EKONOMIKA A MANAŽMENT

Vedecký časopis Fakulty podnikového manažmentu
Ekonomickej univerzity v Bratislave

ECONOMICS AND MANAGEMENT

Scientific Journal of the Faculty of Business Management,
Bratislava University of Economics and Business

Ročník XXIII. Číslo 2 Rok 2026
ISSN 2454-1028

Adresa redakcie
Ekonomika a manažment, Vedecký časopis Fakulty podnikového manažmentu Ekonomickej univerzity v Bratislave, Dolnozemská 1/b, 852 35 Bratislava 5, Slovenská republika
https://fpm.euba.sk/veda-a-vyskum/vedecky-casopis/ekonomika-a-manazment

Výkonný redaktor
Ing. Katarína Grančičová, PhD., e-mail: katarina.grancicova@euba.sk ; tel.: +421 2 67 295 531
doc. Ing. Miroslav Tóth, PhD.; e-mail: miroslav.toth@euba.sk ; tel.: +421 2 67 295 562

Za textovú, jazykovú a grafickú úpravu jednotlivých príspevkov zodpovedajú autori. Príspevky prechádzajú recenzným konaním.

EKONOMIKA A MANAŽMENT
Vedecký časopis Fakulty podnikového manažmentu Ekonomickej univerzity v Bratislave zaregistrovaný na Ministerstve kultúry Slovenskej republiky dňa 26. júna 2003, evidenčné číslo 1577/08. ISSN 2454-1028 pridelené Národnou agentúrou ISSN, Univerzitná knižnica v Bratislave, Michalská 1, 814 17 Bratislava dňa 28. 4. 2017, č. j. 124/2017.
Časopis vychádza 3-krát ročne ako online recenzovaný open access vedecký časopis.

Vydavateľ
Nadácia Manažér, Dolnozemská cesta 1/b, 852 35 Bratislava, IČO 31812562.

Dátum vydania tohto čísla: 17. 07. 2026.

ISSN 2454-1028

EKONOMIKA
A
MANAŽMENT

Ekonomická univerzita v Bratislave

Fakulta podnikového manažmentu

Ročník XXIII. Číslo 2 Rok 2026

Autori príspevkov
(Authors of Contributions)

Federico Banda
Bratislava University of Economics and Business, Faculty of Business Management, Department of Information Management, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: federico.banda@euba.sk
Author's share: 30 % , 30%

Andriana Baziuk
Bratislava University of Economics and Business, Faculty of Business Management, Department of Information Management, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: andriana.baziuk@euba.sk
Author's share: 25 % , 30 %

Vladimír Bolek
Bratislava University of Economics and Business, Faculty of Business Management, Department of Information Management, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: vladimir.bolek@euba.sk
Author's share: 20 %

Nora Grisáková
Bratislava University of Economics and Business, Faculty of Business Management, Department of Business Economy, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: nora.grisakova@euba.sk
Author's share: 33 %

Zuzana Hajduová
Bratislava University of Economics and Business, Faculty of Business Management, Department of Business Finance, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: zuzana.hajduova@euba.sk
Author's share: 30 % , 30 %

Anna Hamranová
Bratislava University of Economics and Business, Faculty of Business Management, Department of Information Management, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: anna.hamranova@euba.sk
Author's share: 33 % , 25 %

Róbert Hanák
Bratislava University of Economics and Business, Faculty of Business Management, Department of Information Management, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: robert.hanak@euba.sk
Author's share: 35 % , 35 %

Vladimír Hojdík
Bratislava University of Economics and Business, Faculty of Business Management, Department of Business Economy, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: vladimir.hojdik@euba.sk
Author's share: 33 %

Dana Hrušovská
Bratislava University of Economics and Business, Faculty of Business Management, Department of Business Economy, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: dana.hrusovska@euba.sk
Author's share: 33 % , 25 %

Simona Kosztanko
Bratislava University of Economics and Business, Faculty of Business Management, Department of Business Finance, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: simona.kosztanko@euba.sk
Author's share: 34 %

Iveta Kufelová
Bratislava University of Economics and Business, Faculty of Business Management, Department of Business Economy, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: iveta.kufelova@euba.sk
Author's share: 50 %

Diana Pallérová
Bratislava University of Economics and Business, Faculty of Business Management, Department of Business Economy, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: diana.palerova@euba.sk
Author's share: 25 % , 40 %

Filip Stovíček
Bratislava University of Economics and Business, Faculty of Business Management, Department of Information Management, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: filip.stovicek@euba.sk
Author's share: 35 % , 35 %

Slavka Šagátová
Bratislava University of Economics and Business, Faculty of Business Management, Department of Business Economy, Dolnozemská cesta 1/b, 852 35 Bratislava, Slovak Republic
e-mail: slavka.sagatova@euba.sk
Author's share: 34 %

OBSAH
(CONTENTS)

VEDECKÉ PRÍSPEVKY
(SCIENTIFIC CONTRIBUTIONS)

VEDECKÉ PRÍSPEVKY

SCIENTIFIC CONTRIBUTIONS

Ekonomika a manažment, Vedecký časopis Fakulty podnikového manažmentu Ekonomickej univerzity v Bratislave
ročník XXIII., číslo 2, rok 2026, ISSN 2454-1028

Implementácia umelej inteligencie v slovenských podnikoch: kvalitatívna analýza motívov, procesov riadenia a bariér na základe pološtrukturovaných rozhovorov

Federico Banda, Andriana Baziuk, Vladimír Bolek, Diana Pallérová

Abstrakt
Cieľom článku je analyzovať proces implementácie umelej inteligencie (AI) v slovenských podnikoch - od spúšťacieho momentu a stanovenia cieľov, cez voľbu technológií a riadenie implementácie, až po bariéry a doterajšie praktické skúsenosti. Empirickú bázu tvorí 18 pološtrukturovaných telefonických rozhovorov realizovaných v rámci projektu AI-ImpactSK so zástupcami 19 slovenských podnikov (jeden rozhovor sa týkal dvoch prepojených spoločností) rôznej veľkosti a odvetvového zamerania, od jednoosobových IT firiem po podniky s vyše dvesto zamestnancami. Dáta boli spracované metódou kvalitatívnej tematickej analýzy, pri ktorej boli identifikované opakujúce sa vzorce a odlišnosti naprieč prípadmi v oblastiach využitia AI, spúšťacích momentoch, cieľoch, iniciátoroch a spôsobe riadenia implementácie. Výsledky ukazujú, že AI sa v skúmaných podnikoch najčastejšie využíva na automatizáciu podporných procesov (marketing, zákaznícka podpora, programovanie, spracovanie dokumentov), pričom iba v menšine prípadov ide o jadrový, strategicky riadený proces. Implementácia je v malých podnikoch typicky iniciovaná vlastníkom alebo jednotlivým „AI šampiónom" organicky a bez formalizovaných cieľov, zatiaľ čo vo väčších firmách má podobu top-down, na správnej úrovni riadenej stratégie. Za najvýznamnejšie bariéry sa označujú nepripravenosť a nekonzistentnosť firemných dát, halucinácie a nedeterministický charakter výstupov AI, nedostatočná AI gramotnosť zamestnancov a legislatívna neistota. Príspevok prináša empiricky podložený pohľad na to, ako sa tvorí biznis-IT alignment a governance AI v prostredí malých a stredných podnikov strednej Európy, a dopĺňa tak medzeru v doterajšej literatúre, ktorá sa opiera prevažne o dáta z veľkých korporácií.

JEL klasifikácia*: D83, L21, M15, O33*
Kľúčové slová*: implementácia AI, digitálna transformácia, malé a stredné podniky, business-IT alignment, governance AI, kvalitatívny výskum*

1 Úvod

Umelá inteligencia sa v priebehu ostatných rokov posunula z okrajovej experimentálnej technológie do polohy jedného z kľúčových faktorov konkurencieschopnosti podnikov naprieč odvetviami. Generatívne jazykové modely, prediktívna analytika a autonómni AI agenti menia spôsob, akým podniky spracúvajú dáta, komunikujú so zákazníkmi, vyvíjajú softvér aj riadia interné procesy. Táto zmena však neprebieha rovnomerne - kým časť podnikov integruje AI do jadrových procesov a stavia na nej nové obchodné modely, iné podniky zostávajú vo fáze individuálneho, neriadeného experimentovania jednotlivých zamestnancov.

Téma je aktuálna aj preto, že tempo vývoja samotnej technológie výrazne prevyšuje tempo, akým sú podniky - najmä malé a stredné - schopné budovať zodpovedajúce organizačné, dátové a riadiace kapacity. Zatiaľ čo veľké korporácie disponujú zdrojmi na formalizované riadenie digitálnej transformácie, vrátane governance AI a dedikovaných rolí (napr. Chief AI Officer), malé a stredné podniky sú často odkázané na neformálne, improvizované prístupy, ktorých úspešnosť závisí od osobnej iniciatívy jednotlivca.

V doterajšej vedeckej literatúre prevažujú štúdie založené na veľkých kvantitatívnych vzorkách alebo na skúsenostiach nadnárodných korporácií, pričom hĺbková kvalitatívna evidencia o tom, ako presne prebieha implementácia AI v prostredí malých a stredných podnikov strednej Európy - vrátane spúšťacích momentov, deľby zodpovednosti medzi biznisom a IT a reálne zažívaných bariér - zostáva pomerne obmedzená. Práve túto medzeru sa snaží čiastočne vyplniť tento článok.

Cieľom článku je na základe pološtrukturovaných rozhovorov so zástupcami slovenských podnikov analyticky opísať a interpretovať proces zavádzania AI - od motivácie a cieľov, cez voľbu technológií a organizáciu implementácie, až po bariéry a doterajšie skúsenosti - a tieto zistenia konfrontovať s existujúcou vedeckou literatúrou. Výskum je súčasťou projektu AI-ImpactSK, ktorého empirickú bázu tvorí 18 telefonických rozhovorov so zástupcami 19 podnikov rôznej veľkosti a odvetvového zamerania.

2 Súčasný stav riešenej problematiky doma a v zahraničí

2.1 Motívy a faktory úspešnej implementácie AI v podnikoch

Vedecká literatúra sa zhoduje na tom, že AI predstavuje technológiu so signifikantným potenciálom meniť procesy, produkty aj obchodné modely, no zároveň upozorňuje, že mnohé organizácie tento potenciál nedokážu premeniť na reálnu hodnotu (Hamm & Klesel, 2021). Hamm a Klesel (2021) na základe systematického prehľadu literatúry identifikovali 36 faktorov úspešnej implementácie AI, ktoré usporiadali do rámca technológia–organizácia–prostredie (TOE), pričom rozlíšili 12 technologických, 13 organizačných a 11 environmentálnych faktorov. Tento rámec sa opakovane potvrdzuje aj v novšej literatúre zameranej špecificky na malé a stredné podniky - Sánchez et al. (2025) na základe kombinácie TOE rámca a teórie difúzie inovácií identifikovali desať kritických bariér AI adopcie v MSP, siahajúcich od nedostatočného prístupu k dátam a nedostatku kvalifikovaných pracovníkov, cez kultúrny odpor, až po slabú infraštruktúru a nedostatočné governance praktiky. Podobne Oldemeyer, Jede a Teuteberg (2024) systematickým prehľadom stavu poznania zdôrazňujú, že hlavné implementačné bariéry MSP nie sú primárne technologické, ale organizačné - nedostatok interných kompetencií, finančných zdrojov a jasnej stratégie.

Faktory ovplyvňujúce rozhodnutie o zavedení AI možno rozdeliť na interné (potreba zvýšenia efektivity, úspora nákladov, tlak na inováciu) a externé (konkurenčný tlak, očakávania zákazníkov, regulačné zmeny). Yesuf, Fields, Jain a Kassa (2025) v bibliometrickej a systematickej analýze poukazujú na to, že AI v MSP pôsobí ako katalyzátor produktovej aj procesnej inovácie a posilňuje podnikateľské rozhodovanie prostredníctvom prediktívnej analytiky, avšak miera dosiahnutého prínosu je vysoko podmienená veľkosťou firmy, odvetvím a manažérskou pripravenosťou. Schwaeke, Peters, Kanbach, Kraus a Jones (2025) v štúdii „nového normálu“ adopcie AI v MSP zdôrazňujú, že hoci sa AI stala bežnou súčasťou fungovania väčšiny malých firiem, prevažná časť adopcie zostáva na úrovni jednotlivca a ad hoc riešení, nie systematickej firemnej stratégie - zistenie, ktoré je pre interpretáciu empirickej časti tohto článku obzvlášť relevantné.

2.2 Strategické ciele, organizačné zmeny a technologické aspekty implementácie

Vial (2019) v jednej z najcitovanejších koncepčných prác o digitálnej transformácii definuje tento proces ako reťazec, v ktorom digitálne technológie vyvolávajú narušenia (disruptions), na ktoré organizácie reagujú strategicky, pričom výsledkom je transformácia štruktúr, procesov aj hodnotových ponúk organizácie, sprevádzaná bariérami na viacerých úrovniach - individuálnej, organizačnej aj environmentálnej. Implementácia AI predstavuje v tomto zmysle špecifický, no štrukturálne podobný prípad digitálnej transformácie, keďže si vyžaduje nielen technologickú investíciu, ale aj zmenu procesov, rolí a niekedy aj obchodného modelu.

Davenport a Ronanki (2018) na základe analýzy desiatok podnikových AI projektov rozlišujú tri typy cieľov, ktoré podniky pri zavádzaní AI sledujú: automatizáciu podnikových procesov, získavanie poznatkov prostredníctvom analýzy dát a angažovanie zamestnancov a zákazníkov pomocou kognitívnych nástrojov. Autori pritom upozorňujú, že najvyššiu mieru úspechu dosahujú projekty s jasne definovaným, úzko vymedzeným cieľom, zatiaľ čo ambiciózne, plošne koncipované projekty transformácie zlyhávajú častejšie. Táto téza korešponduje aj so závermi Hamm a Klesela (2021), podľa ktorých je jasná definícia očakávaného prínosu (KPI, merateľné ciele) jedným z kľúčových organizačných faktorov úspechu.

2.3 Úloha vrcholového manažmentu, leadershipu a IT oddelenia

Rola top manažmentu pri implementácii AI je v literatúre chápaná ako kriticky dôležitá. Bevilacqua, Masárová, Perotti a Ferraris (2025) v systematickom prehľade 63 článkov, opierajúcom sa o teóriu horných ešalónov (upper echelons theory), preukazujú, že strategická orientácia a otvorenosť top manažérov voči AI zásadne ovplyvňuje úspešnosť digitálnych iniciatív. Autori zdôrazňujú, že líderstvo v ére AI si vyžaduje nové kompetencie - „AI open mindset“, schopnosť fungovať ako strategický spoluautor v spolupráci s AI, prepájanie viacerých organizačných úrovní a riadenie etických rizík. Podobne MIT Sloan Management Review (Davenport, cit. in Sloanreview, 2026) poukazuje na to, že mnohé AI iniciatívy zlyhávajú nie pre technologické, ale pre lídерské a governance dôvody - organizácie potrebujú novú architektúru vedenia, ktorá integruje technológiu, stratégiu, riziko a organizačnú zmenu.

Vzťah medzi biznisom a IT oddelením (business–IT alignment) je v kontexte AI osobitne dôležitý, keďže úspešná implementácia si vyžaduje, aby technické riešenie zodpovedalo reálnej biznisovej potrebe a aby biznisoví vlastníci procesu boli aktívne zapojení do definovania požiadaviek a hodnotenia výsledkov, nielen do formálneho schvaľovania rozpočtu. V praxi malých a stredných podnikov pritom hranica medzi biznisovou a technickou rolou často splýva - tú istú osobu zastáva vlastník alebo konateľ firmy.

2.4 Governance AI a organizačné zmeny

S narastajúcim rozsahom nasadenia AI rastie aj potreba governance rámcov, ktoré zosúlaďujú investície do AI s cieľmi organizácie, riadia etické a regulačné riziká a zabezpečujú konzistentnosť a auditovateľnosť výstupov (Databricks, 2025; AWS Cloud Adoption Framework, 2025). Governance AI pritom nie je jednorazovým opatrením, ale kontinuálnym procesom monitorovania výkonnosti modelov, driftu dát a súladu s reguláciou. Na úrovni Európskej únie predstavuje kľúčový regulačný rámec Akt o umelej inteligencii (AI Act), ktorý zavádza rizikovo orientovaný prístup k regulácii AI systémov a harmonizované požiadavky na ich vývoj a nasadenie naprieč členskými štátmi.

2.5 Organizačné zmeny, odpor zamestnancov a psychologické aspekty

Súbežne s technologickými a riadiacimi aspektmi venuje literatúra značnú pozornosť ľudskému rozmeru implementácie AI. Golgeci, Ritala, Arslan, McKenna a Ali (2025) na základe integratívneho prehľadu literatúry identifikujú kľúčové kognitívne dimenzie odporu zamestnancov voči AI - strach zo straty zamestnania, obavy z technologickej zložitosti, vnímanú neistotu a hrozbu pre profesijnú identitu - a navrhujú procesuálny rámec, podľa ktorého sa odpor dá zmierniť transparentnou komunikáciou, zapojením zamestnancov do rozhodovania a poskytnutím adekvátneho vzdelávania. Savolainen, Ylinen, Grönroos a Oksanen (2026) v systematickom prehľade výskumov postojov zamestnancov k AI za posledných päť rokov konštatujú, že zamestnanci vnímajú AI ambivalentne - súčasne ako príležitosť aj ako zdroj obáv, pričom miera expozície, vzdelávania a komplementarity úloh koreluje s pozitívnejším postojom. Frey a Osborne (2017) vo svojej klasickej štúdii o citlivosti pracovných miest na automatizáciu upozornili, že riziko nahradenia sa netýka iba manuálnych, ale aj kognitívne náročných povolaní, čo koreluje aj s novšími zisteniami o tom, že práve vysoko intelektuálne profesie (právo, medicína, marketing) sú vystavené významnej miere disrupcie umelou inteligenciou.

2.6 Syntéza a otvorené otázky

Súhrnne možno konštatovať, že literatúra sa zhoduje na viacerých bodoch: (1) úspešnosť implementácie AI závisí od súčasného pôsobenia technologických, organizačných a environmentálnych faktorov (TOE rámec); (2) kvalita a pripravenosť dát predstavuje jednu z najčastejšie citovaných bariér; (3) vedenie zo strany top manažmentu a jasné vymedzenie biznisového vlastníctva procesu sú kritické; (4) odpor zamestnancov je bežný a manažovateľný najmä prostredníctvom komunikácie a vzdelávania. Zároveň však literatúra prevažne čerpá z veľkých organizácií alebo kvantitatívnych prierezových štúdií, pričom hĺbkový kvalitatívny pohľad na to, ako presne tieto procesy prebiehajú v malých a stredných podnikoch strednej Európy - vrátane neformálnych, improvizovaných ciest k implementácii - zostáva menej preskúmaný. Práve túto medzeru sa snaží vyplniť predkladaná empirická analýza.

3 Výskumný dizajn

Cieľom výskumu bolo zmapovať a analyticky interpretovať proces implementácie umelej inteligencie v slovenských podnikoch - od spúšťacieho momentu a stanovenia cieľov, cez voľbu technológií a organizáciu implementácie, až po bariéry, doterajšie skúsenosti a plány do budúcnosti. Výskum bol vedený nasledujúcimi výskumnými otázkami:

1. V ktorých oblastiach a procesoch podniky AI najčastejšie využívajú a čo je dôvodom tejto voľby?
2. Aké boli spúšťacie momenty a hlavní iniciátori implementácie AI?
3. Aké ciele si podniky stanovili a do akej miery boli formalizované a merateľné?
4. Ako je organizované riadenie implementácie z pohľadu biznisovej a technickej zodpovednosti?
5. Aké bariéry a výzvy podniky pri implementácii zažili a ako ich riešili?

Empirickú bázu tvorí 18 pološtrukturovaných telefonických rozhovorov realizovaných v rámci projektu AI-ImpactSK, financovaného z prostriedkov Európskej únie - NextGenerationEU prostredníctvom Plánu obnovy a odolnosti SR. Rozhovory boli vedené na základe jednotnej sady otvorených otázok pokrývajúcich oblasť využitia AI, spúšťací moment, ciele, výber technológie, priebeh implementácie, deľbu zodpovednosti, bariéry a plány do budúcnosti, pričom moderátor v priebehu rozhovoru pružne reagoval na odpovede respondenta. Respondentmi boli konatelia, majitelia, riadiaci alebo technickí pracovníci zodpovední za oblasť AI v danom podniku. Analyzovaná vzorka pokrýva 19 podnikov (jeden rozhovor sa týkal súčasne dvoch prepojených spoločností v skupine), pričom veľkosť podnikov sa pohybovala od jednoosobových firiem až po spoločnosti s vyše dvesto zamestnancami a odvetvové zameranie zahŕňalo softvérový vývoj a AI konzultačné služby, e-commerce, výrobu, stavebníctvo, farmaceutický priemysel, marketing, energetiku a služby v oblasti bezpečnosti práce.

4 Výsledky výskumu

4.1 Oblasti využitia AI

Analýza rozhovorov naznačuje, že využitie AI v skúmaných podnikoch sa výrazne líši podľa odvetvia a veľkosti firmy, no naprieč prípadmi možno identifikovať niekoľko dominantných oblastí. Najčastejšie zastúpenou oblasťou je podpora vývoja softvéru - AI asistovaný zápis kódu využívajú takmer všetky IT firmy vo vzorke, pričom vo viacerých prípadoch ide už o nasadenie viacerých súbežne pracujúcich AI agentov namiesto jednotlivých promptov. Druhou výraznou oblasťou je marketing a tvorba obsahu, kde sa AI využíva na generovanie textov, sociálne siete, e-mailovú komunikáciu a analýzu trhu. Treťou oblasťou je zákaznícka podpora a hlasoví agenti, kde AI plní úlohu buď priameho komunikačného kanála so zákazníkom, alebo nástroja na hodnotenie kvality ľudskej komunikácie. Štvrtou oblasťou je spracovanie a klasifikácia štruktúrovaných aj neštruktúrovaných dát - kategorizácia produktov, analýza dokumentov a legislatívy, OCR a spracovanie logistických dát a technické výpočty v stavebníctve.

Zaujímavým zistením je, že iba v menšine prípadov respondenti opísali AI ako súčasť jadrového procesu podniku; vo väčšine podnikov ide o podporné procesy, hoci hranica medzi „jadrovým" a „podporným" procesom sa v odpovediach viacerých respondentov ukázala ako pojmovo nejasná - viacerí respondenti mali problém pojem interpretovať alebo naň odpovedali len po vysvetlení. To potvrdzuje zistenie zo súčasnej literatúry, že koncept „jadrovosti" AI procesu je v praxi menej ostro vymedzený, než predpokladajú teoretické rámce (Oldemeyer et al., 2024), a že klasifikácia procesu skôr závisí od miery, do akej si podnik uvedomuje strategický význam daného procesu, než od jeho objektívnej pozície v hodnotovom reťazci.

Z hľadiska technológií dominuje vo vzorke generatívna AI (veľké jazykové modely), ktorú v nejakej forme používajú všetky skúmané podniky. AI agentov aktívne nasadzuje približne polovica podnikov, prevažne tie s vlastnou vývojárskou kapacitou. Prediktívna analytika sa vyskytuje zriedkavejšie a spravidla v kombinácii so skladovým alebo výrobným plánovaním. Počítačové videnie využívajú iba podniky s konkrétnym use-case, pričom viacerí respondenti uviedli, že experimentovanie s počítačovým videním v minulosti bolo náročnejšie a nákladovo menej efektívne než použitie hotových jazykových modelov.

4.2 Spúšťací moment implementácie AI

Rozhovory odhalili niekoľko opakujúcich sa vzorcov spúšťacích momentov, ktoré možno zoradiť na kontinuu od čisto reaktívneho k plne strategickému rozhodnutiu. Na jednom póle stoja prípady, v ktorých bola implementácia priamou reakciou na konkrétny biznisový problém alebo požiadavku zákazníka - klasickým príkladom je aj firma, kde spúšťačom bola neschopnosť klientskej stavebnej firmy spracovať dopyty na cenové ponuky (z pôvodných desiatich spracovaných zo sto prijatých dopytov na súčasných sedemdesiat ponúk týždenne), alebo ďalšia firma, kde klient čelil sťažnostiam koncových zákazníkov na nesprávne kategorizovaný tovar. V ďalšej firme vznikla ako priama reakcia na legislatívnu zmenu (novela stavebného zákona v roku 2025), ktorá spôsobila chaos a dopyt po prehľadnom, presnom nástroji na orientáciu v predpisoch.

Na opačnom póle stoja prípady, v ktorých bola implementácia výsledkom top-down strategického rozhodnutia vedenia alebo materskej organizácie, kde iniciatíva vzišla z pravidelného vyhodnocovania procesov na úrovni vedenia (board), alebo kde bola implementácia „nariadená" materskou spoločnosťou. Medzi týmito pólmi sa nachádza veľká skupina prípadov, v ktorých bol spúšťačom skôr všeobecný technologický trend a osobné nadšenie jednotlivca („organický" vývoj) - firmy opisujú príchod ku AI ako plynulé nadviazanie na celosvetový „bum" okolo generatívnych modelov bez formálneho rozhodovacieho procesu.

Empirické zistenia poukazujú na to, že veľkosť podniku a existencia vlastnej vývojárskej kapacity významne súvisia s charakterom spúšťacieho momentu: firmy s dlhoročnou skúsenosťou s AI technológiami pred nástupom generatívnych modelov prijali rozhodnutie o plošnom nasadení jazykových modelov takmer okamžite po dosiahnutí dostatočnej kvality technológie, zatiaľ čo firmy bez predchádzajúcej skúsenosti postupovali opatrnejšie a fázovo. Toto zistenie je konzistentné so zisteniami Bevilacqua et al. (2025), podľa ktorých strategická orientácia a predchádzajúca technologická skúsenosť vedenia výrazne skracuje čas potrebný na rozhodnutie o zavedení AI.

4.3 Ciele implementácie AI

Analýza cieľov, ktoré si podniky pri zavádzaní AI stanovili, odhaľuje výrazný rozdiel medzi formálne artikulovanými a implicitnými cieľmi. Vo väčšine malých podnikov respondenti explicitne uviedli, že žiadne formalizované, merateľné ciele stanovené neboli - zavedenie AI bolo motivované všeobecnou snahou „uľahčiť si prácu“ alebo udržať krok s trendom. Naproti tomu vo firmách poskytujúcich AI riešenia tretím stranám boli ciele od začiatku formulované kvantitatívne a naviazané priamo na obchodný prípad klienta - napríklad skrátenie doby spracovania cenovej ponuky zo štyroch až piatich mesiacov na jeden týždeň a zníženie nákladov klienta z približne 4 500 eur na 500 eur za posúdenie projektu, alebo zvýšenie presnosti kategorizácie produktov z 60 - 70 % na približne 90 %.

