j.patcog.2017.10.013.

Haidar, A. and Bertholom, F. (2023) 'Fine-Tuning BERT For Monolingual Intent Classification', p. 6. Available at: https://openreview.net/pdf?id=dQgzBBpNvS.

Hochreiter, S. and Schmidhuber, J. (1997) 'Long Short-Term Memory', *Neural Computation*, 9(8), pp. 1735–1780. Available at: https://doi.org/10.1162/neco.1997.9.8.1735.

Holder, L., Gruenbichler, R. and Grbenic, S.O. (2022) 'The use of artificial intelligence in business valuation: Status quo and trends based on a literature review', in. Available at: https://graz.elsevierpure.com/en/publications/the-use-of-artificial-intelligence-in-business-valuation-status-q.

Jagrič, T. and Herman, A. (2024) 'AI Model for Industry Classification Based on Website Data', *Information*, p. 19. Available at: https://doi.org/https://doi.org/10.3390/info15020089.

Kazlauskiene, V. and Christauskas, Č. (2008) 'Business Valuation Model Based on the Analysis of Business Value Drivers'. Available at: https://www.ceeol.com/search/article-detail?id=952729.

Kingma, D.P. and Ba, J. (2017) 'Adam: A Method for Stochastic Optimization', p. 15. Available at: https://doi.org/https://doi.org/10.48550/arXiv.1412.6980.

Kohonen, T. (1995) 'Learning Vector Quantization', pp. 175–189. Available at: https://doi.org/10.1007/978-3-642-97610-0_6.

Koklev, P. (2023) 'Prerequisites for the Use of Machine Learning for Business Valuation', *Relacoes Internacionais no Mundo Atual*, 6(39). Available at: https://doi.org/10.21902/Revrima.v6i39.6267.

Koller, T., Goedhart, M. and Wessels, D. (2010) *Valuation: Measuring and Managing the Value of Companies*. Available at: https://books.google.com/books?hl=sl&lr=&id=iI3J4b2hWlwC&oi=fnd&pg=PT9&dq=Valuation:+Measuring+and+Managing+the+Value+of+Companies&ots=IL1BoHiI3k&sig=XXQozt89oB2Y4-ATP12UdcorUWE.

Kulwizira Lukanima, B. (2023) 'An Overview of Corporate Valuation', pp. 3–24. Available at: https://doi.org/10.1007/978-3-031-28267-6_1.

Laux, C. and Leuz, C. (2010) 'Did fair-value accounting contribute to the financial crisis?', *Journal of Economic Perspectives*, 24(1), pp. 93–118. Available at: https://doi.org/10.1257/jep.24.1.93.

Logeswaran, L. and Lee, H. (2018) 'An efficient framework for learning sentence representations', p. 16. Available at: https://doi.org/https://doi.org/10.48550/arXiv.1803.02893.

Reis, C. *et al.* (2020) 'Assessing the drivers of machine learning business value', *Journal of Business Research*, 117, pp. 232–243. Available at: https://doi.org/10.1016/j.jbusres.2020.05.053.

Seo, M. *et al.* (2018) 'Bidirectional Attention Flow for Machine Comprehension', p. 13. Available at: https://doi.org/https://doi.org/10.48550/arXiv.1611.01603.

Vaswani, A. *et al.* (2023) 'Attention Is All You Need', p. 15. Available at: https://doi.org/https://doi.org/10.48550/arXiv.1706.03762.

Wilimowska, Z. and Krzysztoszek, T. (2013) 'The use of artificial neural networks in company valuation process', *Studies in Computational Intelligence*, 457, pp. 279–288. Available at: https://doi.org/10.1007/978-3-642-34300-1_27.

Witten, D.M. and Tibshirani, R. (2010) 'A framework for feature selection in clustering', *Journal of the American Statistical Association*, 105(490), pp. 713–726. Available at: https://doi.org/10.1198/jasa.2010.tm09415.

ZBS Združenje bank Slovenije
The Bank Association of Slovenia

BANKING CONFERENCE

Geopolitical and economic conditions and challenges of Slovenian banking and economy

Friday, 14 June 2024
Brdo pri Kranju, Auditorium Splendens

Programme:

08.30 – 09.00	Registration
09.00 – 09.05	Welcome address **Stanislava Zadravec Caprirolo**, **M.I.A**., Conference moderator, Managing Director, The Bank Association of Slovenia
09.05 – 09.20	Address by the Chairman of the Supervisory Board of Bank Association of Slovenia **Blaž Brodnjak**, **MSc**, CEO, Nova Ljubljanska banka d.d.
09.20 – 09.35	Government response to current geopolitical and economic conditions **Klemen Boštjančič,** Minister, Ministry of Finance
09.35 – 09.50	Address by Governor of Banka Slovenije **Boštjan Vasle, MSc**, Governor, Banka Slovenije
09.50 – 10.00	Discussion
10.00 – 10.30	Key Geopolitical Challenges for the EU **Prof. Dr. Mojmir Mrak**, University of Ljubljana, School of Economics and business
10.30 – 11.00	Break
11.00 – 11.30	Financing the Future: A Strategic Banking Sector for a Competitive Europe **Sebastien de Brouwer,** Deputy CEO**,** European Banking Federation
11.30 – 12.45	Panel Discussion: The importance of a stable business environment and predictable legal framework Chair: **Stanislava Zadravec Caprirolo**, **M. I. A**., Managing Director, The Bank Association of Slovenia Panellists: **Blaž Brodnjak, MSc**, CEO, Nova Ljubljanska banka d.d. **Marko Lotrič,** President of National Council **Prof. Dr. Damijan Možina,** Faculty of Law in Ljubljana **Prof. Dr. Mojmir Mrak,** University of Ljubljana, School of Economics and business **Vesna Nahtigal**, General Manager, Chamber of Commerce and Industry of Slovenia **Prof. Dr. Verica Trstenjak,** Former Advocate General at the Court of Justice of the European Union
12.45 -14.00	Lunch
14.00 – 14.30	Opportunities and challenges of utilizing artificial intelligence in banking and the economy **Maja Škrjanc,** Senior Researcher, Institute Jožef Stefan
14.30– 15.45	Panel Discussion: Opportunities and challenges of utilizing artificial intelligence in banking and the economy Chair: **Stanislava Zadravec Caprirolo**, **M. I. A**., Managing Director, The Bank Association of Slovenia Panellists: **Dr. Jelena Virant Burnik**, Information Commissioner **Dr. Primož Dolenc**, Deputy Governor, Banka Slovenije **Mag. Mitja Podpečan,** parter, Jadek & Pensa Law firm **Prof. Dr. Timotej Jagrič,** University of Maribor **Mag. Simona Špilak**, BOC Instituite d.o.o. **Dr. Aleksandra Brdar Turk,** Nova KBM d.d.
15.45. – 16.00	Concluding remarks **Stanislava Zadravec Caprirolo**, **M. I. A**., Managing Director, The Bank Association of Slovenia

We will be happy to provide you with any further information regarding the organisation of the conference at **ic@zbs-giz.si**.
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