Vo väčšine prípadov sa napriek chýbajúcej formálnej metrike opakovane objavujú tri kategórie deklarovaného prínosu: úspora času, úspora nákladov (často vyjadrená ako ekvivalent zníženého počtu potrebných pracovníkov) a zvýšenie kvality výstupov. Viacerí respondenti explicitne opísali efekt „urobiť to isté s menším počtom ľudí“ - napríklad projekt, ktorý predtým vyžadoval tri až štyri osoby, dnes zvláda jedna osoba v spolupráci s projektovým manažérom. Menšia, no analyticky zaujímavá skupina odpovedí poukazuje na kvalitatívne odlišný typ prínosu - nie zrýchlenie existujúcej práce, ale umožnenie práce, ktorá by inak nebola realizovateľná pre časovú alebo kapacitnú náročnosť. Tento typ prínosu je v literatúre menej zdôrazňovaný než klasická úspora nákladov, hoci práve on môže mať najväčší dlhodobý strategický význam, keďže rozširuje množinu ekonomicky uskutočniteľných projektov firmy.

Viacerí respondenti zároveň explicitne spochybnili možnosť presnej finančnej kvantifikácie prínosu AI, čo poukazuje na metodologické obmedzenie, s ktorým sa stretávajú podniky pri hodnotení návratnosti investície do AI - rozdiel medzi obdobím pred a po zavedení AI je pozorovateľný, no jeho pripísanie výlučne AI technológii je podľa respondentov empiricky ťažko obhájiteľné.

4.4 Iniciátor implementácie AI

Vo väčšine skúmaných malých a stredných podnikov bol iniciátorom implementácie priamo vlastník alebo konateľ spoločnosti, čo potvrdzuje kľúčovú úlohu vrcholového manažmentu zdôrazňovanú v literatúre (Bevilacqua et al., 2025). V týchto prípadoch splýva rola strategického iniciátora s rolou operatívneho realizátora - vlastník je súčasne biznisovým aj (čiastočne) technickým vlastníkom projektu, čo je typický znak menších organizácií s plochou organizačnou štruktúrou.

V stredne veľkých a väčších firmách sa objavuje odlišný vzorec - iniciátorom je buď špecializovaný interný „AI šampión“, teda zamestnanec s neformálne, ale fakticky vymedzenou zodpovednosťou za oblasť AI bez toho, aby to bolo súčasťou formálnej organizačnej štruktúry, alebo je iniciatíva výsledkom kolektívneho rozhodnutia vedenia. Vo výnimočných prípadoch je iniciátorom externý subjekt - materská spoločnosť alebo dodávateľ technológie, ktorý implementáciu prezentoval ako riešenie. Zaujímavým zistením je, že v prípade viacerých firiem respondenti nemali úplný prehľad o priebehu vlastnej internej implementácie, čo poukazuje na riziko nedostatočného zapojenia zodpovedných osôb a informačnej asymetrie medzi realizátormi a formálne poverenými respondentmi v menej vyspelých organizáciách.

Diskusia týchto zistení potvrdzuje ústrednú tézu literatúry o vodcovstve v ére AI (Bevilacqua et al., 2025) - úspešná a rýchla implementácia je úzko naviazaná na osobnú angažovanosť a technologickú gramotnosť najvyššieho vedenia, najmä v prostredí malých podnikov, kde neexistuje samostatná IT alebo inovačná jednotka. Zároveň rozhovory naznačujú, že v mnohých malých podnikoch neexistuje jasne definovaná rola „vlastníka AI iniciatívy" v zmysle formálnej organizačnej štruktúry - zodpovednosť vzniká ad hoc, na základe osobného záujmu alebo predchádzajúcich technických zručností konkrétneho zamestnanca.

4.5 Riadenie implementácie: biznis a technická stránka

Biznisová stránka

Vo väčšine mikro- a malých podnikov je biznisová zodpovednosť sústredená v osobe vlastníka alebo konateľa, ktorý súčasne definuje požiadavky, hodnotí výsledky a spravidla sa priamo podieľa aj na testovaní riešenia. V stredne veľkých firmách sa objavuje deľba práce medzi biznis analytikov, ktorí opisujú a formalizujú podnikové procesy, a technických architektov, ktorí navrhujú riešenie. Jedna z firiem navyše ako explicitnú podmienku úspešnej implementácie u klienta vyžaduje ustanovenie „biznisového vlastníka" na strane klienta - teda osoby, ktorá do detailov pozná daný proces a je schopná AI riešenie priebežne dolaďovať, čo je v súlade s literatúrou zdôrazňujúcou dôležitosť aktívneho zapojenia biznisu, nielen formálneho schválenia projektu (business-IT alignment).

Technická stránka

Technické riadenie implementácie vykazuje tri odlišné modely. Prvým je čisto interný model, pri ktorom AI riešenie vyvíja a spravuje interný IT alebo vývojársky tím bez účasti externých partnerov - tento model prevažuje najmä medzi firmami, ktoré samotný vývoj softvéru považujú za svoju hlavnú činnosť. Druhým je hybridný model kombinujúci interný tím s externými špecialistami alebo dodávateľmi - typický najmä pre podniky mimo IT sektora, ktoré nemajú vlastnú dostatočnú vývojársku kapacitu, no chcú si zachovať čiastočnú kontrolu nad riešením. Tretím je model nákupu a konfigurácie hotových nástrojov tretích strán bez vlastného vývoja, ktorý je typický pre firmy mimo technologického sektora, kde AI slúži ako podporný nástroj, nie ako súčasť produktového portfólia.

Osobitne zaujímavým zistením naprieč prípadmi je vedomé rozhodnutie viacerých firiem kombinovať lokálne (on-premise) a externé cloudové modely v závislosti od citlivosti spracúvaných dát - tento prístup najexplicitnejšie opísali dve firmy, ktoré citlivé alebo regulované dáta („ktoré nemôžu opustiť firmu") spracúvajú výhradne lokálnymi modelmi, zatiaľ čo pre menej citlivé úlohy využívajú výkonnejšie externé modely. Ide o konkrétny prejav governance AI na úrovni jednotlivého podniku, ktorý spontánne reflektuje princípy odporúčané v literatúre o riadení rizika a súlade s reguláciou (Databricks, 2025), hoci ani jeden zo skúmaných podnikov neuviedol existenciu formalizovaného, zdokumentovaného governance rámca alebo štandardizovaného procesu pre AI projekty - vo väčšine prípadov na explicitnú otázku, či majú štandardizovaný proces zavádzania AI projektov, respondenti odpovedali záporne alebo otázke nerozumeli v kontexte vlastnej praxe.

4.6 Bariéry a výzvy implementácie

Naprieč takmer všetkými rozhovormi sa opakuje niekoľko kategórií bariér. Prvou a najčastejšie spomínanou je nepripravenosť a nekonzistentnosť firemných dát – firmy opisujú situáciu, keď sú dáta „kade-tade", každý zamestnanec ich ukladá inak a chýba jednotná štruktúra, pričom AI natrénovaná na testovacích alebo „laboratórnych" dátach zlyháva pri nasadení na reálne, neusporiadané dáta klienta - rovnaký jav (rozdiel medzi výkonom na fiktívnych a reálnych dátach) nezávisle opísala aj ďalšia firma vo vzťahu k výkresovej dokumentácii, keďže každý architekt používa odlišnú štruktúru súborov. Toto zistenie priamo koreluje so závermi literatúry, podľa ktorej je práve dátová pripravenosť najčastejšie citovanou technickou bariérou implementácie AI v MSP (Sánchez et al., 2025; Oldemeyer et al., 2024).

Druhou opakujúcou sa témou je nedeterministický charakter a halucinácie výstupov generatívnej AI. Viacerí respondenti nezávisle od seba opísali potrebu neustálej ľudskej kontroly a verifikácie výstupov a kvantifikovali mieru halucinácií jednotlivých nástrojov na úrovni približne 30 %. Firmy ilustrovali nedeterministickosť analógiou, že opakovaný dopyt nemusí stopercentne viesť k rovnakej odpovedi. Taktiež tento jav zovšeobecnili na explicitný organizačný princíp - keďže AI generuje iba pravdepodobnostné výstupy, monitoring a verifikácia musia byť podstatne dôslednejšie ako pri práci výhradne s ľudskými pracovníkmi. Táto skupina zistení koncepčne zodpovedá dôrazu, ktorý na spoľahlivosť a dôveryhodnosť AI výstupov kladie literatúra o AI governance (AWS Cloud Adoption Framework, 2025; Databricks, 2025).

Treťou kategóriou bariér je nedostatočná AI gramotnosť zamestnancov a s ňou súvisiace nerealistické očakávania. Jedna z firiem konkrétne opísala prípad zamestnanca, ktorý po niekoľkých týždňoch prestal používať zaplatenú licenciu AI nástroja, pretože nevedel formulovať zadanie a očakával, že nástroj „urobí všetko sám“; podobný motív sa opakuje aj u ďalších firmách, kde kvalita výstupu AI priamo závisí od kvality a podrobnosti zadania úlohy. Toto zistenie je v súlade s literatúrou zdôrazňujúcou dôležitosť vzdelávania a tréningu ako nástroja na zmierňovanie odporu a nesprávneho používania AI (Golgeci et al., 2025).

Štvrtou kategóriou sú právne a etické bariéry, ktoré sa objavujú menej frekventovane, ale s vyššou závažnosťou tam, kde sa vyskytujú - ochrana osobných údajov, autorské práva k technickým normám a zdrojovým kódom a otázka transparentnosti voči zákazníkovi pri komunikácii s hlasovým AI agentom - v oboch posledných prípadoch sa podniky rozhodli pre pragmatické, nedokumentované riešenie (neinformovať aktívne, ale umožniť prepojenie na človeka na požiadanie), čo poukazuje na absenciu jednotného, externe stanoveného štandardu correct disclosure practice v prostredí MSP.

Piatou kategóriou je organizačný odpor a obavy zo straty zamestnania. Odpor sa v skúmanej vzorke prejavil vo viacerých formách: otvorená skepsa a nezáujem, pasívna sabotáž zo strany zamestnancov obávajúcich sa o svoju pozíciu, odmietnutie komunikovať s AI zo strany koncových zákazníkov a symbolický odpor zamestnancov verejnej správy pri prezentácii AI riešenia. Zaujímavé je, že vo firmách poskytujúcich AI riešenia sa interný odpor takmer nevyskytoval - zamestnanci vidia AI ako súčasť svojej profesijnej identity a produktu firmy - zatiaľ čo odpor sa presúva na stranu koncového zákazníka alebo klienta. Toto zistenie čiastočne rozširuje závery Golgeciho et al. (2025) a Savolainen et al. (2026) o tom, že miera expozície a profesijná blízkosť k technológii koreluje s pozitívnejším postojom, keďže v tomto prípade sa ukazuje, že odpor sa nevytráca, ale presúva sa medzi rôznymi skupinami stakeholderov (zamestnanec verzus koncový zákazník) v závislosti od toho, kto má k technológii bližšie.

5 Diskusia

Empirické zistenia vo viacerých bodoch potvrdzujú závery existujúcej literatúry, no zároveň prinášajú niekoľko nových akcentov. Po prvé, potvrdzuje sa centrálna úloha kvality a pripravenosti dát ako limitujúceho faktora (Sánchez et al., 2025; Oldemeyer et al., 2024) - vo vzorke slovenských podnikov sa tento problém prejavuje výraznejšie ako nedostatok technológie samotnej, čo je v súlade so závermi, že bariéry adopcie AI v MSP sú prevažne organizačné, nie technologické.

Po druhé, potvrdzuje sa kľúčová úloha vrcholového manažmentu a jeho technologickej gramotnosti (Bevilacqua et al., 2025) - v skúmanej vzorke je táto väzba mimoriadne priama, keďže vo väčšine malých podnikov je vlastník/konateľ súčasne aj hlavným, často jediným nositeľom AI kompetencie.

Po tretie, zistenia o odpore zamestnancov korešpondujú so závermi Golgeciho et al. (2025) a Savolainen et al. (2026), pričom empirický materiál prináša doplňujúci poznatok, že v prostredí, kde je AI súčasťou produktu firmy, sa odpor zamestnancov výrazne znižuje, avšak presúva sa na úroveň koncového zákazníka - tento presun stakeholderskej lokalizácie odporu nie je v analyzovanej literatúre takto explicitne opísaný a predstavuje čiastočne nový poznatok prinesený analýzou rozhovorov.

Po štvrté, zistenia o hybridnom využívaní lokálnych a cloudových modelov v závislosti od citlivosti dát predstavujú praktický, spontánne vzniknutý prejav governance AI, ktorý sa v literatúre spravidla opisuje ako odporúčaný, formalizovaný postup (Databricks, 2025; AWS, 2025) - v analyzovanej vzorke však ide o neformalizovanú, intuitívne vytvorenú prax bez podpory zdokumentovaného rámca, čo naznačuje, že aj v prostredí bez formálneho governance môžu podniky spontánne dospieť k funkčným, rizikovo diferencovaným riešeniam.

Napokon, zistenie o type prínosu presahujúcom jednoduché zrýchlenie existujúcej práce - teda umožnenie práce, ktorá by inak nebola ekonomicky realizovateľná - rozširuje klasickú trichotómiu cieľov AI (automatizácia procesov, získavanie poznatkov, angažovanie používateľov) podľa Davenporta a Ronankiho (2018) o štvrtý typ prínosu, ktorý by bolo možné pojmovo označiť ako „rozšírenie realizovateľnej množiny úloh“ (expansion of the feasible task set), a ktorý si podľa doterajšej analýzy zasluhuje v budúcom výskume samostatnú pozornosť.

Limity výskumu

Predložený výskum má viacero metodologických obmedzení, ktoré je potrebné zohľadniť pri interpretácii výsledkov. Ide o kvalitatívny výskum s malou, účelovo neprobabilistickou vzorkou 19 podnikov, ktorého výsledky preto nie je možné štatisticky zovšeobecniť na celú populáciu slovenských podnikov. Vzorka navyše vykazuje nerovnomerné zastúpenie odvetví, s výraznou prevahou podnikov z oblasti softvérového vývoja a IT služieb, čo mohlo skresliť závery smerom k technologicky vyspelejším prípadom. Výpovede sú založené na subjektívnom vnímaní jednotlivých respondentov, ktorí v niektorých prípadoch neboli priamymi realizátormi implementácie alebo nemali úplný prehľad o všetkých aspektoch procesu, čo mohlo viesť k neúplným alebo nepresným odpovediam v niektorých tematických okruhoch (najmä pri otázkach týkajúcich sa presnej deľby zodpovednosti a metodiky merania prínosov). Rozhovory boli realizované telefonicky v obmedzenom časovom rozsahu, čo mohlo v niektorých prípadoch limitovať hĺbku odpovedí. Napokon, keďže ide o rýchlo sa vyvíjajúcu technologickú oblasť, zistenia odrážajú stav poznania a praxe v čase realizácie rozhovorov a ich platnosť môže byť v priebehu krátkeho času prekonaná ďalším technologickým vývojom.

6 Záver

Predložený článok analyzoval na základe 18 pološtrukturovaných rozhovorov so zástupcami 19 slovenských podnikov proces implementácie umelej inteligencie - od spúšťacieho momentu, cez stanovenie cieľov a organizáciu riadenia, až po bariéry a doterajšie praktické skúsenosti. Cieľ článku bol naplnený: podarilo sa identifikovať opakujúce sa vzorce aj významné rozdiely medzi podnikmi rôznej veľkosti a odvetvového zamerania, a tieto zistenia zasadiť do kontextu existujúcej vedeckej literatúry o adopcii AI, digitálnej transformácii, vodcovstve a governance.

Medzi hlavné zistenia patrí, že implementácia AI v malých podnikoch prebieha prevažne organicky, bez formalizovaných cieľov a s vlastníkom firmy ako súčasným iniciátorom, biznisovým aj technickým nositeľom projektu, zatiaľ čo vo väčších firmách nadobúda podobu formalizovanejšieho, strategicky riadeného procesu s jasnejšou deľbou biznisovej a technickej zodpovednosti. Za najvýznamnejšie bariéry sa ukázali nepripravenosť firemných dát, nedeterministický charakter a halucinácie výstupov AI, nedostatočná AI gramotnosť zamestnancov a chýbajúci formalizovaný governance rámec, hoci viaceré podniky spontánne vyvinuli funkčné, rizikovo citlivé praktiky (napríklad kombináciu lokálnych a cloudových modelov).

Vedeckým prínosom článku je najmä empiricky podložený, hĺbkový pohľad na implementáciu AI v prostredí malých a stredných podnikov strednej Európy, ktorý dopĺňa doterajšiu literatúru opierajúcu sa prevažne o veľké organizácie alebo kvantitatívne prierezové dáta, a identifikácia dvoch čiastočne nových poznatkov - presunu lokalizácie zamestnaneckého odporu smerom ku koncovému zákazníkovi vo firmách, kde je AI súčasťou produktu, a rozšírenia typológie prínosov AI o kategóriu „rozšírenia realizovateľnej množiny úloh“.

Z praktického hľadiska zistenia naznačujú, že malé a stredné podniky by mali venovať systematickejšiu pozornosť príprave a štruktúre firemných dát ešte pred zavádzaním AI riešení, investovať do vzdelávania zamestnancov v oblasti efektívneho zadávania úloh AI nástrojom a explicitne definovať, aspoň na neformálnej úrovni, biznisového vlastníka každého AI projektu. Pre ďalší výskum sa odporúča realizovať kvantitatívnu, reprezentatívnu štúdiu overujúcu mieru zovšeobecniteľnosti identifikovaných vzorcov, ako aj longitudinálny výskum sledujúci vývoj governance praktík a organizačných zmien v čase, keďže technológia aj prax jej nasadenia sa vyvíjajú mimoriadne rýchlo.

Acknowledgement

Tento príspevok bol podporený Európskou úniou – NextGenerationEU prostredníctvom Plánu obnovy a odolnosti pre Slovensko v rámci projektu č. 09I05-03-V02-00003/2025/VA (AI-impactSK); 100 % podiel.

Použitá literatúra (References)

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188–2244.

Bevilacqua, S., Masárová, J., Perotti, F. A., & Ferraris, A. (2025). Enhancing top managers' leadership with artificial intelligence: insights from a systematic literature review. Review of Managerial Science, 19(9), 2899–2935. https://doi.org/10.1007/s11846-025-00836-7

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280.

Golgeci, I., Ritala, P., Arslan, A., McKenna, B., & Ali, I. (2025). Confronting and alleviating AI resistance in the workplace: An integrative review and a process framework. Human Resource Management Review, 35(2), Article 101075. https://doi.org/10.1016/j.hrmr.2024.101075

Hamm, P., & Klesel, M. (2021). Success factors for the adoption of artificial intelligence in organizations: A literature review. In Proceedings of the 27th Americas Conference on Information Systems (AMCIS 2021). Association for Information Systems.

Sánchez, E., Calderón, R., & Herrera, F. (2025). Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges. Applied Sciences, 15(12), 6465. https://doi.org/10.3390/app15126465

Savolainen, I., Ylinen, L., Grönroos, R., & Oksanen, A. (2026). AI transformation in working life: A systematic review of usage and attitudes towards AI among workers. Digital Business, 6(1), Article 100162. https://doi.org/10.1016/j.digbus.2025.100162

Schwaeke, J., Peters, A., Kanbach, D. K., Kraus, S., & Jones, P. (2025). The new normal: The status quo of AI adoption in SMEs. Journal of Small Business Management, 63(3), 1297–1331. https://doi.org/10.1080/00472778.2024.2379999

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. Journal of Strategic Information Systems, 28(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Yesuf, Y., Fields, Z., Jain, A., & Kassa, E. (2025). Artificial intelligence adoption as a driver of innovation and competitiveness in SMEs: A bibliometric and systematic review. F1000Research, 14, 1187. https://doi.org/10.12688/f1000research.171494.1

Key drivers influencing AI adoption in Slovak enterprises

Anna Hamranová, Dana Hrušovská, Simona Kosztanko

Abstract
The aim of the paper is to identify the key motivational factors influencing the adoption of artificial intelligence (AI) in enterprises operating in Slovakia and to examine their underlying structure. The research focuses on identifying the factors that most strongly support the implementation and practical use of AI in business practice.
Methods: The empirical research was conducted through a questionnaire survey involving a sample of 816 enterprises. The data were analysed using descriptive statistics and exploratory factor analysis, applying the Minimum Residual (MinRes) extraction method with Oblimin oblique rotation. The suitability of the data for factor analysis was confirmed by Bartlett's test of sphericity and a high Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy.
Results: The most significant motivational factors driving AI adoption include the pursuit of higher efficiency, the automation of business processes, cost reduction, and improved decision-making. The factor analysis identified two interrelated factors, with the dominant factor encompassing enterprises' internal strategic and performance-oriented motivations. The findings indicate that AI adoption is primarily driven by the need to enhance organizational performance, innovation, and competitiveness, whereas external drivers, such as competitive pressure, play a less significant role.

JEL classification: *L25, M15, O33*
Keywords: *AI adoption, motivational factors, Slovak enterprises*

1 Introduction

Artificial intelligence (AI) has emerged as one of the most transformative technologies of the digital economy, fundamentally changing the way organizations create value, make decisions, and achieve competitive advantage. Through advanced data analytics, machine learning, natural language processing, and intelligent automation, AI enables organizations to optimize business processes, improve operational efficiency, and develop innovative products and services (Dwivedi et al., 2021; Verhoef et al., 2021). Consequently, AI is increasingly regarded not only as a technological innovation but also as a strategic capability that enhances organizational resilience, fosters innovation, and supports long-term competitiveness. Despite the growing availability of AI technologies, their adoption across organizations remains highly uneven. While some enterprises have successfully integrated AI into their strategic management and day-to-day operations, many organizations continue to postpone or reject its implementation due to technological, organizational, financial, regulatory, and behavioral barriers (Jöhnk et al., 2021). Understanding the factors that motivate or discourage AI adoption has therefore become an important research topic for both academics and policymakers seeking to accelerate digital transformation and strengthen economic competitiveness. This study addresses these challenges by examining the motivational factors, managerial attitudes, and organizational conditions that influence the adoption of artificial intelligence in organizations at different stages of the adoption process. Particular attention is devoted to identifying the key drivers of AI adoption in enterprises and uncovering the latent dimensions that shape organizational decision-making regarding AI implementation. The aim of the paper is to contribute to a deeper understanding of the factors influencing AI adoption and to provide empirical evidence that can support the development of digital transformation strategies at both the organizational and national levels.

2 Current State of the Solved Problem at Home and Abroad

The adoption of artificial intelligence has become one of the central research topics in the fields of digital transformation, information systems, and innovation management. Existing studies consistently demonstrate that the successful implementation of AI depends on the complex interaction of technological, organizational, environmental, and behavioral factors rather than on technological availability alone (Dwivedi et al., 2021; Mikalef & Gupta, 2021). One of the most influential theoretical frameworks explaining organizational technology adoption is the Technology–Organization–Environment (TOE) framework, which argues that innovation adoption is jointly determined by technological characteristics, organizational readiness, and environmental conditions (Baker, 2012). Numerous recent studies have successfully applied and extended this framework to AI adoption by incorporating managerial commitment, organizational culture, digital maturity, ethical concerns, and organizational readiness as additional explanatory variables (Jöhnk et al., 2021). Behavioral perspectives also play an important role in explaining AI adoption within organizations. The Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) suggest that adoption decisions are influenced by perceived usefulness, perceived ease of use, social influence, and facilitating conditions. In organizational settings, these behavioral determinants are complemented by leadership support, employee competencies, organizational learning, and an innovation-oriented culture (Vial, 2019; Dwivedi et al., 2021).

Mikalef and Gupta (2021) identify four major groups of determinants influencing AI adoption. The first comprises technological factors, including data quality, IT infrastructure, cybersecurity, interoperability, and technological complexity. The second encompasses organizational factors such as financial resources, digital capabilities, workforce skills, leadership commitment, and organizational readiness. The third includes environmental determinants, particularly government policies, competitive pressure, regulatory frameworks, and access to external expertise. Finally, behavioral factors—including trust in AI, perceived risks, resistance to change, ethical concerns, and managerial attitudes—have become increasingly important predictors of organizational adoption decisions.

Research further suggests that organizations face different challenges depending on their stage of AI adoption. Organizations that have already implemented AI primarily focus on maximizing business value, integrating AI into business processes, and scaling existing solutions. Potential adopters tend to emphasize financial uncertainty, insufficient technical expertise, and uncertainty regarding the expected business benefits. In contrast, non-adopting organizations most frequently cite limited awareness of AI opportunities, insufficient organizational capabilities, inadequate employee competencies, concerns about implementation costs, and regulatory compliance as the main barriers to adoption (Jöhnk et al., 2021). An increasingly recognized phenomenon in AI adoption research is organizational uncertainty. Many organizations neither reject nor actively pursue AI adoption but remain undecided due to limited knowledge, insufficient practical experience, or uncertainty regarding implementation outcomes. Such neutrality has been identified as a significant barrier delaying AI diffusion and slowing the digital transformation of organizations (Jöhnk et al., 2021; Vial, 2019).

Although international research on AI adoption has expanded considerably, empirical evidence from Slovakia and other Central and Eastern European countries remains relatively limited. Existing studies have focused predominantly on technologically advanced economies and large multinational enterprises, while organizations operating in smaller economies with different institutional and digital environments have received substantially less attention. Moreover, only a limited number of studies simultaneously compare organizations that have already adopted AI, enterprises planning adoption, and organizations that have not yet adopted

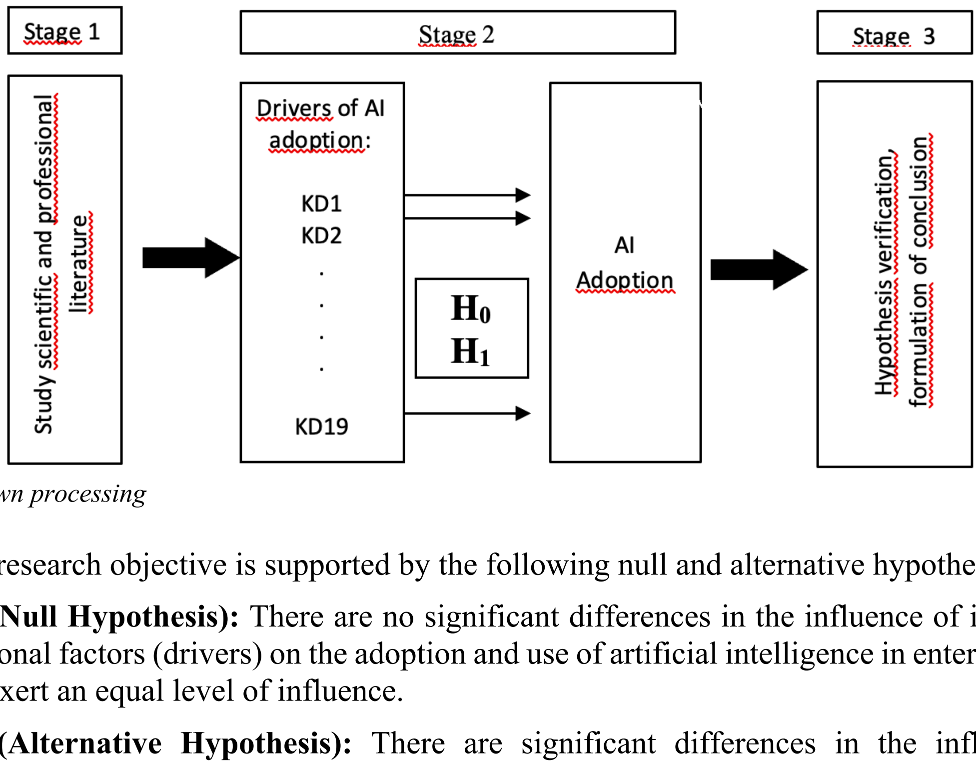
AI within a unified analytical framework. Addressing this research gap is essential for understanding the diversity of AI adoption pathways and for designing differentiated policy instruments and managerial strategies that reflect the specific needs of organizations at different stages of AI readiness. Building upon these theoretical and empirical insights, the present study adopts a multidimensional analytical framework integrating technological, organizational, behavioral, and environmental perspectives to examine the motivational factors, adoption barriers, managerial commitment, and employment-related impacts associated with AI adoption. This approach provides a comprehensive understanding of AI adoption in organizations and supports the formulation of evidence-based recommendations for both business practice and public policy.

3 Research Design and Methodology

This chapter presents the research objective, the conceptual research framework, the research variable model, and the methodological approach applied in the study.

The main objective of the paper is to examine the key motivational factors driving the implementation of artificial intelligence in enterprises operating in Slovakia and to identify the factors that have the greatest influence on its adoption and practical use. Investigating these factors is particularly important given the growing role of artificial intelligence as a tool for enhancing competitiveness, improving process efficiency, and strengthening the innovation potential of enterprises. The conceptual research framework, which systematizes the relationships among the research variables and the analysed factors, is presented in Figure 1.

Figure 1
Research framework



Source: own processing

The research objective is supported by the following null and alternative hypotheses:

H0 (Null Hypothesis): There are no significant differences in the influence of individual motivational factors (drivers) on the adoption and use of artificial intelligence in enterprises; all factors exert an equal level of influence.

H1 (Alternative Hypothesis): There are significant differences in the influence of individual motivational factors (drivers) on the adoption and use of artificial intelligence in enterprises; some factors exert a substantially stronger influence than others.

Testing these hypotheses makes it possible to identify the relative importance of individual motivational factors and contributes to a deeper understanding of the determinants of artificial intelligence implementation, providing important implications for the development of strategies that support its effective adoption in business practice.

The research was conducted through a questionnaire survey based on a conceptual model of research variables. The questionnaire was designed to capture the perceptions and attitudes of organizations at different stages of AI adoption. The research model consisted of two groups of variables. The first group (P1, P2…P4) comprised selected organizational characteristics, including enterprise size, ownership structure, length of operation in Slovakia, and business sector. These variables were measured at the nominal level, and the characteristics of the research sample based on these variables are presented in Table 1.

Table 1
Research Sample Characteristics

Selected firm characteristics		**No.**	**%**
P1 – Company size	Small (10–49 employees)	222	27.21
	Medium (50–249 employees)	246	30.15
	Large (250+ employees)	348	42.65
P2 – Ownership	Private domestic ownership	391	47.92
	Private foreign ownership	326	39.95
	Public ownership*	0	0.00
	Mixed ownership	99	12.13
P3 – Duration of business activity in Slovakia	< 5 years	0	0.00
	5–10 years	248	30.39
	> 10 years	568	69.61
P4 – Business sector	A – Agriculture, forestry, and fishing	7	0.86
	B – Mining and extraction	4	0.49
	C – Industrial production	201	24.63
	D – Supply of electricity, gas, steam, cold air	13	1.59
	E – Water supply, sewage and waste management	7	0.86
	F – Construction	56	6.86
	G – Wholesale and retail trade; repair of motor vehicles	18	2.21
	H – Transportation and storage	65	7.97
	I – Accommodation and food services	33	4.04
	J – Information and communication	87	10.66
	K – Financial and insurance activities	73	8.95
	L – Real estate activities	12	1.47
	M – Professional, scientific, and technical activities	33	4.04
	N – Administrative and support services	41	5.02
	O – Compulsory social security	7	0.86
	P – Education	20	2.45
	Q – Health and social assistance	41	5.02
	S – Other activities	98	12.01

Source: own processing

The second group of variables (KD1, KD2…KD19) captured the perceived motivational factors identified from the literature, including competitive pressure, increased efficiency, cost reduction, growing volumes of data, labor shortages, and management enthusiasm for AI. These variables were measured using a five-point Likert scale ranging from 1 ("Not important at all") to 5 ("Key factor"). The motivational factors together with the respondents' evaluations are presented in Table 2.

Data collection was carried out between September 2025 and January 2026. Respondents were middle- and senior-level managers, as they were expected to possess sufficient knowledge of their organizations' strategic orientation, internal capabilities, and attitudes toward the implementation of artificial intelligence. The target population consisted of enterprises operating in Slovakia with at least 10 employees, an annual turnover of at least EUR 200,000, and a minimum of five years of business operations; public enterprises were excluded from the study. After data cleaning, the final analytical sample comprised 816 enterprises. Organizations operating for less than five years were excluded from the sample to ensure that all respondents represented enterprises with established internal structures and accumulated organizational experience relevant to evaluating strategic decisions related to artificial intelligence. The duration of business operations in Slovakia was measured using three predefined categories (<5 years, 5–10 years, and >10 years); however, due to the exclusion criterion, only the latter two categories were represented in the final sample.

The data were processed using Microsoft Excel. Standard descriptive statistical methods and exploratory factor analysis were employed to evaluate the data and reduce the dimensionality of the observed variables. Statistical analyses were performed using jamovi (Version 2.6; The jamovi Project, 2025).

4 Research Result

The results are presented in the following structure: the percentage distribution of individual responses, descriptive statistics, and the results of the exploratory factor analysis.

4.1 Percentage Distribution of Survey Responses

The percentage distribution of respondents' responses, together with the importance of the individual motivational factors, is presented in Table 2.

The results presented in Table 2 and Figure 2 indicate that organizations primarily perceive the implementation of artificial intelligence as a means of improving internal performance and operational efficiency. The most important motivating factor is the pursuit of greater efficiency, with more than 60% of respondents identifying this aspect as either important or a key driver. Similarly, the automation of business processes is regarded as highly important, reflecting its close association with process optimization and the reduction of manual intervention. Cost reduction also represents a major driver, confirming that organizations approach AI implementation from a predominantly economic perspective.

Another important motivational factor is the ability to respond more rapidly to customer demand and changing market conditions, together with improved speed and quality of decision-making. These findings suggest that organizations view AI as a tool for enhancing organizational adaptability and managerial decision-making, particularly in environments characterized by rapid change and increasing volumes of available data. This interpretation is further supported by the relatively high importance assigned to factors such as real-time big data analytics, improvements in the quality of internal processes, and the reduction of human error.

Table 2
Motivational factors influencing AI adoption

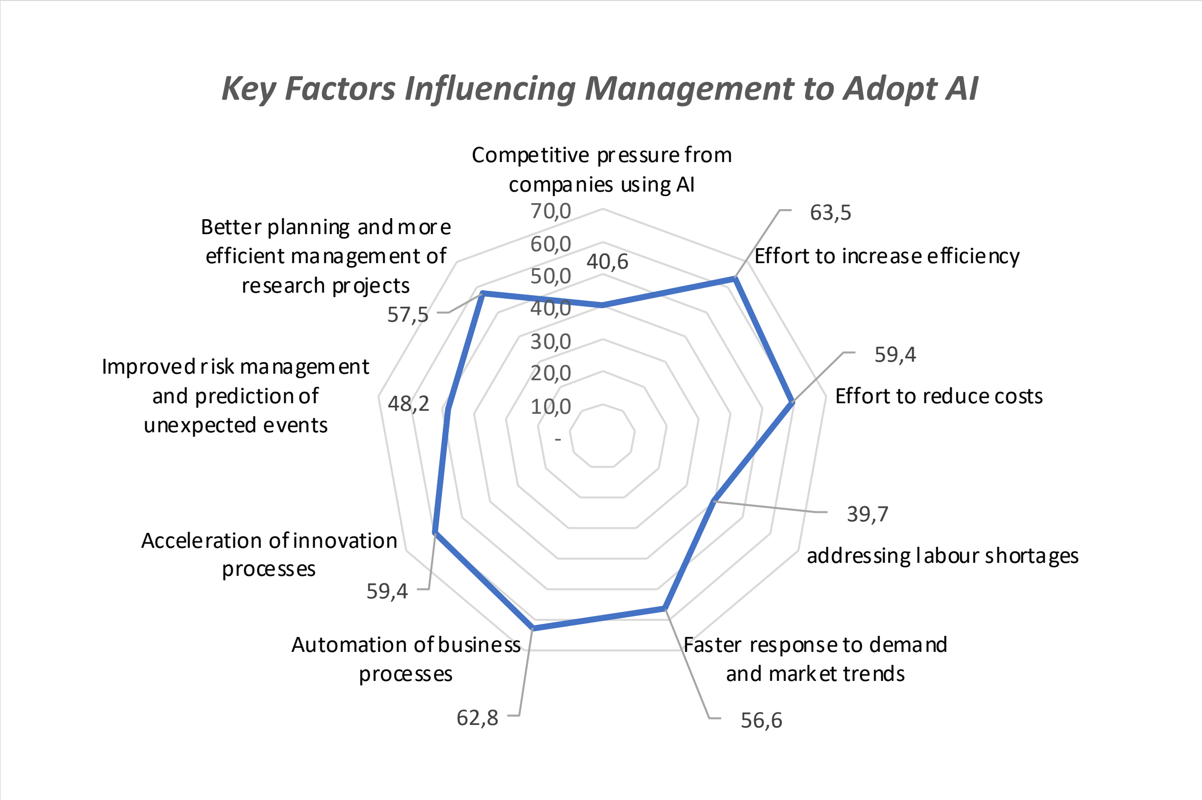
Label	The meaning of motivational factors	Not important at all	Rather not important	Neutral	Rather important	Key factor
KD1	Competitive pressure from companies using AI	8.54%	19.22%	31.67%	32.38%	8.19%
KD2	Effort to increase efficiency	2.49%	10.32%	23.67%	44.48%	19.04%
KD3	Effort to reduce costs	3.20%	11.03%	26.33%	42.70%	16.73%
KD4	Response to the growing volume of corporate data	3.38%	10.14%	32.03%	40.04%	14.41%
KD5	Addressing labor shortages	7.83%	18.33%	34.16%	29.89%	9.79%
KD6	Ability to analyze large volumes of data in real time	4.09%	9.25%	29.72%	44.48%	12.46%
KD7	Faster response to demand and market trends	3.74%	9.25%	30.43%	40.39%	16.19%
KD8	Automation of business processes	2.67%	8.72%	25.80%	45.37%	17.44%
KD9	Improvement of customer relationships	4.09%	12.63%	30.78%	38.79%	13.70%
KD10	More accurate and faster decision-making	3.91%	11.21%	29.72%	41.10%	14.06%
KD11	Creation of new business models	5.52%	12.28%	33.99%	38.79%	9.43%
KD12	Improvement of internal business process quality	3.56%	11.74%	28.83%	41.81%	14.06%
KD13	Acceleration of innovation processes	3.56%	8.54%	28.47%	46.26%	13.17%
KD14	Improved risk management and prediction of unexpected events	4.63%	12.63%	34.52%	37.54%	10.68%
KD15	Increased security requirements and threats	5.69%	12.99%	30.96%	38.08%	12.28%
KD16	Reduction of human error	4.63%	10.85%	28.65%	42.70%	13.17%
KD17	Rapid identification of weaknesses in products and services	3.20%	11.03%	32.74%	39.32%	13.70%
KD18	Better planning and more efficient management of research projects	3.56%	9.07%	29.89%	45.73%	11.74%
KD19	Enthusiasm of leadership or management for AI	4.09%	11.03%	33.10%	39.86%	11.92%

Source: own processing

In contrast, external and more transformative drivers are perceived as less influential. Competitive pressure from firms already using AI ranks among the least important factors, with a relatively large proportion of respondents evaluating it as neutral or of low importance. Similarly, labor shortages and management enthusiasm for AI are not considered dominant motivations for implementation. The development of new business models also receives comparatively lower importance, suggesting that organizations have not yet fully exploited the transformative potential of artificial intelligence.

Overall, the findings indicate that AI adoption in the surveyed organizations is primarily driven by internal objectives related to operational optimization and performance improvement, whereas strategic and innovation-oriented motivations play a secondary role. This pattern suggests that most enterprises remain at a stage of gradual AI implementation, using the technology mainly to improve the efficiency of existing processes rather than to fundamentally transform their business models.

Figure 2
Motivational factors influencing AI adoption



Source: Own processing

4.2 Descriptive Statistics of the Motivational Factors

The mean values of the individual items range from 3.12 to 3.67 on a five-point Likert scale, indicating a moderate to moderately high level of agreement with the respective statements. The highest mean was recorded for AIAfaktorymotivacia_2 (M = 3.67; SD = 0.98), followed closely by AIAfaktorymotivacia_8 (M = 3.66; SD = 0.95). In contrast, the lowest mean was observed for AIAfaktorymotivacia_1 (M = 3.12; SD = 1.08); however, this value still exceeds the midpoint of the scale.

The median equals 4 for most items, indicating that at least half of the respondents selected a response of 4 or higher. The exceptions are items 1, 5, 11, and 14, for which the median is 3. The mode is 4 in the majority of cases, whereas item 5 has a mode of 3, further confirming respondents' general tendency toward agreement.

The standard deviation ranges from 0.94 to 1.08, indicating a moderate level of variability in the responses. Thus, respondents' answers do not exhibit excessive dispersion and can be considered relatively consistent.

All items display slight negative skewness (ranging from –0.22 to –0.67), indicating that the distributions are moderately skewed to the left, with respondents tending to select higher response categories (4 and 5). None of the skewness values exceeds the commonly accepted threshold of ±1, suggesting that the distributions are sufficiently symmetrical.

Kurtosis values range from –0.62 to 0.36, remaining close to zero. This indicates that the distributions of the individual items deviate only minimally from a normal distribution.

Overall, the descriptive statistics indicate that respondents evaluated the motivational factors for AI adoption positively, with the mean values of all items exceeding the midpoint of the scale. The variability of responses is moderate, and the distributions exhibit only minor departures from normality. Based on the observed skewness and kurtosis values, the data satisfy commonly accepted assumptions of normality and are therefore suitable for the application of parametric statistical techniques, including correlation analysis, regression analysis, and exploratory factor analysis.

4.3 Results of the Exploratory Factor Analysis

The exploratory factor analysis (EFA) was conducted using the Minimum Residuals (MinRes) extraction method followed by Oblimin oblique rotation. The MinRes method identifies latent factors by minimizing the discrepancies between the observed and model-reproduced correlation matrices. Oblimin rotation allows the extracted factors to be correlated, making it particularly suitable for organizational research, where the motivational drivers of artificial intelligence adoption are not entirely independent but often complement and influence one another. The number of factors was determined based on parallel analysis (Costello & Osborne, 2005).

Assessment of the suitability of the data for exploratory factor analysis. To evaluate the suitability of the data for EFA, Bartlett's test of sphericity and the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy were applied. Bartlett's test yielded a statistically significant result ($\chi^2 = 4750$, df = 171, $p < 0.001$), indicating the presence of sufficient correlations among the variables. The overall KMO value reached 0.952, representing an excellent level of sampling adequacy for factor analysis. The individual Measure of Sampling Adequacy (MSA) values for all variables ranged from 0.896 to 0.969, indicating very good to excellent adequacy (Kaiser & Meyer, 1974). Based on these results, it can be concluded that the data satisfy the assumptions required for the application of exploratory factor analysis.

Table 3
Exploratory Factor Analysis

	Factor Loadings	**Factor**		
		1	2	Uniqueness
KD1	Competitive pressure from companies using AI		0.336	0.700
KD2	Effort to increase efficiency		0.760	0.378
KD3	Effort to reduce costs	0.382	0.379	0.540
KD4	Response to the growing volume of corporate data	0.629		0.582
KD5	Addressing labor shortages	0.680		0.683
KD6	Ability to analyze large volumes of data in real time	0.518		0.575
KD7	Faster response to demand and market trends	0.519		0.475
KD8	Automation of business processes	0.371	0.410	0.516
KD9	Improvement of customer relationships	0.630		0.582
KD10	More accurate and faster decision-making	0.563		0.524
KD11	Creation of new business models	0.740		0.482
KD12	Improvement of internal business process quality	0.448	0.314	0.535
KD13	Acceleration of innovation processes	0.441	0.320	0.536
KD14	Improved risk management and prediction of unexpected events	0.675		0.506
KD15	Increased security requirements and threats	0.753		0.529
KD16	Reduction of human error	0.589		0.596
KD17	Rapid identification of weaknesses in products and services	0.653		0.544
KD18	Better planning and more efficient management of research projects	0.688		0.524
KD19	Enthusiasm of leadership or management for AI	0.604		0.621
	Note. 'Minimum residual' extraction method was used in combination with a 'oblimin' rotation			

Source: Own processing.

The exploratory factor analysis of the motivational drivers of artificial intelligence adoption identified a two-factor solution (F1 and F2), with the first factor emerging as clearly dominant and accounting for the majority of the shared variance among the examined items. The first factor encompasses a broad range of internal strategic, operational, and development-oriented motivations. The highest factor loadings were observed for the items improving organizational efficiency (0.760), addressing increasing security demands and threats (0.753), developing new business models (0.740), improving the planning and management of research projects (0.688), addressing labor shortages (0.680), and enhancing risk management and the prediction of unexpected events (0.675).

This factor can be interpreted as representing **internal strategic and performance-oriented motivations for AI adoption**, as it captures the expected benefits associated with improved efficiency, innovation, decision-making, risk management, and overall organizational performance. The factor score for F1 can be expressed as follows (after excluding the items that loaded substantially on both factors):

F1=0.628*KD4+0.680*KD5+0.518*KD6+0.519*KD7+0.630KD9+0.630*KD10+0.740*KD11+0.675*KD14+0.753*KD15+0.589*KD16+0.653*KD17+0.688*KD18+0.604*KD19

The second factor is considerably weaker and is represented by only a few items. Although the highest loading is again observed for improving organizational efficiency (0.760), the presented factor structure suggests that the second factor is primarily defined by competitive pressure from organizations already using AI (0.336), the intention to automate business processes (0.410), and, to a lesser extent, the intention to reduce costs (0.379). These items reflect more external or immediate economic motivations; however, their factor loadings are relatively low, and several variables exhibit substantial cross-loadings. Similar to the first composite factor, the factor score for F2 can be expressed as:

$F2 = 0.336 \times KD1 + 0.760 \times KD2$

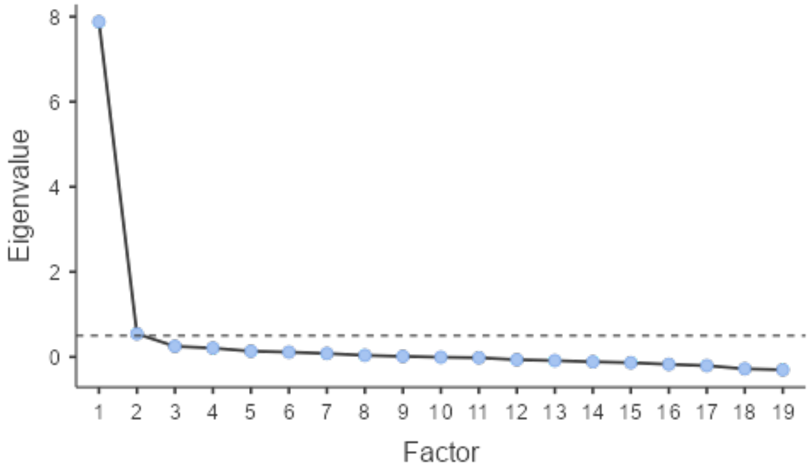
Particular attention should be paid to KD3 – the intention to reduce costs (0.382; 0.379) and KD8 – the intention to automate business processes (0.371; 0.410), which display nearly identical loadings on both factors. Likewise, KD12 – improving the quality of internal business processes (0.448; 0.314) and KD13 – accelerating innovation processes (0.441; 0.320) indicate a certain degree of overlap between the two latent dimensions. The presence of these cross-loadings suggests that the individual motivational drivers are not strictly independent but rather complement one another in practice.

The uniqueness values range from 0.378 to 0.700. The lowest uniqueness is observed for improving organizational efficiency (0.378), indicating that the extracted factors explain a substantial proportion of its variance. In contrast, the highest uniqueness is found for competitive pressure from organizations already using AI (0.700), suggesting that its variability is largely influenced by factors not captured by the present model.

Overall, the findings indicate that the motivations underlying AI adoption are largely unidimensional and primarily focused on the internal strategic and performance-related benefits of AI. Although the analysis identified a second factor, its interpretative value is limited by the small number of items loading uniquely on it and the presence of several cross-loadings. From a practical perspective, the results point to a single dominant motivational dimension centered on improving organizational performance, fostering innovation, and enhancing competitiveness through the adoption of artificial intelligence.

The figure 3 presents a scree plot (eigenvalue plot), which is used to determine the optimal number of factors to retain in exploratory factor analysis.

Figure 3
Scree plot



Source: own processing

The scree plot clearly shows that the first factor has a very high eigenvalue (approximately 7.9), whereas the second factor has an eigenvalue only slightly above 0.5. From the second factor onward, the curve flattens considerably, and all remaining factors exhibit very low eigenvalues. The characteristic elbow occurs between the first and second factors, indicating that the majority of the shared variance among the items is explained by the first factor.

These results suggest that the examined motivational drivers of artificial intelligence adoption are predominantly unidimensional and can be interpreted as manifestations of a single dominant latent construct. Although the exploratory factor analysis identified a two-factor solution, the scree plot provides only limited support for the existence of a distinct second factor. From a methodological perspective, the scree plot therefore supports the interpretation of a single-factor model of AI adoption motivations.

5 Discussion

The comparison of the results obtained from the descriptive statistics and the exploratory factor analysis shows that the two approaches are generally complementary, while providing slightly different perspectives on the motivational drivers of AI adoption.

5.1 Consistent Findings

Both analytical approaches produced consistent findings. The highest percentages of positive responses ("rather important" + "key factor") were recorded for KD2 – improving organizational efficiency (63.52%), KD8 – automating business processes (62.81%), KD3 – reducing costs (59.43%), KD13 – accelerating innovation processes (59.43%), KD18 – improving the planning and management of research projects (57.47%), and KD7 – responding more rapidly to market changes (56.58%). Similarly, the exploratory factor analysis identified the following items as having the strongest factor loadings: KD2 – improving organizational efficiency (0.760), KD15 – increasing security requirements and threats (0.753), KD11 – developing new business models (0.740), KD18 – improving the planning and management of research projects (0.688), KD5 – addressing labor shortages (0.680), and KD14 – improving risk management (0.675). The strongest point of convergence between the two analyses is KD2 – improving organizational efficiency, which achieved both the highest percentage of positive evaluations and the highest factor loading. This finding confirms that improving efficiency represents the core motivation driving AI adoption among enterprises.

Both analyses also consistently identify KD1 – competitive pressure as one of the least influential drivers. This variable received the lowest percentage of positive evaluations (40.57%), exhibited the highest uniqueness value (0.700), and showed a relatively low factor loading (0.336). These findings indicate that competitive pressure is not a dominant motivational factor for AI adoption among Slovak enterprises.

5.2 Differences in the Results

The percentage distributions reflect the absolute importance assigned to individual motivational factors, whereas the exploratory factor analysis identifies which items tend to co-occur and form common latent motivational dimensions. Consequently, several noteworthy differences emerge:

a) **Business process automation (KD8):** This factor received a very high percentage of positive evaluations (62.81%), yet its factor loadings were only 0.371 on F1 and 0.410 on F2. This suggests that, although automation is generally regarded as an important driver, it is not uniquely associated with a single motivational dimension. Instead, respondents link automation to several organizational objectives simultaneously.
b) **Development of new business models (KD11):** Despite receiving a relatively low percentage of positive evaluations (48.22%), this item exhibited a very high factor loading (0.740). This indicates that, although it is not a priority for all enterprises, it constitutes an important component of the broader strategic motivation among organizations pursuing AI-driven transformation.
c) **Security and risk management (KD15 and KD14):** These factors received only moderate importance ratings in the descriptive analysis but emerged among the strongest items in the factor analysis. This suggests that organizations do not perceive them as primary stand-alone drivers of AI adoption; rather, they are closely associated with an overarching strategic orientation toward AI.
d) **Labor shortages (KD5):** Although this factor was among the less important motivators in the descriptive analysis (39.68%), it achieved a high factor loading (0.680). The factor analysis therefore indicates that labor shortages form part of a broader set of strategic motivations for AI adoption, even though respondents do not consider them a decisive driver when evaluated independently.

Overall, the results of the exploratory factor analysis confirm that the motivational drivers of AI adoption in Slovak enterprises do not influence adoption decisions with equal strength but instead exhibit substantially different factor loadings. Accordingly, the **null hypothesis (H0)** is rejected, and the **alternative hypothesis (H1)** is accepted, indicating that individual motivational factors differ significantly in their influence on the adoption and use of artificial intelligence in enterprises.

6 Conclusion

The percentage distributions indicate that Slovak enterprises adopt AI primarily to improve efficiency, automate business processes, reduce costs, and enhance operational performance. However, the exploratory factor analysis reveals a deeper motivational structure: behind these individual evaluations lies a single dominant latent factor that can be interpreted as **the internal strategic and performance transformation of the enterprise through AI**. This dimension encompasses not only efficiency and productivity but also security, risk management, the development of new business models, project planning, and addressing labor shortages.

The descriptive analysis identified efficiency, business process automation, and cost reduction as the most frequently cited reasons for AI adoption. In contrast, the exploratory factor analysis demonstrated that these factors do not represent isolated motivations but rather form part of a broader latent dimension reflecting enterprises' strategic and performance-related expectations of artificial intelligence. Overall, the findings suggest that AI adoption in Slovakia is driven less by competitive pressure than by the pursuit of internal transformation and enhanced organizational performance.

Acknowledgement

This paper was supported by the European Union – NextGenerationEU through the Recovery and Resilience Plan for Slovakia under project No. 09I05-03-V02-00003/2025/VA (AI-impactSK); 100% share.

Data availability

The AI-ImpactSK survey dataset (Černý et al., 2026) is openly available via Zenodo under a CC BY 4.0 licence: https://doi.org/10.5281/zenodo.20699449

References

Baker, J. (2012). *The Technology–Organization–Environment Framework.* In Y. K. Dwivedi et al. (Eds.), Information Systems Theory. Springer. https://doi.org/10.1007/978-1-4419-6108-2_12

Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. Practical assessment, research, and evaluation, 10(1).

Davis, F. D. (1989). *Perceived usefulness, perceived ease of use, and user acceptance of information technology.* MIS Quarterly, 13(3), 319–340.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., et al. (2021). *Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy.* International Journal of Information Management, 57, 101994.

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). *Ready or not, AI comes—An interview study of organizational AI readiness factors.* Business & Information Systems Engineering, 63(1), 5–20.

Kaiser, M. O. (1974). *Kaiser-Meyer-Olkin measure for identity correlation matrix*. Journal of the Royal Statistical Society, 52(1), 296-298.

Mikalef, P., & Gupta, M. (2021). *Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance.* Information & Management, 58(3), 103434.

The jamovi project (2025). jamovi. (Version 2.7) [Computer Software]. Retrieved from https://www.jamovi.org.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). *User acceptance of information technology: Toward a unified view.* MIS Quarterly, 27(3), 425–478.

Verhoef, P. C., Broekhuizen, T., Bart, Y., et al. (2021). *Digital transformation: A multidisciplinary reflection and research agenda.* Journal of Business Research, 122, 889–901.

Vial, G. (2019). *Understanding digital transformation: A review and a research agenda.* Journal of Strategic Information Systems, 28(2), 118–144.

Determinants of Artificial Intelligence Adoption and Segmentation of Slovak Enterprises Based on Their Organizational Maturity Level

Iveta Kufelová, Dana Hrušovská, Anna Hamranová

Abstract
The development of artificial intelligence (AI) represents one of the most significant technological shifts in the modern economy, fundamentally impacting how enterprises operate, compete, and innovate. Despite the increasing availability of AI technologies, their implementation across enterprises remains uneven, with organizational, strategic, technological, and personnel factors playing a crucial role. This paper aims to identify the determinants of AI adoption in Slovak enterprises and create a segmentation based on their organizational maturity level to assess their readiness to implement AI solutions. The empirical analysis utilizes data collected through the AI-impactSK research project from a sample of Slovak enterprises. The research was conducted in two data collection phases, with the primary sample consisting of 312 enterprises and the validation sample including an additional 643 enterprises, creating a robust dataset to verify the stability of the results.

JEL classification*: L15, M22, O13*
Keywords*: artificial intelligence, AI maturity, artificial intelligence adoption, digital transformation, enterprise segmentation, organizational readiness*

1 Introduction

In recent years, Artificial Intelligence (AI) has become a primary driver in transforming business processes, managing organizations, and building competitive advantage. The dynamic growth of generative AI, machine learning, natural language processing, and analytical systems is shifting the core nature of business operations, managerial decision-making, and entire value chains. Implementing AI-driven solutions allows enterprises to automate routine tasks, process vast amounts of data more efficiently, boost labor productivity, foster product and service innovation, and build new business models for the data economy.

However, despite rapid technological progress, AI adoption remains uneven among businesses. While some organizations implement advanced AI solutions as a core part of their strategic activities, a significant portion of enterprises are still in the preparation phase or do not plan to adopt AI at all. This gap indicates that the mere availability of technology does not guarantee successful implementation. Instead, organizational capabilities, management quality, employee readiness, data infrastructure, an innovation-driven corporate culture, and the ability to strategically integrate AI into business processes play a decisive role.

Consequently, academic literature focuses heavily on the concept of AI maturity, which offers a comprehensive assessment of an organization's readiness to implement, manage, and scale AI technologies over the long term. AI maturity is understood as a multidimensional construct encompassing technological, organizational, data, personnel, strategic, and ethical aspects of AI adoption. A higher level of organizational maturity enhances a company's capability to successfully implement AI solutions and effectively leverage their economic potential.

Although AI maturity research is expanding globally, empirical studies analyzing AI adoption determinants in Central European economies remain limited. This deficit is even more pronounced for Slovak enterprises, where there is a lack of comprehensive empirical analyses based on representative data to identify the factors driving AI implementation and segment businesses by their organizational readiness.

This paper addresses this research gap by presenting the findings of an extensive empirical study conducted within the AI-impactSK project. The objective was to analyze AI implementation levels in Slovak enterprises, identify adoption determinants, and segment businesses based on their organizational maturity. The study was executed in two consecutive phases, combining primary and validation data collections to verify the robustness of findings across a total sample of 955 Slovak enterprises.

The main objective of this article is to identify the key determinants of AI adoption in Slovak enterprises and empirically verify the relationship between organizational maturity and the degree of AI implementation. Concurrently, the paper aims to segment businesses according to their AI maturity and identify distinct organizational profiles regarding digital transformation readiness. To achieve this goal, three research questions (RQ1, RQ2, RQ3) and three corresponding research hypotheses (H1, H2, H3) were formulated.

2 Current State of the Solved Problem at Home

Digitization is one of the most powerful transformative forces in the modern economy, and artificial intelligence (AI) is increasingly becoming its core technological component. While the early stages of digital transformation focused primarily on process automation and implementing corporate information systems, the current phase is characterized by a shift from digitization to intelligent systems capable of autonomous data analysis, learning from experience, and supporting managerial decision-making. AI is thus evolving from a mere technological innovation into a strategic resource for business competitiveness.

2.1 Artificial Intelligence as a Driver of Corporate Digital Transformation

In academic literature, AI adoption is understood as a complex process of organizational transformation that goes far beyond the deployment of software solutions. Successful AI implementation requires aligning business strategy, organizational structure, processes, data infrastructure, human resources, and governance systems. Studies increasingly emphasize that technological readiness is only a baseline requirement, while strategic management, corporate culture, and the ability to systematically develop digital competencies play a more critical role.

The advancement of generative AI has vastly expanded the use cases for AI across all business processes - ranging from marketing, finance, and logistics to human resource management, manufacturing, and customer service. However, the growing number of applications also increases the demand for data governance, cybersecurity, ethical AI principles, and the creation of appropriate AI governance frameworks.

2.2 The Concept of AI Maturity and the Methodological Framework of its Measurement

The concept of organizational maturity is an established approach for evaluating the capacity of organizations to systematically manage processes, innovations, and technological transitions. In the domain of artificial intelligence, the concept of AI maturity has evolved as a multidimensional framework that enables the assessment of firms' readiness to implement, develop, and effectively leverage AI technologies. Unlike traditional digitalization indicators, which predominantly focus on the level of a firm's technological equipment, AI maturity represents a complex construct encompassing technological, organizational, human, data, strategic, and ethical dimensions. Modern AI maturity models operate under the assumption that successful AI implementation is the outcome of a coordinated development of multiple, mutually reinforcing organizational capabilities. The foundational dimensions of organizational readiness include the strategic governance of AI, the quality of data infrastructure, technological readiness, an innovation-supportive organizational culture, employees' digital competencies, the AI management system, and ethical and regulatory mechanisms. From this perspective, AI maturity cannot be reduced to the mere number of deployed AI applications. Instead, the decisive criterion becomes the organization's ability to utilize artificial intelligence as an integral component of business processes and strategic decision-making.

In alignment with this theoretical formalization, an empirical framework for measuring and operationalizing the AI maturity of firms within the Slovak economic environment was formulated as part of the AI-impactSK research project. To quantify this complex phenomenon, a composite AI maturity index was developed, the construction of which is grounded in a rigorous, multi-stage statistical procedure. In the primary phase of the maturity research, the index was decomposed into seven dimensions that reflect the core areas of organizational readiness, identified as follows:

1. **Organizational Culture for AI:** Assesses the firm's openness to innovation, learning orientation, and human capital readiness.
2. **AI Strategy:** Evaluates the existence, quality, and level of integration of strategic objectives regarding AI deployment.
3. **Organizational Structure and Processes:** Measures the alignment of internal processes, governance mechanisms, and managerial systems.
4. **Technological Infrastructure:** Captures the availability, robustness, and sophistication of digital and AI-related technologies.
5. **Data Management Capability:** Investigates the firm's capacity to collect, store, process, and govern data assets.
6. **Ethical Readiness:** Monitors the existence of internal policies and the overall organizational awareness regarding responsible AI use.
7. **Privacy and Security Capability:** Evaluates the security level, compliance with legislative frameworks, and risk management mechanisms for data protection.

Each of these dimensions was operationalized and measured across incremental levels of organizational capabilities using a 5-point Likert scale (ranging from 1 to 5). The mathematical aggregation of the parsimonious index subsequently proceeded in three complementary steps:

- **Reliability Analysis:** Prior to the synthesis of the index, the internal consistency and coherence of the proposed scale were verified. For this purpose, Cronbach's alpha and McDonald's omega coefficients were applied, confirming the high reliability and stability of the measurement instrument.
- **Principal Component Analysis:** Given the assumption of high intercorrelation among the individual maturity dimensions, Principal Component Analysis (PCA) was deployed as a tool for data dimensionality reduction. The empirical extraction of the first principal component provided robust evidence of the unidimensionality of the measured construct. This component linearly captures the maximum possible variance of the original variables and serves as the optimal mathematical foundation for the composite score.
- **Index Normalization:** To ensure precise interpretability and facilitate comparison across a heterogeneous population of firms, the resulting composite score (derived from the weights of the first principal component) was normalized to a standardized linear scale ranging from **0 to 100 points**.

The proposed methodological model was empirically verified using two independent datasets representing the business environment of the Slovak Republic. The primary dataset (N = 312) was used for the initial estimation of latent structures, reliability verification, and the calculation of the composite index. In the secondary phase, the validation dataset ((N = 643) was leveraged for the cross-validation of findings, model robustness testing, and a more detailed examination of specific factors (such as managerial approach, enterprise software level, and employee competencies) that influence the transition of organizations through successive stages of AI adoption.

2.3 Determinants of Artificial Intelligence Adoption

The factors determining AI adoption represent one of the fastest-growing areas of current research. Systematic literature reviews indicate that successful AI implementation is influenced by a combination of technological, organizational, human, and environmental factors, with their relative importance varying by enterprise size, industry sector, and stage of digital transformation.

- **Strategic Management and Leadership Support:** Top management support is a primary determinant of AI adoption. Enterprises where leadership actively formulates an AI strategy, fosters experimentation, and supports an innovative culture achieve higher success rates in AI deployment. Transformational leadership positively influences not only the initial decision to implement AI but also its deep integration into core business operations.
- **Technological Infrastructure:** Technological readiness remains a foundational baseline for AI adoption. This includes the availability of computing power, cloud-based solutions, corporate information systems, and the capacity to integrate AI applications into legacy infrastructure. However, empirical studies show that technology alone does not guarantee success unless backed by proper organizational readiness.
- **Data Readiness:** Data quality is a frequently cited prerequisite for effective AI utilization. Having high-quality, consistent, and integrated data sources directly impacts the accuracy and practical utility of AI models (p. 3). Concurrently, data governance is becoming critical to ensure standardization, security, and data sharing across the entire organization.
- **Human Capital:** The digital competencies of employees are widely discussed determinants of AI adoption. Organizations with staff skilled in analysis, technology, and management deploy AI far more successfully than companies facing talent shortages. Consequently, continuous training and upskilling are integral parts of corporate AI strategies.
- **Organizational Culture:** Empirical studies confirm that a corporate culture focused on innovation, experimentation, and knowledge sharing strongly accelerates AI implementation. Conversely, resistance to organizational change, low trust in new technologies, or a lack of cross-functional collaboration serve as major barriers to digital transformation.

2.4 Segmentation of Enterprises Based on AI Maturity Levels

The growing heterogeneity among businesses requires segmenting them by their readiness to adopt AI. Traditional classifications based solely on company size or industry are being replaced by segmentations derived from organizational capabilities. Segmenting by AI maturity allows researchers to identify groups of enterprises with shared characteristics in strategic management, tech readiness, data infrastructure, corporate culture, and human capital. These segments offer a practical basis for tailoring managerial recommendations and designing targeted economic policy tools to support corporate digitization. Cluster analysis, principal component analysis, and latent class models are the primary methods used in literature to identify these homogeneous groups.

2.5 Identification of Research Gaps, Research Questions, and Hypotheses

Most published empirical studies are conducted in technologically advanced economies, leaving insights from Central and Eastern Europe limited (p. 4). Additionally, current research tends to look at isolated adoption determinants, whereas comprehensive models integrating technological, organizational, strategic, human, and ethical dimensions remain rare exceptions Another gap is the small number of validation studies based on large-scale corporate databases.

Based on these theoretical foundations and research objectives, the following research questions and hypotheses were formulated:

- RQ1: Are there statistically significant differences in AI maturity levels among enterprises based on their degree of artificial intelligence adoption?
  - H1: There are statistically significant differences in AI maturity levels among enterprises based on their degree of artificial intelligence adoption.
- RQ2: Which dimensions of organizational maturity have the most significant impact on artificial intelligence implementation?
  - H2: Strategic management, organizational culture, technological readiness, and employee digital competencies significantly increase the probability of artificial intelligence adoption.
- RQ3: Is it possible to identify homogeneous segments of Slovak enterprises with varying readiness to implement AI solutions based on their AI maturity levels?
  - H3: Enterprises can be segmented into homogeneous groups with distinct readiness levels for AI implementation based on their AI maturity dimensions.n

3 Research Design and Methodology

This study utilizes a quantitative research design aimed at identifying the determinants of AI adoption and segmenting Slovak enterprises based on their organizational readiness for AI implementation (AI maturity). The research framework followed a two-phase design. The first phase consisted of exploratory research to map the main dimensions of organizational maturity and their relationship to AI adoption. The second phase served to validate these findings on an independent sample, ensuring higher robustness and reproducibility of the empirical results.

The empirical analysis was conducted on two independent datasets of Slovak enterprises within the national project AI-impactSK. The primary database included 312 enterprises, forming the foundation for constructing the AI maturity model and testing the hypotheses. The second validation database consisted of 643 enterprises and was used to verify the stability and generalizability of the findings. The total aggregated dataset thus comprised 955 enterprises across various sectors of the Slovak economy. Respondents were individuals responsible for strategic or technological management, primarily C-level executives, business owners, IT managers, or heads of digital transformation.

Data processing involved descriptive statistics, group difference testing via the Kruskal-Wallis test with subsequent post-hoc analyses, principal component analysis (PCA), ordinal logistic regression, cluster analysis, and the construction of a composite AI Maturity Index. The results confirm a statistically significant relationship between AI maturity levels and the degree of AI adoption.

3.1 Operationalization of Variables

The primary dependent variable was the level of artificial intelligence adoption. This was operationalized as an ordinal variable with three levels:

- **0** – the enterprise does not use AI and has no plans to implement it,
- **1** – the enterprise does not currently use AI but plans to implement it,

- **2** – the enterprise has actively implemented AI solutions into its business processes.

The independent variables represented individual dimensions of organizational maturity. In the primary phase, seven dimensions were evaluated: organizational culture, AI strategy, organizational structure and processes, technological infrastructure, data readiness, ethical readiness, and data privacy & security. In the validation phase, the analyzed dimensions included: AI awareness, management approach to AI, digital tools, data readiness, IT governance, human resources, and digital competencies. All items were measured on a 5-point Likert scale, where higher values indicated superior organizational readiness.

3.2 Construction of the AI Maturity Index and Reliability Verification

Principal Component Analysis (PCA) was used to reduce data dimensionality and create a synthetic index of organizational readiness. Prior to analysis, all variables were standardized using z-scores to eliminate scale bias across indicators. The selection of principal components was based on Kaiser's criterion (eigenvalue > 1) and a visual analysis of the Scree plot. The first principal component captured the latent variable representing the overall level of organizational readiness for AI implementation. Based on this component, an AI Maturity Index was constructed and normalized to a 0–100 scale to improve interpretability and allow benchmarking across companies.

Before executing inferential analyses, the internal consistency of the components was verified. Reliability was evaluated using Cronbach's α and McDonald's ω coefficients.

An $\alpha \geq 0.70$ was considered acceptable, with higher values indicating strong internal consistency. Utilizing both coefficients eliminated the traditional limitations of Cronbach's alpha and enhanced the methodological reliability of the research.

3.3 Statistical Methods and Mathematical Framework

Data analysis was carried out using Jamovi, Python (Google Colab), and Enginius. Normality and homogeneity of variances were verified via the Shapiro-Wilk and Levene's tests, respectively. Since most variables violated the assumption of normal distribution, non-parametric statistical methods were deployed.

To test hypothesis H1, the Kruskal-Wallis test (the non-parametric equivalent of ANOVA) was used to compare the medians of the three independent enterprise groups based on their level of AI use (AIuse) as follows:

$$H = \frac{12}{N(N-1)} \sum_{i=1}^{K} \frac{R_I^2}{n_i} - 3(N+1) \tag{1}$$

Where:
H - resulting test statistic of the Kruskal-Wallis test.
N - total number of observations across the sample (N = 312 in the primary phase).
k - number of independent groups compared (k = 3, for AIuse = 0, 1, 2).
n - i - sample size (number of enterprises) in the specific i-th group.
R -i - sum of ranks assigned to the i-th enterprise group after pooling and ranking all observations.

Hypothesis H2 was tested using an ordinal logistic regression model (proportional odds model) given the ordinal nature of the dependent variable AIuse. The model assumes equal effects of the independent variables across all cumulative logits, mathematically expressed as:

$$ln\left(\frac{P(Y \leq j)}{1-P(Y \leq j}\right) = \alpha_j - (\beta 1\ X1 + B2\ X2 + \ldots \ldots \beta m Xm) \tag{2}$$

Where:
Y - dependent ordinal variable (AIuse).
j - category thresholds/cut-points for the groups (j = 0, 1).
P (Y \j) - cumulative probability that an enterprise falls into category j or lower.
ln – natural logarithm transforming the odds into a cumulative logit.
alpha -j - intercept/threshold parameter specific to each boundary level.
beta -m – regression coefficients for the independent variables (maturity dimensions).
X (1-m) – independent variables (scores of individual organizational maturity dimensions).

To test hypothesis H3, a hierarchical cluster analysis was conducted using Ward's method and Euclidean distance. Ward's method minimizes the increase in the total error sum of squares (Δ ESS) when merging clusters. The optimal number of segments was determined via dendrogram analysis and the elbow criterion, and cluster stability was verified using non-parametric group difference tests based on these formulas:

Euclidean distance between objects: $d(i,j) = \sqrt{\sum_{k=1}^{m} \left(x_{ik} - x_{jk}\right)^2}$ (3)

Error Sum of Squares (ESS):
$$\text{ESS} = \sum_{i=1}^{n} \sum_{k=1}^{m} (x_{ik} - \bar{x}_k)^2 \quad (4)$$

Ward's variance increment criterion:
$$\Delta\text{ESS} = \text{ESS}_{A\cup B} - (\text{ESS}_A + \text{ESS}_B) = \frac{n_A \cdot n_B}{n_A + n_B} \cdot d^2(C_A, C_B) \quad (5)$$

4 Research Results

4.1 Descriptive Analysis of AI Maturity Levels

The initial step of the empirical analysis evaluated the organizational maturity level of Slovak enterprises relative to AI implementation. This was based on the composite AI maturity model integrating technological, organizational, strategic, data, and human readiness.

The descriptive results highlight clear heterogeneity among the analyzed companies. While one group of organizations demonstrated advanced readiness characterized by systematic AI integration, a significant volume of enterprises remained in the baseline stages of digital transformation. This confirms that AI adoption in Slovakia is highly stratified and driven by interconnected factors.

The highest average scores occurred in technological readiness and core digital infrastructure. Conversely, lower performance was noted in strategic AI management, employee upskilling, and formalized AI governance. This indicates that while many enterprises have established an adequate technical baseline, their AI deployment lacks strategic oversight and organizational support structures.

The validation sample mirrored these trends, reinforcing their stability. In the validation phase, management's attitude toward AI, awareness of AI opportunities, and employee digital competency emerged as the primary differentiating factors. Meanwhile, variations in digital tool availability were less pronounced, showing that hardware and software assets are no longer the primary bottleneck for AI deployment. This supports the premise that successful AI adoption depends mostly on organizational and managerial factors, while technical setups are a necessary but insufficient condition for digital transformation.

4.2 Statistical Differences Between Enterprise Groups (H1)

Before testing the core hypotheses, distribution normality and variance homogeneity were verified. Shapiro-Wilk and Leven's tests indicated that the data violated parametric test requirements; hence, non-parametric methods were utilized.

The Kruskal-Wallis test compared the three enterprise groups: non-adopters (AIuse=0), planning adopters (AIuse=1), and active AI users (AIuse=2). The results confirmed statistically significant differences across all analyzed dimensions of organizational maturity ($p < 0.001$).

Table 1
Kruskal-Wallis Test Results (Primary Phase)

AI Maturity Dimension	χ^2	df	p	ε^2	Effect Size Interpretation
Culture	68.3197	2	<.0001	0.2197	strong
Strategy	62.3998	2	<.0001	0.2006	strong
Organization	59.7894	2	<.0001	0.1922	strong
Technology	150.2047	2	<.0001	0.4830	very strong
Data	37.6820	2	<.0001	0.1212	medium strong
Ethics	51.8930	2	<.0001	0.1669	strong
Privacy	40.6182	2	<.0001	0.1306	medium to strong

Source: processed based on Deliverable D3.4 AI-impactSK

The highest effect size appeared in technological readiness ($\varepsilon^2 = 0.483$), making it the strongest differentiator between groups. Substantial effects were also logged for organizational culture, strategy, structure, and ethical considerations. Data readiness and privacy protection showed lower, yet still statistically significant effects. These metrics confirm that advancing AI adoption correlates with the systemic development of multiple organizational capacities, proving that tech infrastructure is merely one part of a broader AI maturity concept. Consequently, hypothesis H1 is fully supported.

4.3 Pairwise Group Analysis (Post-Hoc Testing)

To pinpoint specific variances between the groups, post-hoc analyses were performed using the DSCF and Dunn's tests with Bonferroni adjustment, yielding consistent and robust results.

Comparing non-adopters (AIuse=0) with planning enterprises (AIuse=1) revealed significant differences primarily in corporate culture, strategy, governance, and ethics. Conversely, variations in data readiness and privacy controls were not yet significant, implying that these technical dimensions materialize during later deployment stages.

The sharpest contrasts appeared between non-adopters (AIuse=0) and active AI users (AIuse=2), with significant gaps validated across all maturity dimensions. Exceptionally highs test values occurred in technological readiness, illustrating a profound structural divide between legacy organizations and those with advanced AI adoption.

Significant variations were also evident between planners (AIuse=1) and active users (AIuse=2). This finding implies that having strategic plans does not automatically equal sufficient organizational readiness. The critical factor is the capability to translate strategic intent into concrete processes, human capital investments, and governance modifications.

4.4 Determinants of AI Adoption and Their Organizational Context (H2)

A core objective was verifying the relationship between organizational maturity and actual AI deployment. The results established a positive dependency between higher AI Maturity Index scores and the probability of adopting AI; companies with advanced maturity metrics demonstrated a substantially greater likelihood of successful process integration.

Hypothesis H2 posited that selected dimensions positively drive AI adoption. Ordinal logistic regression confirmed that strategic management, an innovative culture, technological readiness, and employee digital competencies statistically increase the likelihood of progressing to higher AI adoption levels.

Table 2
Ordinal Logistic Regression Model Coefficients (Dependent Variable: AIuse)

Predictor	Estimate (beta)	95% CI Lower	95% CI Upper	SE	Z	p-value	Odds Ratio (OR)
Culture	0.2415	-0.0272	0.5209	0.1393	1.7337	.0830	1.2731
Strategy	0.4868	0.0148	0.9791	0.2446	1.9906	.0465	1.6272
Organization	0.2688	-0.2883	0.8413	0.2877	0.9343	.3502	1.3084
Technology	1.9141	1.5009	2.3560	0.2178	8.7881	<.0001	6.7810
Data	0.2260	-0.1651	0.6471	0.2056	1.0995	.2716	1.2536
Ethics	0.3743	-0.1620	0.9325	0.2785	1.3441	.1789	1.4540
Privacy	-0.2423	-0.5599	0.0758	0.1609	-1.5062	.1320	0.7848

Source: processed based on Deliverable D3.4 AI-impactSK

The ordinal logistic regression model demonstrates a high level of statistical significance ($\chi^2 = 211.94$; $p < 0.001$) and accounts for approximately 43% of the variance in the positioning of enterprises across individual phases of AI adoption (Nagelkerke $R^2 = 0.4283$), with an overall classification accuracy of 71.8%.

When simultaneously controlling for all seven dimensions of digital and AI maturity, only Technology and Strategy emerged as statistically significant predictors:

- **Technological Readiness:** This dimension represents the dominant and most stable predictor ($\beta = 1.9141$; $p < 0.0001$). Holding all other variables constant, a one-standard-deviation increase in technological maturity multiplies the odds of an enterprise advancing to a higher category of AI implementation by approximately 6.8 times (OR = 6.7810).
- **Strategic Management:** This predictor achieved statistical significance at the 5% level ($\beta = 0.4868$; $p = 0.0465$). Each unit increase in strategic maturity elevates the probability of transitioning to a more advanced stage of AI adoption by 63% (OR = 1.6272).
- **Other Dimensions (Culture, Organization, Data, Ethics, Privacy):** Their independent direct effects were not statistically confirmed in this model. Notably, the Privacy dimension exhibited a negative coefficient ($\beta = -0.2423$), indicating a theoretical trend where an excessive emphasis on privacy protection may slightly impede the pace of AI implementation; however, this relationship is not statistically significant ($p = 0.1320$).

The active utilization odds (expressed via Odds Ratio – OR) climbed sharply with each point increase in strategic management and leadership support, demonstrating that "soft" managerial factors are overriding determinants of success. Based on the regression model, hypothesis H2 is partially confirmed.

4.5 Cluster Segmentation of Enterprises (H3)

Hypothesis H3 assumed that Slovak enterprises could be segmented into homogeneous groups based on their AI maturity profiles. Hierarchal cluster analysis mapped clear, stable segments with highly distinctive readiness levels.

Table 3
Final Cluster Profiles of Enterprises Based on AI Maturity Dimensions (Z-Scores)

AI Maturity Dimension	Cluster 3: Digital Laggards	Cluster 2: Strategic Planners	Cluster 1: AI Leaders
Share of Sample (%)	37.8%	34.3%	27.9%
Culture	-0.62 *(Low)*	+0.21 *(Average)*	+1.04 *(High)*
Strategy	-0.74 *(Low)*	+0.48 *(High)*	+1.12 *(High)*
Organization	-0.55 *(Low)*	+0.12 *(Average)*	+0.89 *(High)*
Technology	-0.81 *(Very Low)*	-0.04 *(Average)*	+1.41 *(Very High)*
Data and Analytics	-0.48 *(Low)*	+0.08 *(Average)*	+0.76 *(High)*
Ethics	-0.39 *(Below Average)*	+0.15 *(Average)*	+0.68 *(High)*
Privacy and Security	+0.02 *(Average)*	-0.11 *(Average)*	+0.54 *(High)*
Overall AI Readiness	**AI-Unready**	**Fragmented / Soft**	**Comprehensive (AI-Ready)**

Source: own processing based on AI-impactSK project data (N = 312)

Non-parametric tests validated that cluster differences were statistically significant across all observed maturity dimensions ($p < 0.05$). Three primary organizational profiles were identified:

1. **AI Leaders (High Maturity):** Enterprises scoring above average across all dimensions, including strategic management, ethics, and IT governance. These entities possess a formalized AI strategy and an integrated tech and data foundation.
2. **Technological Optimists (Medium/Unbalanced Maturity):** Companies with well-established IT infrastructure and digital tools that lag behind in strategic management, innovation culture, and comprehensive data governance.
3. **Digitally Laggards Enterprises (Low Maturity):** A cluster exhibiting below-average marks across all dimensions, lacking baseline competencies, managerial focus, and strategic interest in AI.

This structural split confirms the high heterogeneity of the business landscape; thus, hypothesis H3 is confirmed.

5 Discussion

The presented research expands the understanding of factors influencing the adoption of artificial intelligence in business practice through a comprehensive assessment of the organizational maturity of Slovak enterprises. Unlike several previous empirical studies that analyzed isolated determinants of AI implementation, this research is based on a multidimensional concept of AI maturity. This framework integrates strategic, organizational, technological, data, ethical, and personnel aspects of corporate readiness for artificial intelligence implementation. Such an approach allowed for a more comprehensive explanation of inter-company differences and identified the domains that most significantly determine the success of digital transformation.

One of the most significant findings of this study is the confirmation of statistically significant differences between enterprises operating at various levels of artificial intelligence implementation. The results of the Kruskal-Wallis test and subsequent post-hoc analyses demonstrated that an increasing level of AI adoption is accompanied by a systematic growth of organizational maturity across all examined dimensions. Particularly pronounced differences were identified between enterprises that do not utilize artificial intelligence and those with actively implemented AI solutions.

These findings correspond with international studies, according to which the successful implementation of artificial intelligence is not the result of isolated technological investments, but rather the long-term development of organizational capabilities. Multiple authors point out that AI represents a transformative technology whose effective utilization depends on the organization's ability to link technological innovations with strategic management, human capital development, and effective data governance. The results of the presented research confirm this thesis within the context of Slovak enterprises as well.

The significance of strategic and organizational factors deserves special attention. The analysis showed that variations between enterprises emerge as early as the initial phases of AI implementation, manifesting most prominently in the fields of strategy, organizational culture, and governance). Conversely, the dimensions of data readiness and data privacy differentiate significantly only during the transition to more advanced stages of artificial intelligence implementation. This result suggests that successful AI adoption begins with a strategic decision by top management and the creation of organizational prerequisites for digital transformation, while technical and regulatory aspects gain greater importance only during the actual implementation process.

A significant contribution of this research is also the confirmation of the multidimensional character of the AI maturity concept. The results indicate that technological infrastructure alone does not constitute a sufficient prerequisite for the successful implementation of artificial intelligence. Although enterprises possessing modern information technologies create favorable conditions for introducing AI, the decisive factor is the organization's ability to strategically manage the digital transformation process, foster an innovation culture, and systematically develop the digital competencies of employees. This conclusion supports the current understanding of AI maturity as a complex organizational construct that transcends traditional assessments of a company's technological equipment.

From a methodological standpoint, we consider the construction of a composite AI maturity index - based on Principal Component Analysis (PCA) and its subsequent validation on an independent research sample - to be a key contribution. Validation on a dataset of 643 enterprises confirmed the stability of the identified relationships and enhanced the reliability of the proposed model. At the same time, the deployed research design contributed to eliminating the risk of accidental findings that may appear in analyses based on a single research sample.

The results of the enterprise segmentation highlight substantial heterogeneity within the Slovak business environment regarding readiness to implement artificial intelligence. The identified segments represent not only distinct levels of technological readiness but also different organizational approaches to innovation management, employee development, and the strategic utilization of data. From a managerial practice perspective, these results suggest that universal, "one-size-fits-all" support strategies for AI implementation may not be sufficiently effective. A differentiated approach that respects the level of organizational maturity of individual enterprise groups appears to be far more appropriate.

A comparison of the results with selected foreign studies shows a high degree of consistency between the findings of the AI-impactSK project and the current state of knowledge in the field of organizational readiness for artificial intelligence implementation. In all analyzed studies, strategic management, top management support, data quality, technological readiness, and the development of employees' digital competencies repeatedly emerge as key determinants of successful AI adoption.

The results of the presented research confirm these insights within the context of Slovak enterprises as well.

Table 4
Comparison of AI-impactSK Project Results with International Studies

Author(s)	Focus of Research	Main Findings of the International Study	Results of the AI-impactSK Project	Contribution of the Presented Research
Jöhnk et al. (2021)	Organizational readiness for AI implementation.	Key determinants are management support, AI strategy, data availability, and digital competencies.	Significant differences were identified primarily in the strategy, culture, and governance dimensions.	Confirms the importance of strategic AI management in the context of the Slovak Republic and expands knowledge on relationships.
Uren & Edwards (2023)	Factors of successful AI adoption.	Implementation requires the simultaneous development of people, processes, technologies, and data; technology alone is insufficient.	Technological readiness was significant; however, without strategy, it did not lead to higher adoption.	Empirically confirms the multidimensional character of AI maturity on a representative sample.
Wyrtki et al. (2025)	AI Capability Maturity Model.	AI maturity is a complex model encompassing strategy, data, technologies, human resources, and AI governance.	AI-impactSK created a composite AI Maturity Index based on 7 dimensions of readiness.	Expands models through their empirical verification and validation on two independent samples.
OECD (2024)	AI adoption in enterprises across OECD countries.	Barriers include a lack of competencies, data quality, funding, and management uncertainty.	The significance of competencies, management support, and data readiness was also confirmed in the Slovak Republic.	Confirms that barriers identified at the global level are fully relevant to Slovak enterprises as well.

Source: compiled based on international studies and results of the AI-impactSK project

To further demonstrate the value of the proposed approach, Table 3 compares the AI-impactSK model with the most prominent international frameworks for maturity diagnostic. While the majority of commercial and international indices operate primarily on a descriptive or expert basis without robust mathematical-statistical validation on independent datasets, the AI-impactSK model combines a comprehensive integration of 7 dimensions with advanced inferential testing across a total of 955 enterprises.

Table 5
Comparison of the AI-impactSK Model with International AI Maturity Models

Model Characteristic	Deloitte AI Maturity Model	IBM AI Adoption Index	Gartner AI Maturity Model	OECD AI Capability Framework	AI-impactSK (Proposed Model)
Primary Goal	Assessment of organizational readiness for AI	Monitoring the global level of AI adoption	Evaluation of maturity in AI implementation	Evaluation of readiness of economies and enterprises	Evaluation of AI maturity and identification of adoption determinants
Level of Analysis	Organization	Organization	Organization	Organization / State	Organization
Composite Index	X	X	X	X	✓
Validation on an Independent Sample	Usually no	No	No	No	✓ (312 + 643 enterprises)
Determinant Modeling	Partial	Partial	X	Partial	✓ (Ordinal Logistic Regression)
Statistical Validation	Limited	Descriptive	Expert-based	Descriptive	Robust (PCA, Cronbach α, McDonald ω, Kruskal-Wallis, Clusters)

Source: compiled based on Deloitte, IBM, Gartner, OECD, and the results of the AI-impactSK project

Despite the achieved results, the research is subject to several limitations. First, the analysis relies on data obtained through a questionnaire survey, which is based on the subjective evaluation of respondents. Although managers and individuals responsible for AI implementation were involved in the research, the risk of subjective response bias cannot be completely eliminated. Second, the research has a predominantly cross-sectional character and therefore does not capture the dynamic changes in organizational maturity over time. Longitudinal monitoring of enterprises could provide more detailed insights into the evolution of AI maturity and the factors influencing the transition between individual maturity levels.

6 Conclusion

6.1 Theoretical Contributions

The primary theoretical contribution of this article can be considered the expansion of the AI maturity concept through an empirically validated multidimensional model linking strategic, organizational, technological, data, personnel, and ethical aspects of artificial intelligence implementation. Concurrently, the research contributes to broadening the knowledge of AI adoption factors within the context of Central and Eastern European countries, which are currently represented in international literature to a limited extent. The validation of the model on two independent research samples represents a significant methodological contribution and enhances the robustness of the proposed approach, shifting the theoretical framework from exclusively conceptual reflections toward exact empirical verification.

6.2 Practical Implications for Managerial Practice

The results confirm that the successful implementation of artificial intelligence requires a comprehensive approach encompassing not only technology investments but also the development of strategic management, digital competencies, data infrastructure, and an organizational culture that supports innovation.

Managers should not reduce the introduction of AI to the mere procurement of software; they must primarily build an innovation culture and a clear AI strategy backed by top leadership. In practice, the designed AI Maturity Index can serve as a diagnostic and benchmarking tool to identify corporate strengths and weaknesses when planning digital transformation initiatives.

6.3 Recommendations for Policymakers

The acquired insights carry significant implications for public policy formulation. Existing digitization support programs are often oriented primarily toward the direct financing of technological investments, such as purchasing hardware and infrastructure. However, the results of this research indicate that investments in developing managerial competencies, employee education, building data infrastructure, and creating corporate artificial intelligence strategies play an equally crucial role.

Therefore, state support for digital transformation should be designed more comprehensively. Furthermore, segmenting enterprises according to their AI maturity level creates the prerequisites for a more targeted setup of public support measures that reflect the varying readiness and actual needs of individual corporate groups, rather than applying ineffective flat-rate solutions.

Acknowledgement

Research activities are funded by the EU NextGenerationEU through the Recovery and Resilience Plan for Slovakia under the project No. 09I05-03-V02-00003/2025/VA (AI-impactSK).

References

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99–120. doi.org.

Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review Digital Articles*.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108 -116.

Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., Al-Debei, M. M., ... Wamba, S. F. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994.

Enholm, I., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, 24(5), 1709–1734.

Gartner. (2024). *Gartner AI Maturity Model*.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, 61(4), 5–14.

IBM. (2024). *Global AI Adoption Index 2024*. IBM Institute for Business Value.

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes - An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63(1).

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons*, 63(1), 37–50.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, 58(3), 103434.

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. A. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, 57(2), 103169.

MITRE. (2023). *The MITRE AI Maturity Model and Organizational Assessment Tool Guide*.

Organisation for Economic Co-operation and Development. (2024). *The adoption of artificial intelligence in firms*. OECD Publishing.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210.

Russell, S., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.

Teece, D. J. (2018). Business models and dynamic capabilities. *Long Range Planning*, 51(1), 40–49.

Uren, V., & Edwards, J. S. (2023). Technology, people, processes and data: A systematic review of artificial intelligence adoption. *International Journal of Information Management*, 71, 102640.

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

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *Journal of Strategic Information Systems*, 28(2), 118–144.

Warner, K. S. R., & Wäger, M. (2019). Building dynamic capabilities for digital transformation. *Long Range Planning*, 52(3), 326–349.

Wyrtki, K., Jöhnk, J., & Mendling, J. (2025). Understanding artificial intelligence diffusion through an AI capability maturity model. *Information Systems Frontiers*.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications. *International Journal of Educational Technology in Higher Education*, 16(39).

Zhang, N., Wang, H., & Wang, X. (2023). Organizational artificial intelligence capability and firm innovation performance: Evidence from manufacturing enterprises. *Technological Forecasting and Social Change*, 190, 122420.

The Perceived Competitive Value of Artificial Intelligence in Slovak SMEs

Diana Pallérová, Andriana Baziuk, Federico Banda

Abstract
Artificial intelligence is increasingly discussed as a source of competitiveness for SMEs, but less is known about how firms perceive its competitive value at different stages of adoption. Existing research often focuses on AI adoption itself, while the perceived measurability and managerial visibility of AI benefits remain less examined. The aim of this paper is to examine how Slovak SMEs perceive the competitive value of artificial intelligence and whether these perceptions differ according to AI adoption stage and sector. The study is based on primary CAWI survey data from 234 Slovak SMEs. Six dimensions of perceived AI competitive value were analyzed: AI as a competitive advantage, efficiency of key tasks, AI as a better way of working, better business results, measurability of AI benefits, and visibility of AI outcomes for management. Due to the ordinal character of the data, non-parametric methods were applied, including descriptive statistics, the Friedman test, Kruskal-Wallis tests, Dwass-Steel-Critchlow-Fligner post-hoc comparisons, and Spearman's rank correlations. The results show that SMEs evaluate AI most positively in relation to efficiency of key tasks and better business results. Measurability of AI benefits and visibility of AI outcomes for management were evaluated less strongly. Higher AI adoption stages were significantly associated with more positive evaluations of all six AI value dimensions. Sectoral differences were found mainly in practical and observable aspects of AI value. The paper contributes by showing that perceived AI competitive value in SMEs is multidimensional and develops gradually from operational benefits toward strategic and managerial value.

JEL classification: *L25, M15, O33*
Keywords: *Artificial intelligence, Competitiveness, Business value, SMEs*

1 Introduction

Artificial intelligence is increasingly discussed as a technology with the potential to reshape how firms organize work, make decisions, improve processes and compete in changing markets. In business research, AI is no longer treated only as a technical tool, but also as a source of business value, organizational capability and potential competitive advantage. Prior studies show that AI can contribute to firm performance through process improvement, better decision-making, automation and new forms of value creation (Wamba-Taguimdje et al., 2020; Enholm et al., 2022). At the same time, the ability to benefit from AI depends not only on access to technology, but also on how firms adopt, integrate and evaluate AI in their own organizational context (Mikalef & Gupta, 2021).

The issue is particularly relevant for small and medium-sized enterprises. SMEs are often expected to benefit from AI through efficiency gains, automation of routine tasks and improved decision-making, but they usually operate with more limited financial, technological and human resources than large enterprises. OECD notes that AI has significant promise for productivity and innovation in SMEs, while SME adoption remains relatively low compared with large firms and with other digital technologies (OECD, 2025). This creates an important research problem: AI may offer competitive value to SMEs, but its benefits may be unevenly perceived and may depend on the actual stage of adoption.

Existing research on AI adoption in SMEs emphasizes that adoption is shaped by digital capabilities, innovation capabilities, organizational readiness and the external business environment (Arroyabe et al., 2024; Badghish & Soomro, 2024). However, less attention is often paid to how SMEs perceive different components of AI-related competitive value. Firms may generally believe that AI has strategic potential, but this does not necessarily mean that they can observe, measure or communicate its benefits internally. In SME contexts, this distinction is important because managers often need practical and visible evidence before AI can become a sustained part of business strategy.

This paper therefore focuses on the perceived competitive value of AI in Slovak SMEs. Instead of treating AI competitiveness as a single index, the article analyzes six separate aspects: AI as a source of competitive advantage, efficiency of key tasks, AI as a better way of performing selected tasks, better business results, measurability of AI benefits and visibility of AI outcomes for management. This approach allows us to identify whether Slovak SMEs perceive AI mainly as an operational tool, a strategic source of advantage or a managerial value that can be observed and evaluated.

The aim of the paper is to examine how Slovak SMEs evaluate these aspects of AI-related competitive value and whether the evaluations differ by the stage of AI adoption and by sector. The central argument is that the competitive value of AI is not perceived uniformly. SMEs may first recognize AI through practical and operational benefits, while measurability and managerial visibility may become more evident only at higher stages of adoption. This distinction helps move the analysis beyond the simple statement that firms using AI evaluate it more positively. The article instead asks which specific forms of AI value are most visible to SMEs and which remain less developed.

2 Current State of the Solved Problem at Home

2.1 AI and business value

The theoretical starting point of the article is the concept of AI business value. AI business value refers to the organizational and performance-related benefits that firms may obtain from the use of AI technologies. These benefits may include process automation, improved decision-making, better prediction, operational efficiency, innovation and improved business performance. However, prior literature stresses that business value is not created by AI technology alone. It depends on the ability of the firm to apply AI in specific processes and to translate technological potential into organizational outcomes (Enholm et al., 2022).

This distinction is important for the present article. If AI value is treated only as a general expectation, the analysis risks overlooking the difference between abstract belief in AI and practical ability to use AI. For this reason, the article separates several aspects of perceived AI competitive value. The first aspect is AI as a competitive advantage, which captures a general strategic perception. Other aspects are more operational: efficiency of key tasks, better ways of performing tasks and improved business results. The final two aspects, measurability of benefits and visibility of AI outcomes for management, capture whether AI value is observable and managerially usable.

The literature supports this multidimensional view. Wamba-Taguimdje et al. analyze AI-based transformation projects and argue that AI can affect firm performance through business value generated at both process and organizational levels (Wamba-Taguimdje et al., 2020). This is directly relevant to SME competitiveness because AI may first become visible through process improvements before it becomes embedded in broader strategic decision-making.

In this article, AI competitiveness is therefore not understood only as market dominance or objective financial performance. It is understood as perceived competitive value: the extent to which firms believe that AI improves their work, results, measurability of benefits and managerial visibility. This framing is suitable because the dataset captures managerial perceptions rather than objective performance indicators.

2.2 AI capability and competitive advantage

A second relevant theoretical perspective is the AI capability view. AI capability refers to a firm's ability to deploy and combine AI-related technological, human and organizational resources. From this perspective, AI does not generate value simply because a firm has access to tools. Value is created when the firm has the capacity to integrate AI into workflows, use data effectively, mobilize employees and connect AI outputs to business decisions (Mikalef & Gupta, 2021).

This perspective is important for interpreting why firms at different adoption stages may perceive AI value differently. A firm that only plans to use AI may evaluate AI mainly as a promising technology. A firm that has already implemented AI in selected processes may be more able to observe efficiency improvements, performance effects or managerial outputs. Therefore, higher adoption stages are expected to be associated not only with more positive attitudes, but also with a more concrete perception of AI value.

In this article, the distinction between general and concrete value is central. AI as a competitive advantage represents a broader strategic expectation. Efficiency, better task performance and better business results represent operational value. Measurability and managerial visibility represent the extent to which AI outcomes are becoming part of evaluation and management practice. The theoretical expectation is that practical and visible dimensions of AI value should become stronger as adoption progresses.

2.3 AI adoption in SMEs

AI adoption in SMEs has specific characteristics. SMEs often have more flexible decision-making structures than large firms, but they also face constraints in finance, skills, data infrastructure and internal expertise. Recent empirical research on European SMEs shows that digital capabilities, innovation capabilities and environmental support are important drivers of AI adoption (Arroyabe et al., 2024). This indicates that AI adoption in SMEs is not only a technological decision, but also a capability-building process.

Badghish and Soomro examine AI adoption in SMEs using the Technology-Organization-Environment framework and connect AI adoption with sustainable business performance (Badghish & Soomro, 2024). Their approach is relevant because it shows that adoption depends on technological, organizational and external conditions. Although the present article does not test the full TOE model, it builds on the same idea that AI adoption must be understood in relation to business outcomes and perceived value.

Recent work also combines the TOE framework with the diffusion of innovations perspective to study AI adoption in SMEs (Sánchez et al., 2025). This is relevant for the present article because the analyzed items are linked to perceived relative advantage and observability of AI benefits. The combination of TOE and DOI suggests that adoption is shaped not only by structural conditions, but also by how firms perceive the usefulness, compatibility and visibility of innovation outcomes (Sánchez et al., 2025).

2.4 Diffusion of innovations and perceived AI value

The diffusion of innovations theory helps explain why some aspects of AI value may be easier for firms to recognize than others. According to this perspective, adoption is shaped by perceived attributes of an innovation, especially relative advantage, compatibility, complexity, trialability and observability (Rogers, 2003). In the context of AI, relative advantage refers to whether firms see AI as better than existing solutions, while observability refers to whether AI benefits are visible, measurable and communicable inside the organization.

These perceived characteristics are important in technology adoption research more broadly. Relative advantage, compatibility and complexity have been identified as some of the most consistent predictors of innovation adoption (Tornatzky & Klein, 1982). Similarly, research on IT innovation adoption distinguishes between perceived usefulness, visibility and result demonstrability, which is relevant for understanding whether firms can not only use a technology, but also recognize and communicate its outcomes (Moore & Benbasat, 1991).

This logic is also relevant for AI adoption in SMEs. Prior studies show that AI adoption should be understood through both organizational conditions and perceived innovation attributes, including usefulness, compatibility and observability (Oliveira & Martins, 2011; Sánchez et al., 2025).

2.5 Research gap and analytical focus

The reviewed literature shows that AI can contribute to business value and firm performance, that AI capability is important for translating technology into outcomes, and that SME adoption depends on technological, organizational and environmental conditions (Wamba-Taguimdje et al., 2020; Mikalef & Gupta, 2021; Arroyabe et al., 2024; Badghish & Soomro, 2024). However, for the purposes of this article, the key issue is more specific: how SMEs perceive different aspects of AI-related competitive value and whether these perceptions vary by adoption stage.

The article therefore does not attempt to explain the full adoption process. Instead, it focuses on the perceived value side of AI adoption. This narrower focus allows a clearer analysis of whether AI is seen mainly as an operational tool, a source of strategic advantage or a managerially visible and measurable contributor to business outcomes. This framing is especially suitable for SMEs, where practical usefulness and visible benefits may be more important for further adoption than abstract technological potential.

Based on this theoretical background, the article assumes that higher AI adoption stages will be associated with more positive evaluations of AI competitive value. At the same time, it expects that the strongest insights will come not only from whether this relationship exists, but from identifying which aspects of AI value are most and least developed among Slovak SMEs.

3 Research design and methodology

3.1 Research design and data source

The aim of this paper is to examine how Slovak small and medium-sized enterprises perceive the competitive value of artificial intelligence and whether these perceptions differ according to the stage of AI adoption and sector of business activity. More specifically, the paper focuses on whether SMEs perceive AI mainly as a source of operational efficiency, as a tool for achieving better business results, as a potential competitive advantage, or as a technology whose benefits are measurable and visible to management.

The study therefore does not treat AI competitiveness as one general construct, but analyzes several separate dimensions of perceived AI value. The paper addresses the following research questions:

- RQ1: Which aspects of perceived AI competitive value are evaluated most positively by Slovak SMEs?
- RQ2: Do evaluations of perceived AI competitive value differ across AI adoption stages?
- RQ3: Do evaluations of perceived AI competitive value differ across sectors?

The following hypothesis was formulated:

H1: Higher stages of AI adoption are associated with more positive evaluations of individual aspects of perceived AI competitive value in Slovak SMEs.

The study applies a quantitative research design based on primary survey data. Since the analyzed variables were measured using ordinal Likert-scale responses, the empirical analysis relies on non-parametric statistical methods.

3.2 Research sample and variables

The research object consists of small and medium-sized enterprises operating in Slovakia. The unit of analysis is the enterprise, while the respondent is treated as an organizational informant providing information about the firm's AI adoption stage and perceived AI-related benefits.

The final analytical sample consisted of 234 Slovak SMEs. Small enterprises represented 76.9% of the sample, while medium-sized enterprises accounted for 23.1%. The enterprises operated across several sectors of the Slovak economy. Firm size and sector were used to describe the structure of the sample, while sector was also included in a supplementary comparison of perceived AI value. The focus on SMEs is justified by their specific position in digital transformation. Compared with large enterprises, SMEs usually operate with more limited financial, technological and human resources. These constraints may influence both the adoption of AI and the ability to observe and evaluate its business value (Arroyabe et al., 2024; OECD, 2025).

The main explanatory variable was AI adoption stage, measured as an ordinal variable with five successive stages of implementation:

1. Non-adoption – the enterprise does not use AI and has no current adoption plans.
2. Planned adoption – the enterprise does not currently use AI but plans to adopt it in the future.
3. Pilot adoption – the enterprise is testing or piloting AI solutions.
4. Partial adoption – AI is used in selected business processes.
5. Advanced adoption – AI is used across multiple organizational areas.

This operationalization reflects the assumption that AI adoption is a gradual process rather than a simple yes/no decision. The outcome variables were six individual items measuring perceived AI competitive value (Table 1).

Table 1
Description of the Competitive value variables

Variable	Meaning	Code
AI as a competitive advantage	AI has the potential to create a competitive advantage in the firm's industry.	AI_CV1
Efficiency of key tasks	Using AI allows the firm to perform key tasks more efficiently.	AI_CV2
AI as a better way of working	AI represents a better way of performing selected tasks than existing solutions.	AI_CV3
Better business results	Using AI helps achieve better results compared with not using it.	AI_CV4
Measurability of AI benefits	The benefits of AI are observable and measurable in practice.	AI_CV5
Visibility of AI outcomes for management	The results of using AI are visible to management.	AI_CV6

Source: own processing

Note: AI_CV (AI Competitive value)

All six items were measured on a five-point Likert scale, where higher values indicate stronger agreement with the statement. Since the response categories are ordered, these variables were treated as ordinal.

3.3 Data processing and procedure

The analysis began with a description of the sample structure in terms of firm size, sector and AI adoption stage. This provided the empirical context for interpreting how perceived AI value differs across Slovak SMEs.

Descriptive statistics were then calculated for the six items measuring perceived AI competitive value. Since these items were measured on ordinal Likert scales, the interpretation focused primarily on medians and interquartile ranges. Means and standard deviations were also reported as supplementary indicators to make the comparison between individual items more transparent.

To examine whether SMEs evaluate the six aspects of AI value differently, the Friedman test was applied. This test was suitable because the same enterprises assessed all six items. It allowed us to determine whether some dimensions of perceived AI value are rated more strongly than others.

Differences across AI adoption stages were then tested using the Kruskal-Wallis test. The test was applied separately to each of the six AI value items in order to assess whether firms at different adoption stages differ in their evaluation of AI as a competitive advantage, a source of efficiency, a better way of working, a source of better results, a measurable benefit and a managerially visible outcome. As a supplementary analysis, sectoral differences were also tested using the Kruskal-Wallis test. Before testing sectoral differences, the distribution of firms across sectors was examined. Due to the small number of observations in several original NACE categories, the sector variable was recoded into broader sectoral groups before the analysis. Manufacturing was classified as Industrial / Manufacturing. Construction remained a separate category. Wholesale and retail trade, transportation and logistics, and accommodation and food service activities were grouped into Trade, logistics and hospitality. Information and communication and other services were grouped into Knowledge-intensive services. Scientific and technical activities, human health and social work activities, and other activities were grouped into Social and other services. Sector was treated as a nominal grouping variable, while the six perceived AI value items were used as outcome variables. This analysis made it possible to examine whether the perception of AI value differs across sectors.

The relationship between AI adoption stage and each aspect of perceived AI competitive value was further examined using Spearman's rank correlation. This method was selected because both the AI adoption stage and the analyzed AI value items have an ordinal character. All statistical analyses were conducted in Jamovi. Statistical significance was evaluated at the level of $p < 0.05$.

4 Research results

4.1 AI adoption in SMEs and descriptive statistics of perceived AI competitive value items

This section first describes the distribution of SMEs across AI adoption stages and then presents descriptive statistics for the six items measuring perceived AI competitive value.

Table 2
Frequency distribution of AI adoption stages

AI Adoption Stage	Counts	% of Total	Cumulative %
1	33	14.1%	14.1%
2	65	27.8%	41.9%
3	60	25.6%	67.5%
4	42	17.9%	85.5%
5	34	14.5%	100.0%

Source: own processing using Jamovi

Table 2 shows the distribution of firms across AI adoption stages. The largest share of firms was located in stage 2 (27.8%) and stage 3 (25.6%), indicating that more than half of the sample consisted of firms planning or piloting AI adoption. Firms in the most advanced adoption stage represented 14.5% of the sample.

Table 3
Descriptive statistics of variables by company size

Variables	Company Size	N	Mean	Median	SD	IQR
AI Adoption Stage	SMALL	180	2.84	3.00	1.298	2.00
	MEDIUM	54	3.13	3.00	1.133	2.00
AI_CV1	SMALL	180	3.64	4.00	1.076	1.00
	MEDIUM	54	3.85	4.00	0.940	2.00
AI_CV2	SMALL	180	3.86	4.00	0.916	2.00
	MEDIUM	54	4.24	4.00	0.699	1.00
AI_CV3	SMALL	180	3.63	4.00	0.897	1.00
	MEDIUM	54	3.83	4.00	0.637	1.00
AI_CV4	SMALL	180	3.87	4.00	0.852	1.00
	MEDIUM	54	4.02	4.00	0.687	0.00
AI_CV5	SMALL	180	3.54	4.00	0.874	1.00
	MEDIUM	54	3.65	4.00	0.828	1.00
AI_CV6	SMALL	180	3.49	4.00	0.972	1.00
	MEDIUM	54	3.56	4.00	0.861	1.00

Source: own processing using Jamovi

Table 3 presents descriptive statistics for AI adoption stage and the six perceived AI competitive value items by company size. The median value of AI adoption stage was 3 for both small and medium-sized enterprises, while the mean value was slightly higher among medium-sized enterprises (M = 3.13) than among small enterprises (M = 2.84). This indicates that medium-sized firms were, on average, somewhat further in AI adoption.

Across all six AI competitive value items, the median value was 4 in both small and medium-sized enterprises, suggesting generally positive evaluations of AI-related competitive value. However, the mean values show some differences between the two size groups. Medium-sized enterprises reported higher mean scores across all six items. The largest difference was observed for AI_CV2 – Efficiency of key tasks, where medium-sized enterprises reached a mean of 4.24, compared with 3.86 among small enterprises. This suggests that medium-sized firms perceive AI somewhat more strongly as a tool for improving the efficiency of key tasks.

The highest mean values among small enterprises were observed for AI_CV4 – Better business results (M = 3.87) and AI_CV2 – Efficiency of key tasks (M = 3.86). Among medium-sized enterprises, the highest mean value was recorded for AI_CV2 – Efficiency of key tasks (M = 4.24), followed by AI_CV4 – Better business results (M = 4.02). In contrast, the lowest mean values in both groups were found for AI_CV6 – Visibility of AI outcomes for management (small enterprises: M = 3.49; medium-sized enterprises: M = 3.56) and AI_CV5 – Measurability of AI benefits (small enterprises: M = 3.54; medium-sized enterprises: M = 3.65). This indicates that SMEs tend to associate AI more strongly with operational efficiency and better results than with clearly measurable and managerially visible outcomes.

4.2 Comparison of perceived AI competitive value items

Following the descriptive analysis (Table 3), the Friedman test (Table 4) was applied to examine whether the six aspects of perceived AI competitive value were evaluated equally. The test result was statistically significant, $\chi^2(5) = 100.00$, $p < .001$, indicating that Slovak SMEs did not evaluate all aspects of AI competitive value in the same way.

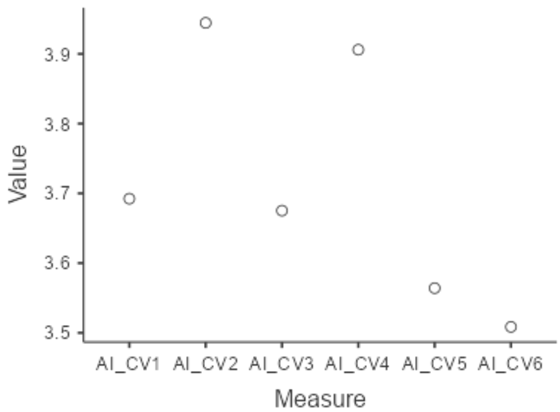
Table 3
Friedman test

χ^2	df	p
100	5	<.001

Source: own processing using Jamovi

As shown in Figure 1, the highest mean values were observed for AI_CV2 – Efficiency of key tasks (M = 3.94) and AI_CV4 – Better business results (M = 3.91). In contrast, the lowest mean values were recorded for AI_CV6 – Visibility of AI outcomes for management (M = 3.51) and AI_CV5 – Measurability of AI benefits (M = 3.56). This suggests that SMEs tend to associate AI more strongly with operational efficiency and improved business outcomes than with clearly measurable and managerially visible results.

Figure 1
Mean values of perceived AI competitive value items



Source: own processing using Jamovi

4.3 Differences in Perceived AI Competitive Value Across AI Adoption Stages

The Kruskal-Wallis test was used to examine whether the six aspects of perceived AI competitive value differed across AI adoption stages.

Table 5
Kruskal-Wallis test for differences in perceived AI competitive value by AI adoption stage

Variable	χ^2	df	p	Significant post-hoc differences
AI_CV1	64.8	4	< .001	1–2, 1–3, 1–4, 1–5, 2–4, 2–5, 3–5
AI_CV2	47.2	4	< .001	1–3, 1–4, 1–5, 2–5, 3–5, 4–5
AI_CV3	26.3	4	< .001	1–3, 1–4, 1–5, 2–5, 3–5
AI_CV4	43.8	4	< .001	1–2, 1–3, 1–4, 1–5, 2–5
AI_CV5	27.1	4	< .001	1–3, 1–4, 1–5, 2–4, 2–5
AI_CV6	59.5	4	< .001	1–3, 1–4, 1–5, 2–3, 2–4, 2–5, 3–5

Source: own processing using Jamovi

Note: Post-hoc comparisons were conducted using the Dwass-Steel-Critchlow-Fligner procedure. Only statistically significant pairwise differences at $p < .05$ are reported.

The Kruskal-Wallis test was used to examine whether the six aspects of perceived AI competitive value differed across AI adoption stages. The results show statistically significant differences for all six variables: AI_CV1, $\chi^2(4) = 64.8$, $p < .001$; AI_CV2, $\chi^2(4) = 47.2$, $p < .001$; AI_CV3, $\chi^2(4) = 26.3$, $p < .001$; AI_CV4, $\chi^2(4) = 43.8$, $p < .001$; AI_CV5, $\chi^2(4) = 27.1$, $p < .001$; and AI_CV6, $\chi^2(4) = 59.5$, $p < .001$. These findings indicate that firms at different stages of AI adoption evaluate all aspects of perceived AI competitive value differently.

Post-hoc pairwise comparisons using the Dwass-Steel-Critchlow-Fligner procedure show that the most consistent differences occur between the lowest adoption stage and higher adoption stages. For most AI competitive value items, firms in stage 1 differ significantly from firms in stages 3, 4 and 5. This suggests that firms with no or very low AI adoption evaluate the competitive value of AI less positively than firms that are already testing, partially implementing or more extensively using AI. The strongest pattern appears for AI_CV1 and AI_CV6. In the case of AI_CV1, significant differences were found between stage 1 and all higher stages, as well as between stage 2 and stages 4 and 5, and between stage 3 and stage 5. This indicates that the perception of AI as a competitive advantage increases with higher adoption stages. Similarly, for AI_CV6, significant differences were found between stage 1 and stages 3, 4 and 5, between stage 2 and stages 3, 4 and 5, and between stage 3 and stage 5. This suggests that the visibility of AI outcomes for management becomes stronger as firms move toward more advanced AI adoption.

The results show that the perceived competitive value of AI is not evenly distributed across adoption stages. The difference is not only between non-users and advanced users. In several cases, especially for AI_CV1 and AI_CV6, the results suggest a gradual shift from general awareness of AI toward more concrete recognition of its strategic and managerial value.

4.4 Differences in Perceived AI Competitive Value Across Sectors

Before testing sectoral differences, the distribution of firms across sectors was examined. As shown in Table 5, the largest group consisted of industrial/manufacturing firms (N = 85; 36.3%), followed by trade, logistics and hospitality (N = 52; 22.2%) and knowledge-intensive services (N = 44; 18.8%). Social and other services represented 15.4% of the sample, while construction accounted for 7.3%.

Table 6
Frequency distribution of Sectors

Sector	N	%
Social & other services	36	15.4
Trade, logistics & hospitality	52	22.2
Construction	17	7.3
Knowledge-intensive services	44	18.8
Industrial / Manufacturing	85	36.3

Source: own processing using Jamovi

A supplementary Kruskal-Wallis test was conducted to examine whether the perceived competitive value of AI differs across sectors.

Table 7
Kruskal-Wallis test for differences in perceived AI competitive value by sectors

Variable	χ^2	df	p	Significant post-hoc differences
AI_CV1	7.62	4	0.107	—
AI_CV2	11.18	4	0.025	none
AI_CV3	11.48	4	0.022	Social & other services – Construction
AI_CV4	4.70	4	0.320	—
AI_CV5	9.73	4	0.045	none
AI_CV6	10.89	4	0.028	Social & other services – Industrial/Manufacturing

Source: own processing using Jamovi

The results indicate statistically significant sectoral differences for four out of six items: AI as a better way of working (AI_CV3), $\chi^2(4) = 11.48$, $p = 0.022$; efficiency of key tasks (AI_CV2), $\chi^2(4) = 11.18$, $p = 0.025$; measurability of AI benefits (AI_CV5), $\chi^2(4) = 9.73$, $p = 0.045$; and visibility of AI outcomes for management (AI_CV6), $\chi^2(4) = 10.89$, $p = 0.028$. No statistically significant sectoral differences were found for AI as a competitive advantage (AI_CV1), $\chi^2(4) = 7.62$, $p = 0.107$, or better business results (AI_CV4), $\chi^2(4) = 4.70$, $p = 0.320$.

Post-hoc pairwise comparisons using the Dwass-Steel-Critchlow-Fligner procedure showed only limited sectoral differences. A statistically significant difference was found for AI as a better way of working (AI_CV3) between social and other services and construction ($p = 0.046$). Another significant difference was found for visibility of AI outcomes for management (AI_CV6) between social and other services and industrial/manufacturing firms ($p = 0.040$). For efficiency of key tasks (AI_CV2) and measurability of AI benefits (AI_CV5), the overall Kruskal-Wallis tests were significant, but the post-hoc comparisons did not identify clear statistically significant pairwise differences at $p < 0.05$.

Overall, the sectoral analysis suggests that sectors do not differ in the general perception of AI as a competitive advantage or in the perception of AI as a source of better business results. Sectoral differences appear mainly in more practical and observable aspects of AI value, especially whether AI is perceived as a better way of working, whether its benefits are measurable, and whether its outcomes are visible to management.

4.5 Correlation analysis

Spearman's rank correlation was used to examine the relationship between AI adoption stage and the six aspects of perceived AI competitive value.

Table 8
Spearman correlations between AI adoption stage and perceived AI competitive value items

Variables	AI Adoption Stage	AI_CV1	AI_CV2	AI_CV3	AI_CV4	AI_CV5	AI_CV6
AI Adoption Stage	—						
AI_CV1	0.510***	—					
AI_CV2	0.408***	0.679***	—				
AI_CV3	0.315***	0.494***	0.581***	—			
AI_CV4	0.405***	0.563***	0.569***	0.592***	—		
AI_CV5	0.337***	0.479***	0.537***	0.507***	0.593***	—	
AI_CV6	0.497***	0.549***	0.512***	0.443***	0.532***	0.587***	—

Source: own processing using Jamovi

All correlations were positive and statistically significant at the level of $p < .001$. The strongest relationship was found between AI adoption stage and AI as a competitive advantage (AI_CV1), $\rho = 0.510$, $p < .001$. This indicates that firms at higher stages of AI adoption tend to evaluate AI more strongly as a source of competitive advantage.

The second strongest correlation was observed for visibility of AI outcomes for management (AI_CV6), $\rho = 0.497$, $p < .001$. This suggests that as firms progress to higher stages of AI adoption, AI outcomes become more visible and recognizable at the managerial level. Moderate positive correlations were also found for efficiency of key tasks (AI_CV2), $\rho = 0.408$, $p < .001$, and better business results (AI_CV4), $\rho = 0.405$, $p < .001$.

Weaker, although still statistically significant, correlations were found for measurability of AI benefits (AI_CV5), $\rho = 0.337$, $p < .001$, and AI as a better way of working (AI_CV3), $\rho = 0.315$, $p < .001$. Overall, the results indicate that higher AI adoption stages are associated with more positive evaluations of all analyzed aspects of AI competitive value. The relationship is strongest for strategic and managerial dimensions, namely AI as a competitive advantage and visibility of AI outcomes for management. The correlations among the AI competitive value items were also positive and statistically significant, suggesting that the individual aspects are related but not identical dimensions of perceived AI value.

5 Discussion

Thee aim of this paper was to examine how Slovak SMEs perceive the competitive value of AI and whether these perceptions differ by AI adoption stage and sector. The results show that AI value is not perceived uniformly. SMEs evaluate AI most positively in relation to efficiency of key tasks (AI_CV2) and better business results (AI_CV4), while measurability of AI benefits (AI_CV5) and visibility of AI outcomes for management (AI_CV6) are rated lower.

This supports the view that the value of AI is first recognized through operational improvements rather than through fully measurable or strategically embedded outcomes. This is consistent with the business value literature, which argues that AI creates value through changes in processes, decision-making and organizational activities rather than through technology adoption alone (Wamba-Taguimdje et al., 2020; Enholm et al., 2022). It also corresponds with the AI capability perspective, according to which firms need technological, human and organizational capabilities to convert AI into performance outcomes (Mikalef & Gupta, 2021).

5.1 Research questions

RQ1 asked which aspects of perceived AI competitive value are evaluated most positively by Slovak SMEs. The results show that SMEs rate efficiency of key tasks (AI_CV2) and better business results (AI_CV4) highest. This suggests that AI is perceived mainly as an operational tool that helps firms improve work processes and outcomes. Lower ratings for measurability of AI benefits (AI_CV5) and visibility of AI outcomes for management (AI_CV6) indicate that SMEs may recognize AI as useful before they are able to systematically measure or communicate its results. This finding is aligned with diffusion of innovations theory, where relative advantage and observability are key attributes influencing adoption (Rogers, 2003).In this paper, AI_CV2 and AI_CV4 capture perceived usefulness and relative advantage, while AI_CV5 and AI_CV6 capture observability and result demonstrability.

RQ2 asked whether perceptions of AI competitive value differ across AI adoption stages. The results confirm significant differences for all six AI value items. Post-hoc comparisons show that the most consistent differences appear between lower and higher adoption stages. This means that firms in more advanced adoption stages evaluate AI value more positively than firms with little or no adoption.However, the more important finding is that the strongest relationships with AI adoption stage were found for AI as a competitive advantage (AI_CV1) and visibility of AI outcomes for management (AI_CV6). This suggests that as SMEs move from early adoption to more advanced AI use, AI becomes not only an efficiency tool but also a more strategic and managerially visible resource. This supports prior SME adoption research showing that AI adoption is shaped by digital capabilities, innovation capabilities and organizational readiness (Arroyabe et al., 2024; Badghish & Soomro, 2024).

RQ3 asked whether perceptions of AI competitive value differ across sectors. Sectoral differences were found for four items: AI as a better way of working (AI_CV3), efficiency of key tasks (AI_CV2), measurability of AI benefits (AI_CV5) and visibility of AI outcomes for management (AI_CV6). No significant sectoral differences were found for AI as a competitive advantage (AI_CV1) or better business results (AI_CV4). This suggests that sectors do not differ strongly in the general belief that AI has strategic potential or can improve results. Differences appear mainly in practical and observable dimensions of AI value. This is plausible because sectors differ in processes, data availability, digital maturity and opportunities for AI use. Studies on AI adoption in SMEs similarly emphasize that adoption depends on both firm-level capabilities and the external environment (Arroyabe et al., 2024; Sánchez et al., 2025).

5.2 Hypothesis evaluation

The hypothesis stated that higher stages of AI adoption are associated with more positive evaluations of individual aspects of perceived AI competitive value in Slovak SMEs. The hypothesis is supported.

All Kruskal-Wallis tests were statistically significant, and all Spearman correlations between AI adoption stage and the six AI value items were positive and significant. The strongest associations were found for AI as a competitive advantage (AI_CV1) and visibility of AI outcomes for management (AI_CV6). This means that higher AI adoption is linked not only to more positive views of AI, but especially to stronger recognition of its strategic and managerial value. This finding is in line with the idea that AI adoption is a gradual process rather than a binary decision. The TOE and DOI perspectives both suggest that firms move toward adoption when they perceive the technology as useful, compatible, observable and supported by organizational conditions (Tornatzky & Klein, 1982; Tornatzky & Fleischer & Chakrabarti, 1990; Rogers, 2003). It also reflects recent AI adoption studies in SMEs, which stress that firms need digital capabilities, innovation capabilities, skills and organizational support to benefit from AI (Arroyabe et al., 2024; Badghish & Soomro, 2024; Sánchez et al., 2025).

6 Conclusion

This paper examined how Slovak SMEs perceive the competitive value of artificial intelligence and whether these perceptions differ by AI adoption stage and sector. The results show that SMEs perceive AI value mainly through operational benefits, especially the efficiency of key tasks and better business results. Measurability of AI benefits and visibility of AI outcomes for management were evaluated less strongly, suggesting that AI is often seen as useful before its effects are systematically measured or managerially embedded.

The hypothesis was supported. Higher AI adoption stages were associated with more positive evaluations of all six aspects of perceived AI competitive value. The strongest relationships were found for AI as a competitive advantage and visibility of AI outcomes for management. This indicates that as SMEs progress in AI adoption, AI becomes not only an operational tool but also a more strategic and managerially visible resource.

The sectoral analysis showed that sectors differ mainly in practical and observable aspects of AI value, not in the general perception of AI as a competitive advantage. Overall, the findings suggest that the competitive value of AI in Slovak SMEs develops gradually from operational efficiency toward strategic and managerial value.

The study has several limitations. First, it measures perceived AI value, not objective performance indicators such as productivity, profitability or market share. Second, the cross-sectional design does not allow causal conclusions. Third, sectoral results should be interpreted cautiously because some original sector categories were merged into broader groups due to small sample sizes. Finally, the analysis is limited to Slovak SMEs.

Acknowledgement

This paper is funded by the EU NextGenerationEU through the Recovery and Resilience Plan for Slovakia under the project No. 09I05-03-V02-00003/2025/VA (AI-impactSK); 100% share.

References

Arroyabe, M. F., Arranz, C. F. A., Fernandez de Arroyabe, I., & Fernandez de Arroyabe, J. C. (2024). Analyzing AI adoption in European SMEs: A study of digital capabilities, innovation, and external environment. Technology in Society, 79, Article 102733. https://doi.org/10.1016/j.techsoc.2024.102733

Badghish, S., & Soomro, Y. A. (2024). Artificial intelligence adoption by SMEs to achieve sustainable business performance: Application of Technology–Organization–Environment framework. Sustainability, 16(5), Article 1864. https://doi.org/10.3390/su16051864

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. Information Systems Frontiers, 24, 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), Article 103434. https://doi.org/10.1016/j.im.2021.103434

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. Information Systems Research, 2(3), 192–222. https://doi.org/10.1287/isre.2.3.192

OECD. (2025). AI adoption by small and medium-sized enterprises: OECD discussion paper for the G7. OECD Publishing. https://doi.org/10.1787/426399c1-en

Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. Electronic Journal of Information Systems Evaluation, 14(1), 110–121. DOI not available.

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press. DOI not available.

Sánchez, E., Calderón, R., & Herrera, F. (2025). Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges. Applied Sciences, 15(12), Article 6465. https://doi.org/10.3390/app15126465

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). The processes of technological innovation. Lexington Books. DOI not available.

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. IEEE Transactions on Engineering Management, EM-29(1), 28–45. https://doi.org/10.1109/TEM.1982.6447463

Wamba-Taguimdje, S.-L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. Business Process Management Journal, 26(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411

Digital Readiness and the Adoption of Artificial Intelligence in Slovak Enterprises: A Firm-Level Analysis

Filip Stovíček, Róbert Hanák, Zuzana Hajduová

Abstract
Artificial intelligence (AI) is increasingly regarded as a source of competitive advantage, yet firm-level evidence on how the diffusion of AI relates to the underlying digital infrastructure of enterprises remains limited, particularly in smaller Central European economies. This paper examines the relationship between digital readiness and AI adoption among Slovak enterprises using firm-level survey evidence collected within the AI-impactSK project. The analysis draws on a computer-assisted telephone interviewing (CATI) survey of 643 Slovak enterprises, which jointly measured the current stage of AI adoption, managerial awareness and attention, and four dimensions of digital readiness (digital tools, data storage, IT capabilities, and workforce skills). Using descriptive statistics and a composite digital readiness index, the study finds that Slovak enterprises report a moderate overall level of digital readiness (index mean = 2.43 on a 1-3 scale), driven mainly by strong electronic data storage (77.3 percent) and IT support (69.1 percent), while workforce-related readiness lags considerably behind. In contrast, only 31.4 percent of enterprises report active use of AI, while a further 28.0 percent report no plans for adoption at all. The results reveal a descriptive gap between the technological and data-related foundations already in place and the comparatively limited translation of these foundations into operational AI use. The study contributes firm-level evidence on this gap for a small open EU economy and discusses managerial and policy implications for narrowing it, while explicitly noting that the cross-sectional, self-reported nature of the data does not permit causal or inferential claims.

JEL classification*: M15, O32, O33*
Keywords*: artificial intelligence adoption, digital readiness, Slovak enterprises*

1 Introduction

Artificial intelligence is widely presented as a general-purpose technology capable of reshaping how enterprises organise production, make decisions and compete in domestic and international markets, while simultaneously raising new managerial challenges regarding its responsible and effective use (Kaplan & Haenlein, 2020). Across the European Union, the diffusion of AI technologies among enterprises has accelerated markedly in recent years, rising from roughly 8 percent of EU enterprises with 10 or more employees in 2023 to 20.0 percent in 2025, with adoption strongly concentrated among large firms and in the information and communication sector (Eurostat, 2025b).

This aggregate growth, however, conceals substantial cross-country and cross-firm heterogeneity. Recent Eurostat-based evidence shows that Slovak enterprises have consistently trailed the EU27 average in AI adoption across all enterprise size classes between 2021 and 2024, and that the gap has not narrowed over time despite gradual growth in absolute terms (Eurostat, 2025a). This pattern raises a question that country-level statistics alone cannot answer: to what extent does the relatively modest AI adoption observed in Slovak enterprises reflect a lack of AI-specific technology, and to what extent does it reflect broader unevenness in the underlying digital foundations - digital tools, data infrastructure, IT support and workforce skills - upon which AI implementation typically depends.

A growing body of literature suggests that digital and technological readiness constitutes a necessary, though not sufficient, precondition for successful AI adoption at the firm level. Studies applying the Technology-Organization-Environment framework to small and medium-sized enterprises consistently identify organisational capability gaps, existing digital infrastructure maturity and change-management constraints - rather than cost alone - as the most significant barriers separating AI-aware firms from AI-adopting firms. Comparable evidence from Central and Eastern Europe indicates that digital maturity in the region remains uneven and, in several respects, structurally lower than in Western Europe, which may compound the barriers facing enterprises seeking to move from basic digitalisation towards AI-enabled operations.

Despite this growing international literature, firm-level survey evidence that jointly measures digital readiness and AI adoption stage within the same enterprise population remains scarce for Slovakia. Existing Slovak and EU27 comparative evidence relies mainly on harmonised statistical indicators collected at highly aggregated levels, which do not capture how individual enterprises simultaneously report their data infrastructure, IT capability, workforce skills and AI adoption stage. This represents a specific research gap: while it is known that Slovakia lags behind the EU27 in AI adoption, and while conceptual literature argues that digital readiness precedes AI adoption, direct firm-level evidence on the descriptive relationship between the two within the Slovak business population has not, to the authors' knowledge, been systematically reported.

This paper addresses this gap using firm-level survey data collected within the AI-impactSK project, funded through the Recovery and Resilience Plan for Slovakia. The analysis draws on a computer-assisted telephone interviewing (CATI) survey of 643 Slovak enterprises that jointly measured (a) the current stage of AI adoption, managerial awareness of AI and managerial attention to AI, and (b) four dimensions of digital readiness combined into a composite index. Because the two sets of items were collected from the same respondents within a single cross-sectional instrument, the data allow a direct descriptive juxtaposition of digital readiness and AI adoption at the level of the surveyed population, without requiring additional harmonised statistical sources.

The main objective of the paper is to describe the current level of AI adoption and digital readiness among Slovak enterprises and to examine, at a descriptive level, whether a gap exists between the two.

The paper is guided by the following research questions:

- RQ1: *What is the current level and structure of AI adoption, awareness and managerial attention among Slovak enterprises?*
- RQ2: *What is the current level of digital readiness of Slovak enterprises across its technological, data-related, infrastructural and human-capital dimensions?*
- RQ3: *Is there a descriptively observable gap between the level of digital readiness and the level of AI adoption among Slovak enterprises?*

Because the underlying survey instrument did not include cross-tabulations, correlation coefficients or regression models linking individual firms' readiness scores to their adoption stage, the study is explicitly framed as descriptive and exploratory rather than as a test of statistical association. This distinguishes the present contribution from studies that rely on inferential techniques and requires an emphasis on transparent, cautious interpretation of the observed patterns.

The paper contributes to the literature in three ways. First, it provides original firm-level survey evidence on digital readiness and AI adoption for a small, open Central European economy that remains underrepresented in the international literature. Second, it offers a transparent methodological account of what a purely descriptive juxtaposition of readiness and adoption indicators can and cannot support, which is relevant for researchers working with similar cross-sectional business survey data. Third, it derives managerial and policy implications aimed at helping enterprises convert existing digital foundations into practical AI use.

2 Current State of the Solved Problem at Home

AI adoption at the firm level is commonly distinguished from mere awareness or experimentation. Firms may become aware of AI's potential, pilot isolated applications, or move to systematic implementation embedded in core operations; these stages differ substantially in the organisational commitment and capability they require. Recent bibliometric and survey-based evidence indicates that among small and medium-sized enterprises (SMEs) already using generative AI, only a minority apply it to core business activities, with most usage remaining peripheral to production or service delivery. Eurostat's harmonised enterprise survey confirms that, at the EU level, AI use remains considerably more common among large enterprises (55.0 percent in 2025) than among small enterprises (17.0 percent), with the most common applications concentrated in text analysis, language generation and workflow automation (Eurostat, 2025b).A substantial stream of research conceptualises digital and technological readiness as a multi-dimensional construct encompassing data availability, IT infrastructure, internal know-how, managerial support and workforce competencies. Building on the resource-based view of the firm, an AI capability has been conceptualised as jointly comprising tangible technological resources, human skills and intangible organisational resources, with empirical evidence indicating that the human-skills and organisational components are frequently the weakest link in translating available technology into realised AI-driven performance (Mikalef & Gupta, 2021). Within the Technology-Organization-Environment (TOE) framework, empirical surveys of SMEs show that organisational readiness factors - particularly digital infrastructure maturity and management's innovation orientation - exert a stronger influence on AI adoption decisions than either the characteristics of the technology itself or external environmental pressures. This is consistent with evidence that digital capability indicators, such as the use of cloud computing or data analytics tools, are more strongly associated with successful AI integration than access to external funding or skilled labour markets alone.

Regional evidence for Central and Eastern Europe (CEE) further indicates that the level of digital maturity in the region remains comparatively uneven, with considerable variation both between countries and between enterprises of different sizes within the same country. Comparative assessments of enterprise digitalisation using multi-criteria methods have identified a lack of dedicated research on digital maturity in CEE economies specifically (Brodny & Tutak, 2021), reinforcing the relevance of country-level, firm-based evidence such as that presented in this paper.

2.1 Barriers to artificial intelligence implementation

The literature identifies a recurring set of barriers hindering the transition from AI awareness to AI implementation, including limited technical skills, employee acceptance, financial constraints, and uncertainty regarding return on investment. Contrary to a common assumption that cost is the principal barrier, some recent SME-focused surveys report that organisational capability gaps and change-management challenges rank above perceived cost barriers (OECD, 2025a), suggesting that policy responses focused solely on financial subsidies may not address the most binding constraints. Workforce-related constraints appear particularly persistent: EU-level survey evidence collected in Slovakia found that more than a third of employees using AI reported an increasing need to further develop their AI-related skills, yet only a small share had participated in relevant training over the preceding year (Digital Skills and Jobs Platform, 2025).

2.2 Firm heterogeneity

AI adoption differs systematically by firm size. Harmonised Eurostat data for the period 2021-2024 show that AI adoption gaps between Slovakia and the EU27 average were present across all three enterprise-size classes (10-49, 50-249 and 250+ employees), with the widest gaps observed among medium-sized and large enterprises (Eurostat, 2025a). At the same time, small enterprises constitute the largest share of the enterprise population in both Slovakia and the EU27, meaning that their comparatively slower AI uptake carries disproportionate weight for aggregate diffusion. These findings underscore the importance of firm-level survey evidence that can capture within-population heterogeneity in both digital readiness and AI adoption, which country-level aggregate indicators cannot reveal.

2.3 Research gap and conceptual framework

Taken together, the reviewed literature establishes two points relevant to the present study. First, digital and organisational readiness is widely regarded as a precondition, though not a guarantee, of successful AI adoption; enterprises with stronger data infrastructure and IT support are generally considered better positioned to exploit AI applications, while enterprises lacking workforce competencies and structured processes face additional barriers even where basic digital infrastructure is present. Second, existing quantitative evidence on Slovakia's position relative to the EU27 relies on harmonised statistical indicators at a highly aggregated level and does not report firm-level co-occurrence of readiness and adoption indicators within the same enterprise population.

Systematic reviews of the strategic use of AI in the digital era have similarly called for more empirical research linking firms' digital foundations to the stage of AI implementation they subsequently reach (Borges et al., 2021). This creates a specific and previously unaddressed empirical gap: whether, within the population of Slovak enterprises surveyed in the AI-impactSK project, the pattern suggested by the literature - readiness as a necessary but not sufficient condition - is descriptively observable when digital readiness and AI adoption are measured concurrently among the same respondents. The conceptual framework guiding this study therefore treats digital readiness (comprising digital tools, data storage, IT capabilities and workforce skills) as the input side of AI transformation, and AI adoption stage, awareness and managerial attention as the output side, without assuming or testing a causal or statistically inferential link between the two, consistent with the descriptive character of the underlying data.

3 Research design and methodology

The aim of this paper is to describe the current level of digital readiness and AI adoption among Slovak enterprises and to examine, at a descriptive level, the extent to which a gap between the two is observable within the surveyed population. The partial objectives are: (1) to characterise the distribution of AI adoption stages, awareness of AI capabilities and managerial attention to AI; (2) to characterise the level of digital readiness across its four constituent dimensions and its composite index; and (3) to juxtapose the two sets of results in order to describe the extent and nature of the observed gap. Consistent with the descriptive character of the data (Section 3.4), the study does not test formal hypotheses but is guided by the three research questions stated in Section 1.

3.1 Data collection

The data used in this study were collected within the AI-impactSK project ("Assessment of the impact of artificial intelligence on the Slovak labour market and enterprises"), funded by the European Union through the NextGenerationEU instrument under the Recovery and Resilience Plan for Slovakia (project No. 09I05-03-V02-00003/2025/VA). The analysis draws on the computer-assisted telephone interviewing (CATI) component of the project's enterprise survey, which was designed to capture a broad cross-section of Slovak enterprises' awareness, perceptions, adoption intentions and practical experience with AI, complementing a separate web-based (CAWI) survey administered to a self-selected population of enterprises already engaged in AI-related activities.

The CATI survey yielded 643 completed interviews with representatives of Slovak enterprises. The underlying project report does not provide a codebook documenting the exact sampling frame, contact protocol, or response rate for the CATI survey; this is treated as a methodological limitation and is discussed in Section 6. Percentages reported throughout this paper are calculated from the full CATI sample (n = 643) unless otherwise indicated.

3.2 Questionnaire and variables

Two thematic blocks of the CATI questionnaire are used in this study. Section C ("Adoption and Awareness of Artificial Intelligence") comprises three items: current use of AI (four adoption categories plus an unspecified/other response), self-assessed awareness of AI's possibilities (four categories), and management's attention to AI (four categories plus an unspecified/other response). Section D ("Digital Readiness of Companies") comprises four items measured on a three-point scale (Yes / Partly / No, with an additional "don't know" category for the digital-tools item): use of business software (digital tools), electronic storage of business data (data), availability of in-house or outsourced IT capabilities (IT capabilities), and two items relating to workforce skills and training (people and skills).

The four digital-readiness items were combined into a composite Digital Readiness Index by coding responses numerically (1 = No, 2 = Partly, 3 = Yes) and averaging across the items, following the aggregation approach used in the underlying project report. The resulting index ranges from 1 to 3, with higher values indicating greater readiness. Table 1 summarises the variables used in the analysis.

The Digital Readiness Index was not subjected to a dedicated validation procedure beyond an internal-consistency check (Cronbach's alpha) reported in Section 4; no exploratory factor analysis, test-retest reliability or external validation against objective digitalisation indicators was performed on this instrument. The index should therefore be interpreted as a descriptive composite rather than a validated psychometric scale.

Table 1
Definition and measurement of variables

Variable	Operational definition	Scale	Role	Source (CATI section)
AI adoption stage	Current use of AI in the enterprise (active use, testing, planned within 2 years, no plans, other/unknown)	Categorical (4 categories + other)	Outcome / descriptive	Section C, Q1
AI awareness	Self-assessed understanding of AI's possibilities	Ordinal (4 categories)	Descriptive	Section C, Q2
Management attention	Extent to which management addresses AI (budget/plans, active consideration, occasional discussion, not a topic)	Ordinal (4 categories + other)	Descriptive	Section C, Q3
Digital tools	Use of business software for daily operations	Ordinal (Yes/Partly/No/DK)	Readiness component	Section D, item 1
Data	Electronic storage of business data	Ordinal (Yes/Partly/No)	Readiness component	Section D, item 2
IT capabilities	Availability of in-house or external IT support	Ordinal (Yes/Partly/No)	Readiness component	Section D, item 3
People and skills	Employee familiarity with new technologies and training support	Ordinal (Yes/Partly/No), two items	Readiness component	Section D, items 4-5
Digital Readiness Index	Mean of the four readiness items (1 = No, 2 = Partly, 3 = Yes)	Continuous (1-3)	Composite readiness measure	Authors' construction from Section D

Source: Authors' own compilation based on the AI-impactSK enterprise

3.3 Statistical methods

The analysis relies exclusively on descriptive statistics: frequencies and percentages for categorical items, and means, medians, standard deviations, minima and maxima for the composite Digital Readiness Index. Internal consistency of the four-item Digital Readiness Index was assessed using Cronbach's alpha, a standard measure of the internal structure of a multi-item scale (Cronbach, 1951).

The underlying project report does not contain, and this study does not construct, any inferential statistical tests (such as chi-square tests, correlation coefficients, or regression models) linking individual enterprises' digital-readiness scores to their AI adoption stage. Consequently, the "gap" discussed in this paper refers strictly to a descriptive juxtaposition of aggregate indicators (the composite readiness index against the distribution of adoption stages) within the same surveyed population, and not to a statistically tested association between the two constructs at the level of individual firms. This constraint is treated as a defining methodological feature of the study rather than as an incidental omission, and it is revisited in the limitations.

A further methodological caveat concerns the coding of Section C items. The underlying dataset did not include an official response codebook; category labels for AI adoption stage, awareness and management attention were therefore reconstructed by the original project team based on the most plausible mapping to the questionnaire's response options, and are explicitly flagged in the underlying report as interpretive assumptions. This paper adopts the same interpretive labels and carries the same caveat forward: the precise wording and boundaries of these categories should be treated as indicative rather than exact, and the presence of a residual "other/unspecified" category (19.6 percent for adoption stage and 5.8 percent for management attention) further limits the precision of these distributions.

3.4 Reliability and validity

Cronbach's alpha for the four-item Digital Readiness Index was 0.58, indicating moderate internal consistency; this suggests that the four components (digital tools, data, IT capabilities and people/skills) capture related but distinguishable aspects of digital readiness rather than a single unidimensional construct. No further psychometric validation (confirmatory factor analysis, external criterion validation) was performed, and this is noted as a limitation rather than presented as an established, validated index. Participation in the CATI survey was voluntary, and responses were processed for the purposes of the AI-impactSK project without identifying individual enterprises in the analysis. The underlying report does not specify a formal ethics-committee approval reference; consistent with the instruction not to invent such information, this study does not report one. Missing or "don't know" responses were retained as separate categories in the descriptive tables rather than imputed, to preserve transparency about data completeness.

4 Research results

4.1 Sample characteristics

The results reported in this section are based on 643 completed CATI interviews with representatives of Slovak enterprises. The underlying project report does not provide a breakdown of the sample by enterprise size, sector or region; consequently, this study cannot and does not analyse differences in digital readiness or AI adoption across these firm characteristics. Table 2 and Figure 1 summarise the distribution of responses concerning current AI adoption. Approximately one third of enterprises (31.4 percent) reported actively using AI, and a further 5.1 percent reported testing AI solutions. Around 15.9 percent of enterprises reported no current use but planned implementation within two years, while 28.0 percent reported neither current use nor plans to adopt AI. A residual 19.6 percent of responses could not be clearly classified into these categories.

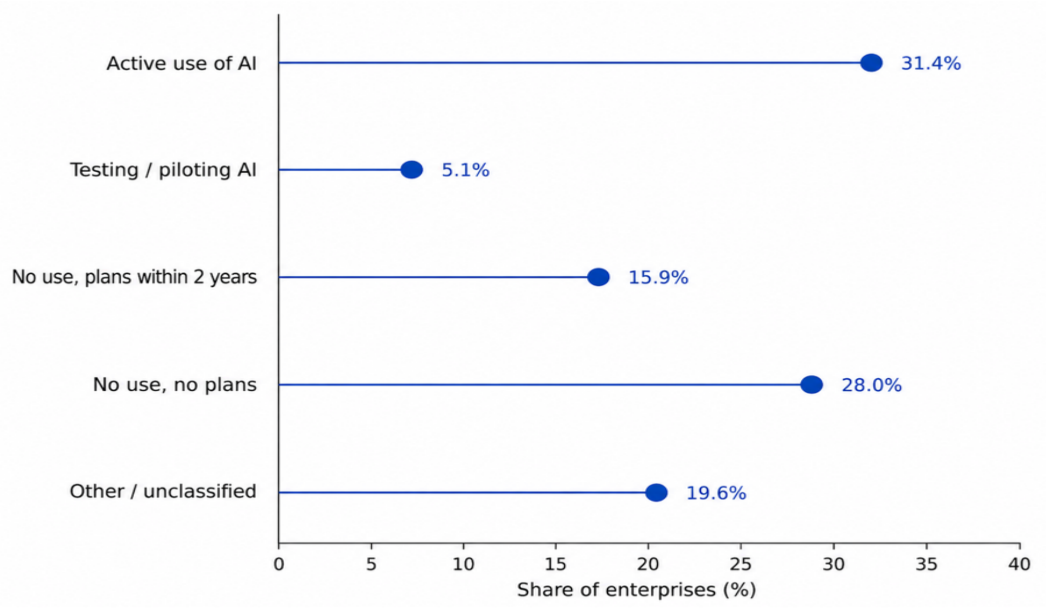
Table 2
Current AI adoption stage among surveyed Slovak enterprises

Adoption stage	Count	Share (%)
Active use of AI	202	31.4
Testing / piloting AI	33	5.1
No current use, plans to implement within 2 years	102	15.9
No current use and no plans to implement	180	28.0
Other / unclassified response	126	19.6
Total	**643**	**100.0**

Source: authors' calculations based on the AI-impactSK enterprise survey (CATI, Section C, Q1)

Awareness of AI's possibilities was more favourably self-assessed than actual adoption: 40.9 percent of respondents reported a good understanding of what AI can do, while 19.3 percent reported only a basic overview and 22.7 percent reported limited awareness or having heard of AI without understanding details. Regarding management attention, the most frequent response (51.8 percent) indicated that AI is occasionally discussed within management circles without concrete implementation steps; only 4.8 percent of enterprises reported that management has specific plans or a dedicated budget for AI, while 21.3 percent reported that AI is not a topic addressed by management at all.

Figure 1
AI adoption stage among surveyed Slovak enterprises



Source: authors' visualisation based on Table 2

Taken together, these three indicators suggest that awareness of AI substantially exceeds active management commitment and actual implementation: the share of enterprises reporting good or fairly good awareness (approximately 58 percent, summing the two highest awareness categories) is considerably higher than the share reporting active use (31.4 percent) or dedicated management budgets and plans (4.8 percent).

4.2 Digital readiness of Slovak enterprises (RQ2)

Table 3 and Figure 2 present the distribution of responses across the four digital-readiness dimensions. Electronic data storage was the most developed dimension, with 77.3 percent of enterprises reporting that they store business data electronically and only 8.1 percent reporting no electronic data storage at all. Access to IT capabilities was also relatively widespread (69.1 percent reporting full access, either in-house or external). Use of digital tools for daily operations was more mixed: 39.2 percent reported full integration, 31.6 percent partial integration, and 19.8 percent reported predominantly manual operations. The weakest dimension concerned workforce skills: only 36.2 percent of enterprises reported that employees are broadly familiar with new technologies, and 42.1 percent reported active support for employee training, with the majority of remaining responses falling into the “partly” category rather than “no”.

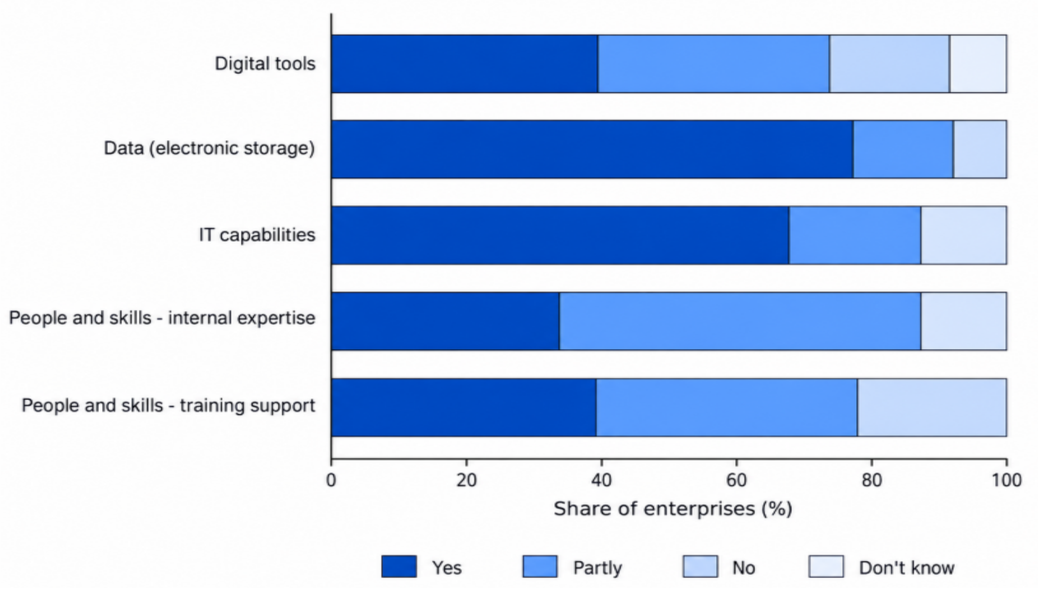
Table 3
Digital readiness dimensions among surveyed Slovak enterprises

Dimension	Yes (%)	Partly (%)	No (%)	Don't know (%)
Digital tools	39.2	31.6	19.8	9.5
Data (electronic storage)	77.3	14.6	8.1	-
IT capabilities	69.1	18.8	12.1	-
People and skills - internal expertise	36.2	52.1	11.7	-
People and skills - training support	42.1	37.2	20.7	-

Source: authors' calculations based on the AI-impactSK

The composite Digital Readiness Index (mean of the four items, scale 1-3) had a mean of 2.43, a median of 2.50 and a standard deviation of 0.46, with values ranging across the full 1.0-3.0 scale, and an internal-consistency (Cronbach's alpha) of 0.58. On a scale where 3.0 represents full readiness across all measured dimensions, an average value of 2.43 indicates a moderately high, though not universal, level of digital readiness among the surveyed enterprises, driven primarily by strong performance in data storage and IT capabilities rather than in digital tools or workforce skills.

Figure 2
Digital readiness dimensions among surveyed Slovak enterprises



Source: authors' visualisation based on Table 3

4.3 Descriptive comparison of digital readiness and AI adoption (RQ3)

Table 4 juxtaposes the two sets of aggregate indicators discussed above. The composite Digital Readiness Index (2.43 on a 1-3 scale, equivalent to roughly 71.5 percent of the maximum attainable score) is considerably higher, in relative terms, than the 31.4 percent share of enterprises reporting active AI use, and even the combined share of enterprises actively using or testing AI (36.5 percent). This descriptive contrast is consistent with the pattern documented in the underlying project report: a majority of surveyed enterprises appear to have already established at least partial digital foundations - most visibly in electronic data storage and IT support - without a corresponding majority having translated these foundations into active AI implementation.

Table 4
Descriptive juxtaposition of digital readiness and AI adoption indicators

Indicator	Value
Digital Readiness Index (mean, scale 1-3)	2.43 (SD = 0.46)
Readiness Index expressed as % of maximum scale value	~71.5%
Enterprises reporting electronic data storage (Yes)	77.3%
Enterprises reporting IT capabilities (Yes)	69.1%
Enterprises reporting active AI use	31.4%
Enterprises actively using or testing AI	36.5%
Enterprises reporting no AI use and no adoption plans	28.0%

Source: authors' calculations based on the AI-impactSK enterprise

This descriptive gap should be interpreted cautiously. Because the underlying data do not permit linking individual enterprises' readiness scores to their own adoption stage, it cannot be established from this dataset whether enterprises with higher readiness scores are, in fact, the same enterprises reporting active AI use, or whether the aggregate contrast reflects two largely distinct sub-populations. The finding is therefore best understood as a population-level descriptive pattern - a coexistence of comparatively developed basic digital foundations with comparatively limited AI implementation - rather than as evidence of a specific firm-level mechanism.

4.4 Supplementary context: organisational AI maturity among AI-engaged enterprises

As supplementary context, the companion CAWI survey conducted within the same project - administered to a distinct and self-selected population of 312 enterprises already engaged in AI-related activities - assessed seven dimensions of organisational AI maturity (culture, strategy, organisation, technology, data, ethics and privacy) on a five-point scale. The composite AI Maturity score for this population was 1.97 (SD = 0.78) on a 1-5 scale, with Culture (M = 2.70) and Technology (M = 2.65) scoring highest and Data (M = 1.63), Organisation (M = 1.66) and Ethics (M = 1.67) scoring lowest; internal consistency was high (Cronbach's alpha = 0.87).

Because the CAWI sample is drawn from a different and self-selected population - enterprises that had already engaged with AI, rather than the broad cross-section captured by the CATI survey - these results are not statistically comparable to the CATI-based findings reported in Sections 4.2-4.4 and are presented here only as contextual background for the discussion in Section 5. They nonetheless offer a consistent narrative: even among enterprises that have already begun engaging with AI, organisational strategy and data-governance maturity lag behind technological experimentation, echoing the technology-skills and technology-strategy imbalance observed in the broader CATI sample.

5 Discussion

The results suggest that Slovak enterprises, as captured by the CATI survey, have established a moderately advanced base of digital infrastructure - particularly with respect to electronic data storage and access to IT support - while a considerably smaller share of enterprises report active use of AI. This pattern is broadly consistent with international literature arguing that digital and data readiness represent necessary, but not sufficient, conditions for AI adoption, and that organisational capability gaps rather than the absence of underlying technology tend to constrain the transition from digitalisation to AI implementation.

The finding that awareness of AI (roughly 58 percent reporting good or fairly good understanding) exceeds active management commitment (4.8 percent reporting dedicated plans or budgets) and actual adoption (31.4 percent) is consistent with the broader diffusion-of-innovation perspective, in which awareness typically spreads faster than the organisational and resource commitments required for implementation. It also resonates with the argument that automation and augmentation applications of AI in management are interdependent and create persistent organisational tensions rather than a single, linear transition from awareness to full implementation, which may help explain why a considerable share of enterprises remain in an intermediate stage of occasional discussion rather than committed action (Raisch & Krakowski, 2021). It is also consistent with recent SME-focused survey evidence indicating that organisational capability gaps and change-management challenges, rather than cost alone, represent the primary obstacles separating AI-aware firms from AI-adopting firms (OECD, 2025a).

The comparatively weak performance of the workforce-skills dimension relative to data storage and IT capabilities echoes findings from the wider digital-maturity literature, which identifies human-capital constraints - rather than technology acquisition - as an increasingly important bottleneck for digital and AI transformation. This pattern also aligns with EU-level survey findings for Slovakia, where a substantial share of employees using AI reported a need for further skills development, while participation in related training remained low (Digital Skills and Jobs Platform, 2025). Read together, these results suggest that the observed gap between readiness and adoption in the present study may be attributable, at least in part, to workforce-related constraints rather than to a lack of basic digital or data infrastructure.

The position of Slovak enterprises relative to the wider EU context reinforces this interpretation. Harmonised Eurostat data indicate that Slovakia has consistently trailed the EU27 average in AI adoption across enterprise size classes between 2021 and 2024 (Eurostat, 2025a), and a recent comparative study found no stable short-term statistical association between AI adoption and labour productivity at the aggregate level for Slovakia, attributing this instead to the need for complementary investments in organisational transformation, digital skills and institutional capacity (Kádárová et al., 2026) - a conclusion that closely parallels the descriptive gap between readiness and adoption identified in the present firm-level data. This is broadly consistent with resource-based evidence suggesting that AI contributes to firm performance mainly when it is embedded within a wider set of organisational resources and capabilities rather than adopted as a stand-alone technology (Chen et al., 2022).

At the same time, several important qualifications must be observed when interpreting these results. First, because the underlying data do not permit linking individual enterprises' readiness scores to their own adoption stage, the study cannot establish whether it is the same enterprises that combine high readiness with low adoption, or whether the aggregate contrast instead reflects two partially distinct groups of enterprises. Second, the self-reported nature of all indicators means that the results reflect managerial perceptions rather than objectively verified technological capability or AI use, and may be affected by social-desirability or interpretation differences across respondents. Third, in the absence of an official response codebook, the precise boundaries of the AI adoption, awareness and management-attention categories should be treated as indicative rather than exact.For enterprise managers, the results suggest that the primary constraint on AI adoption for many Slovak enterprises may lie less in acquiring additional data infrastructure or IT support - both of which appear comparatively well established - and more in building organisational capabilities to exploit these foundations. Concrete implications include: (a) prioritising structured, budgeted AI initiatives over occasional, undocumented management discussion, given that only a small minority of surveyed enterprises reported dedicated AI budgets or plans; (b) investing systematically in employee training on AI-relevant skills, since workforce readiness was the weakest dimension identified; (c) selecting pilot AI use cases that build directly on existing strengths, such as well-established electronic data infrastructure, rather than attempting broader transformation programmes without a clear starting point; and (d) recognising that high self-assessed awareness of AI's possibilities does not by itself indicate organisational readiness to implement AI, and should not be mistaken for it.

5.1 Policy implications

From a policy perspective, the results indicate that support measures focused narrowly on financing AI-specific technology may address only part of the observed gap, given that basic digital and data infrastructure already appears comparatively developed among surveyed enterprises. Instead, the findings point towards a need for policy instruments that support the organisational and human-capital side of AI transformation: structured digital and AI-skills training programmes, particularly for smaller enterprises; advisory or mentoring schemes that help enterprises translate existing data and IT capabilities into concrete AI use cases; and monitoring instruments capable of tracking not only aggregate AI adoption rates but also firm-level co-occurrence of readiness and adoption, which the current data infrastructure does not yet permit. Given Slovakia's persistent position below the EU27 average in AI adoption across enterprise-size classes (cf. OECD, 2025b), targeted support for small and medium-sized enterprises, which constitute the bulk of the domestic enterprise population, appears particularly relevant.

6 Conclusions

This paper set out to describe the current level of digital readiness and AI adoption among Slovak enterprises and to examine, at a descriptive level, whether a gap between the two is observable using firm-level survey data collected within the AI-impactSK project. Drawing on 643 completed CATI interviews, the analysis found that enterprises reported a moderately high level of digital readiness (composite index of 2.43 on a 1-3 scale), underpinned mainly by strong electronic data storage (77.3 percent) and IT support (69.1 percent), while workforce-related readiness lagged behind. In contrast, only 31.4 percent of enterprises reported active AI use, and 28.0 percent reported neither current use nor adoption plans. Awareness of AI's possibilities was considerably more widespread than either active management commitment or actual adoption.

In answer to the research questions, the study finds: (RQ1) that AI adoption among Slovak enterprises remains concentrated in a minority of the surveyed population, with awareness running ahead of both managerial commitment and implementation; (RQ2) that digital readiness is unevenly distributed across its four dimensions, being comparatively strong in data storage and IT capabilities and comparatively weak in workforce skills; and (RQ3) that a descriptive gap between the aggregate level of digital readiness and the aggregate level of AI adoption is observable within the surveyed population, though this cannot be interpreted as a statistically tested or firm-level association given the descriptive design of the underlying data.

The theoretical contribution of the paper lies in providing firm-level survey evidence, for a small open EU economy, that is broadly consistent with the conceptual view of digital readiness as a necessary but not sufficient condition for AI adoption, while explicitly documenting the methodological boundaries within which such evidence should be interpreted. The methodological contribution lies in demonstrating how a purely descriptive juxtaposition of aggregate indicators can be transparently reported and bounded, without overstating the inferential content of cross-sectional business survey data. The managerial and policy contributions point towards the importance of organisational capability-building and workforce-skills development as complements to already comparatively developed digital and data infrastructure.

The study is subject to several limitations. The design is cross-sectional and does not permit any causal interpretation of the observed patterns. All indicators are self-reported by enterprise representatives and are therefore subject to potential social-desirability bias and to variation in respondents' own understanding of the questions asked. The underlying dataset lacked an official response codebook for several items, requiring the categories used in this study to be treated as indicative rather than exact. No breakdown of the sample by enterprise size, sector or region was available, preventing analysis of firm heterogeneity, which the literature identifies as an important dimension of AI adoption. Most importantly, the absence of any cross-tabulation, correlation or regression linking individual enterprises' readiness scores to their own adoption stage means that the "gap" documented in this paper is a population-level descriptive pattern rather than a tested statistical association, and should not be read as evidence of a causal or even correlational firm-level mechanism.

Future research should address these limitations directly. Priority directions include: collecting firm-level data that link individual enterprises' digital-readiness scores to their own AI adoption stage, enabling formal association or regression analysis; incorporating firm-size and sector breakdowns to examine heterogeneity in the readiness-adoption relationship; adopting longitudinal designs capable of tracking whether enterprises with higher initial readiness subsequently show faster AI adoption; complementing self-reported measures with more objective indicators of digital and AI capability; and extending the analysis to allow direct, harmonised comparison with EU27 firm-level surveys. Such research would allow the descriptive pattern identified in this paper to be tested more rigorously and would provide a stronger evidentiary basis for the managerial and policy recommendations outlined above.

Acknowledgement

This paper is based on data collected within the AI-impactSK project, funded by the European Union through the NextGenerationEU instrument under the Recovery and Resilience Plan for Slovakia, project No. 09I05-03-V02-00003/2025/VA. The authors wish to acknowledge the contribution of Matej Černý to the underlying data collection and statistical analysis on which this paper draws.

References

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F. & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. International Journal of Information Management. Vol. 57, 102225. ISSN 0268-4012.

Brodny, J. & Tutak, M. (2021). Assessing the level of digital maturity of enterprises in the Central and Eastern European countries using the MCDM and Shannon's entropy methods. PLOS ONE. Vol. 16, Issue 7, e0253965. ISSN 1932-6203. DOI 10.1371/journal.pone.0253965.

Chen, D., Esperança, J. P. & Wang, S. (2022). The Impact of Artificial Intelligence on Firm Performance: An Application of the Resource-Based View to e-Commerce Firms. Frontiers in Psychology. Vol. 13, 884830. ISSN 1664-1078. DOI 10.3389/fpsyg.2022.884830.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika. Vol. 16, Issue 3, pp. 297-334. ISSN 0033-3123.

Digital Skills and Jobs Platform. (2025). AI is changing workplaces in Slovakia. European Commission, https://digital-skills-jobs.europa.eu/en/latest/news/ai-changing-workplaces-slovakia, [accessed 14.7.2026].

Eurostat. (2025a). Use of artificial intelligence in enterprises. Statistics Explained. Luxembourg: Publications Office of the European Union, https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Use_of_artificial_intelligence_in_enterprises, [accessed 14.7.2026].

Eurostat. (2025b). 20% of EU enterprises use AI technologies. News articles. Luxembourg: Publications Office of the European Union, https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20251211-2, [accessed 14.7.2026].

Kaplan, A. & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Business Horizons. Vol. 63, Issue 1, pp. 37-50. ISSN 0007-6813. DOI 10.1016/j.bushor.2019.09.003.

Kádárová, J., Fiľo, M., Sukopová, D. & Dúlová, M. (2026). Artificial Intelligence Adoption and Labour Productivity in Slovakia and the EU27: Implications for Sustainable Economic Growth. Sustainability. Vol. 18, Issue 4, 2135. ISSN 2071-1050. DOI 10.3390/su18042135.

Kádárová, J., Lachvajderová, L. & Sukopová, D. (2023). Impact of Digitalization on SME Performance of the EU27. Sustainability. Vol. 15, 9973. ISSN 2071-1050. DOI 10.3390/su15139973.

Mikalef, P. & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management. Vol. 58, Issue 3, 103434. ISSN 0378-7206. DOI 10.1016/j.im.2021.103434.

OECD. (2025a). AI adoption by small and medium-sized enterprises. Paris: OECD Publishing, https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/12/ai-adoption-by-small-and-medium-sized-enterprises_9c48eae6/426399c1-en.pdf, [accessed 14.7.2026].

OECD. (2025b). Progress in Implementing the EU Coordinated Plan on AI (Vol. 1): Slovak Republic. Paris: OECD Publishing.

Raisch, S. & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. Academy of Management Review. Vol. 46, Issue 1, pp. 192-210. ISSN 0363-7425. DOI 10.5465/amr.2018.0072.

Stovíček, F., Hanák, R., Hajduová, Z. & Černý, M. (2026). Statistical Analysis Report 3.3 (Deliverable 3.3, AI-impactSK project). Bratislava: Bratislava University of Economics and Business.

Organisational Factors Associated with Artificial Intelligence Adoption: Evidence from Hierarchical Logistic Regression in Slovak Enterprises

Filip Stovíček, Róbert Hanák, Zuzana Hajduová

Abstract
adoption among enterprises, little firm-level evidence explains which organisational characteristics independently distinguish AI adopters from non-adopters once multiple determinants are considered jointly. This paper examines organisational factors associated with AI adoption among Slovak enterprises using hierarchical binary logistic regression estimated on survey data collected within the AI-impactSK project. The dependent variable distinguishes enterprises currently using or piloting AI (coded 1) from enterprises planning or not intending to adopt AI (coded 0). Five nested models sequentially introduce a composite AI Maturity index, a Business Sentiment construct derived from the Technology Acceptance Model, seven Technology-Organization-Environment (TOE) dimensions, and three categories of perceived implementation barriers. Model fit and explanatory power (Nagelkerke R^2 rising from 0.063 to 0.136) improve as organisational-level constructs are added, with the strongest predictor being TOE Organisation (odds ratio 1.93-2.07), followed by AI Maturity (odds ratio 1.55-2.07) and Business Sentiment, significant only once organisational readiness is controlled for. Perceived technological barriers are independently associated with lower adoption odds, while most other TOE dimensions and the organisational and external barrier categories do not retain independent significance. A parsimonious four-predictor model retains about 83 percent of the full model's explanatory power. The findings suggest that internal organisational capability, rather than technology availability or external conditions, is the principal correlate of AI adoption, with implications for managerial practice and innovation policy. Results should be read as statistical association rather than causal determination given the cross-sectional, self-reported data.

JEL classification*: C25, M15, O33*
Keywords*: artificial intelligence adoption, logistic regression, organisational readiness*

1 Introduction

Artificial intelligence has evolved from an emerging digital innovation into a strategic organisational capability with the potential to transform business processes, decision-making and competitive positioning, while simultaneously raising new managerial challenges regarding its responsible and effective deployment (Kaplan & Haenlein, 2020). Enterprises increasingly recognise the potential of AI to enhance operational efficiency, automate repetitive activities and support evidence-based managerial decisions. Nevertheless, considerable differences remain in the extent to which this recognition translates into actual organisational adoption: while some enterprises have already integrated AI into multiple business functions, many others remain at the stage of experimentation or have not initiated implementation at all.

Descriptive statistics can document the prevalence of AI adoption and characterise the organisations involved, but they cannot determine which organisational characteristics independently influence adoption once multiple potential determinants operate simultaneously. Because AI adoption plausibly results from the interaction of organisational capability, managerial attitudes, technological readiness, environmental conditions and perceived implementation barriers, understanding its correlates requires multivariate analytical techniques capable of modelling several explanatory constructs jointly while accounting for their interdependence.

A substantial body of research addresses related questions using two complementary theoretical lenses. The Technology Acceptance Model (TAM) emphasises that favourable perceptions of a technology's usefulness and ease of use shape the willingness of individuals and organisations to adopt it (Davis, 1989). The Technology-Organization-Environment (TOE) framework instead argues that adoption depends jointly on technological, organisational and environmental contexts (Tornatzky & Fleischer, 1990), and has been widely applied to explain enterprise-level adoption of digital and AI technologies (Mikalef & Gupta, 2021). Systematic reviews of the strategic use of AI in the digital era have called for more empirical work linking validated organisational constructs to the probability that firms actually reach the implementation stage, rather than relying on isolated survey items (Borges et al., 2021).

Despite the relevance of both frameworks, firm-level evidence that jointly estimates their relative and incremental contribution to AI adoption specifically among Slovak enterprises has, to the authors' knowledge, not previously been reported. Existing Slovak evidence on AI diffusion relies primarily on descriptive or highly aggregated indicators; for instance, harmonised Eurostat data show that Slovak enterprises trailed the EU27 average in AI adoption across all size classes between 2021 and 2024, without decomposing this gap into organisational-level correlates (Kádárová et al., 2026). This creates a specific empirical gap: which organisational constructs - overall AI maturity, managerial sentiment, the individual TOE dimensions, or perceived implementation barriers - remain statistically associated with AI adoption once they are considered jointly within the same enterprise population.

This paper addresses this gap using data collected within the AI-impactSK project, funded through the Recovery and Resilience Plan for Slovakia. Building on previously validated composite indicators of organisational AI maturity, business sentiment, TOE dimensions and implementation barriers, the analysis estimates five hierarchical binary logistic regression models that sequentially introduce these constructs to explain whether a Slovak enterprise currently uses or pilots AI. The models allow both the incremental explanatory contribution of each theoretical block and the stability of individual predictors to be assessed as additional controls are introduced.

The paper is guided by the following research questions:

- RQ1: Is organisational AI maturity associated with the probability that an enterprise currently adopts AI, and does this association persist after controlling for managerial sentiment, TOE dimensions and implementation barriers?
- RQ2: Does managerial sentiment towards AI (a TAM-derived construct) contribute explanatory power beyond organisational AI maturity?
- RQ3: Which TOE dimensions retain an independent association with AI adoption once organisational maturity and managerial sentiment are controlled for?
- RQ4: Do perceived implementation barriers reduce the odds of AI adoption independently of organisational capability?

Corresponding to these questions, four working hypotheses are formulated:

- H1: Organisational AI maturity is positively associated with the odds of AI adoption.
- H2: Business Sentiment is positively associated with the odds of AI adoption after controlling for AI maturity.
- H3: TOE Organisation is positively associated with the odds of AI adoption independently of AI maturity and Business Sentiment.

- H4: Perceived technological implementation barriers are negatively associated with the odds of AI adoption.

2 Current State of the Solved Problem at Home

2.1 Organisational AI maturity as a predictor of adoption

Organisational AI maturity is commonly conceptualised as a multidimensional capability encompassing strategic orientation, organisational culture, technological readiness, data governance and ethical and privacy preparedness, rather than a single measure of AI usage (Mikalef & Gupta, 2021). Building on the resource-based view of the firm, an AI capability has been characterised as jointly comprising tangible technological resources, human skills and intangible organisational resources, with the human-capital and organisational components frequently representing the weakest link between available technology and realised performance (Mikalef & Gupta, 2021). This perspective implies that AI maturity should predict adoption not because it measures current AI use directly, but because it captures the broader organisational capacity required to sustain implementation. The Technology Acceptance Model posits that perceived usefulness and perceived ease of use are fundamental antecedents of technology acceptance, and that favourable perceptions translate into a greater willingness to adopt a given technology (Davis, 1989). Applied at the organisational level, this suggests that managerial attitudes and expectations regarding AI - captured here as Business Sentiment - should be positively associated with adoption. At the same time, the literature on management and AI cautions that automation and augmentation applications of AI create persistent organisational tensions, so that positive discourse about AI does not automatically translate into a linear progression from favourable sentiment to implementation (Raisch & Krakowski, 2021). This suggests that the independent contribution of managerial sentiment may depend on which other organisational characteristics are simultaneously controlled for.

2.2 The Technology-Organization-Environment framework

The TOE framework explains technology adoption through the joint influence of technological, organisational and environmental contexts (Tornatzky & Fleischer, 1990). Within this framework, the organisational dimension - encompassing governance structures, managerial commitment, resource availability and internal coordination capacity - is frequently found to exert a stronger influence on adoption than technology characteristics or external environmental pressures considered in isolation. This is consistent with resource-based evidence suggesting that AI contributes to firm performance mainly when embedded within a wider set of organisational resources and capabilities rather than adopted as a stand-alone technology (Chen et al., 2022).A recurring theme in the technology-adoption literature is that perceived implementation barriers - technological, organisational and external - can suppress adoption even among enterprises that otherwise display favourable organisational characteristics. Technological barriers, including inadequate infrastructure, insufficient technical expertise and integration difficulties, are commonly identified as one of the most persistent obstacles separating organisations that experiment with AI from those that translate experimentation into sustained implementation. Whether such barriers retain an independent statistical association with adoption once organisational maturity, sentiment and TOE dimensions are controlled for is, however, an empirical question that hierarchical modelling is well suited to address. Taken together, the reviewed literature establishes organisational AI maturity, managerial sentiment (TAM) and the TOE dimensions as complementary, partially overlapping explanatory perspectives on AI adoption, with perceived barriers acting as a potential counterweight to organisational readiness. What remains comparatively underexplored is the relative and incremental contribution of these perspectives when estimated jointly, using validated composite indicators, within a single national enterprise population. The conceptual framework guiding this study therefore treats AI adoption as a binary organisational outcome jointly shaped by (a) overall organisational AI maturity, (b) managerial sentiment, (c) the specific organisational, technological and environmental conditions captured by the TOE framework, and (d) perceived implementation barriers, with hierarchical logistic regression used to trace how the statistical association of each block changes as the others are introduced.

3 Research design and methodology

The aim of this paper is to identify which organisational characteristics are statistically associated with AI adoption among Slovak enterprises, and to assess how the strength and significance of these associations change as additional theoretically motivated predictor groups are introduced. The partial objectives are: (1) to estimate a baseline model relating organisational AI maturity to AI adoption; (2) to assess the incremental contribution of managerial sentiment, TOE dimensions and implementation barriers through successive hierarchical models; and (3) to identify a parsimonious subset of predictors that retains most of the explanatory power of the full model. The study tests hypotheses H1-H4 stated in Section 1.

3.1 Data collection

The data used in this study were collected within the AI-impactSK project ("Assessment of the impact of artificial intelligence on the Slovak labour market and enterprises"), funded by the European Union through the NextGenerationEU instrument under the Recovery and Resilience Plan for Slovakia (project No. 09I05-03-V02-00003/2025/VA). The explanatory variables used in this study - organisational AI maturity, business sentiment, the seven TOE dimensions and the three barrier dimensions - correspond to questionnaire sections that, in the project's companion descriptive report (Statistical Analysis Report 3.3), were administered through the project's web-based (CAWI) survey to a population of 312 Slovak enterprises already engaged in AI-related activities.

The econometric report underlying this study (Econometric Model Outcomes, Deliverable 5.2) does not itself restate the exact sample size used in the estimation of the five logistic regression models; it reports degrees of freedom for the likelihood-ratio tests but not the total number of observations. Based on the correspondence between the composite variables used in the regression models and the CAWI questionnaire sections described in the companion descriptive report, the analytic sample is inferred to be drawn from this n = 312 CAWI population. This inference could not be independently verified from the text of Deliverable 5.2 alone and is treated as a methodological limitation (Section 6). Because the CAWI sample comprises enterprises already engaged with AI rather than a random cross-section of the Slovak enterprise population, the findings should be interpreted as applying to this self-selected population rather than to Slovak enterprises in general.

3.2 Dependent variable

The dependent variable represents current organisational AI adoption. The original questionnaire measured AI implementation using a seven-category ordinal variable ranging from active use of AI across multiple business functions to no current use and no implementation plans. For the purposes of explanatory modelling, this variable was recoded into a binary outcome: enterprises reporting active use of AI in multiple areas, active use in selected processes, or current pilot testing were classified as adopters (AI_use = 1); enterprises reporting no current use, irrespective of their planned implementation horizon, were classified as non-adopters (AI_use = 0). The inclusion of pilot-testing enterprises among adopters reflects the view that piloting represents realised organisational commitment - allocated resources, managerial attention and practical integration into at least part of operations - rather than mere intention.

Binary logistic regression was preferred over ordinal or multinomial alternatives for both theoretical and practical reasons. Ordinal logistic regression would require the proportional-odds assumption to hold across categories that differ substantially in conceptual content (active use vs planning horizons), which is difficult to justify; multinomial regression would require larger within-category sample sizes than are available and would address a different research question (comparing adoption stages rather than the adoption decision itself). This operationalisation is also consistent with the broader literature on enterprise technology adoption, which frequently distinguishes current adopters from non-adopters as the key organisational transition of interest.

The explanatory variables were not derived from individual questionnaire items but from composite indices representing validated latent constructs identified in prior exploratory factor analysis conducted within the AI-impactSK project. For each retained factor, a composite score was calculated as the arithmetic mean of its constituent items, and internal consistency was evaluated using Cronbach's alpha (Cronbach, 1951) prior to inclusion in the regression models. Table 1 summarises the twelve composite variables used across the five hierarchical models.

Table 1
Composite variables used in the hierarchical logistic regression models

Composite index	Underlying construct	Used in models
AI Maturity	Overall organisational AI maturity (culture, strategy, organisation, technology, data, ethics, privacy)	Models 1-5
Business Sentiment (Positive)	Positive organisational attitudes towards AI (TAM)	Models 2-5
Information Formal	Formal sources of AI-related information	Model 4
TOE Organization	Organisational readiness and managerial capability	Models 3-5
TOE AI Benefits	Perceived organisational benefits of AI	Models 3-4
TOE AI Complexity	Perceived implementation complexity	Models 3-4
TOE Technology Readiness	Technological preparedness for AI implementation	Models 3-4
TOE Public Support	Perceived availability of external institutional support	Models 3-4
TOE Market Pressure	Competitive pressure to adopt AI	Models 3-4
TOE Regulatory Risk	Perceived regulatory uncertainty	Models 3-4
Barrier Technology	Perceived technological implementation barriers	Models 4-5
Barrier Organization	Perceived internal organisational barriers	Model 4
Barrier External	Perceived external environmental barriers	Model 4

Source: authors' own elaboration

Prior to estimation, the relationships among all composite variables were examined using Pearson correlation coefficients. AI Maturity showed its strongest association with TOE Organization ($r = 0.705$, $p < .001$) and a strong positive association with Business Sentiment ($r = 0.646$, $p < .001$), while all three barrier constructs correlated negatively with organisational capability measures, most notably Barrier Organization with AI Maturity ($r = -0.283$, $p < .001$) and with TOE Organization ($r = -0.258$, $p < .001$). The strongest observed correlation among any pair of predictors was approximately 0.71, which is below thresholds generally regarded as indicative of severe multicollinearity; this was subsequently confirmed by Variance Inflation Factor (VIF) diagnostics reported alongside each regression model in Section 4.

Because the dependent variable is binary, model parameters were estimated using binary logistic regression via Maximum Likelihood Estimation (MLE), which identifies parameter values that maximise the likelihood of the observed pattern of AI adoption in the sample. The estimated coefficients represent changes in the log-odds of AI adoption associated with a one-unit increase in each predictor; for interpretability, results are reported as odds ratios ($OR = e^\beta$), where $OR > 1$ indicates increasing odds of adoption and $OR < 1$ indicates decreasing odds.

A hierarchical modelling strategy was adopted, in which five nested models were estimated by sequentially introducing additional predictor groups: Model 1 (AI Maturity only); Model 2 (Model 1 plus Business Sentiment); Model 3 (Model 2 plus the seven TOE dimensions); Model 4 (Model 3 plus the three barrier dimensions); and Model 5, a parsimonious specification retaining only the predictors that demonstrated the strongest and most stable contribution across Models 1-4 (AI Maturity, Business Sentiment, TOE Organization and Barrier Technology). This sequencing allows the incremental explanatory contribution of each theoretical block to be assessed and the stability of individual predictors to be evaluated as additional controls are introduced.

Overall model significance was assessed using the likelihood-ratio chi-square statistic relative to the intercept-only model. Explanatory power was evaluated using Nagelkerke's pseudo-R^2, and model fit was additionally compared using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), both of which penalise unnecessary model complexity. Predictive performance was assessed using classification accuracy at the conventional 0.50 probability threshold and the Area Under the Receiver Operating Characteristic Curve (AUC), a threshold-independent measure of discrimination. Multicollinearity was evaluated using Variance Inflation Factors (VIF) for every model.

All composite indices were constructed only after confirming acceptable to excellent internal consistency (Cronbach's alpha) for their constituent items in the prior exploratory factor analysis stage of the project; indices with unsatisfactory reliability were not carried forward into the regression models. No further external validation (e.g., against objective indicators of AI use) was conducted, and the composite indices should therefore be understood as validated in terms of internal consistency rather than externally verified against non-self-reported criteria. As noted in Section 3.2, the exact analytic sample size for the regression models is inferred rather than explicitly stated in the source report, and this is treated as a limitation throughout the interpretation of results.

4 Research results

All five models were statistically significant overall ($p < 0.01$), confirming that each specification explains AI adoption significantly better than an intercept-only model. Explanatory power, as measured by Nagelkerke's pseudo-R^2, rose from 0.063 in the baseline model to a maximum of 0.136 in the full model (Model 4), before declining only slightly to 0.113 in the parsimonious Model 5. Predictive discrimination (AUC) similarly improved from 0.631 in Model 1 to 0.684 in Model 4, remaining below the conventional 0.70 threshold for good discrimination throughout, but showing a consistent, theoretically coherent improvement as organisational-level predictors were added. Table 2 and Figure 1 summarise the fit and predictive-performance statistics for all five hierarchical logistic regression models.

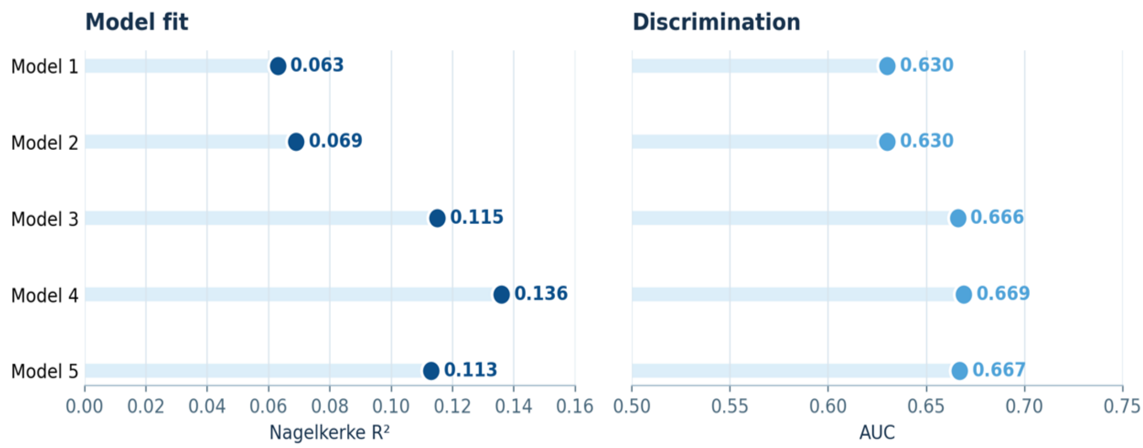
Table 2
Comparative performance of the hierarchical logistic regression models

Model	χ^2	p	Nagelkerke R^2	AIC	BIC	AUC	Significant predictors
Model 1	14.29	<0.001	0.063	388.00	395.42	0.631	AI Maturity
Model 2	15.56	<0.001	0.069	382.72	399.86	0.632	AI Maturity
Model 3	26.46	0.002	0.115	391.82	428.93	0.665	AI Maturity, Business Sentiment, TOE Organization
Model 4	31.57	0.002	0.136	392.72	440.95	0.684	AI Maturity, Business Sentiment, TOE Organization, Barrier Technology
Model 5	26.07	<0.001	0.113	382.21	400.77	0.667	Business Sentiment, TOE Organization

Source: authors' own elaboration

The lowest AIC and BIC values were obtained for the parsimonious Model 5 (AIC = 382.21, BIC = 400.77), indicating that, once model complexity is penalised, the four-predictor specification offers the most efficient representation of AI adoption among those estimated, despite Model 4 achieving marginally higher raw explanatory power and predictive discrimination.

Figure 1
Model fit and predictive discrimination (AUC) across the five hierarchical models



Source: authors' own elaboration

Model 1: AI Maturity (baseline)

The baseline model, containing only the composite AI Maturity index, was statistically significant ($\chi^2 = 14.29$, $p < 0.001$). The regression coefficient for AI Maturity was positive and highly significant ($\beta = 0.575$, $p < 0.001$), corresponding to an odds ratio of 1.78: each one-unit increase in AI Maturity was associated with an approximately 78 percent increase in the odds of AI adoption. Nagelkerke's R^2 reached 0.063, and the AUC was 0.631, indicating a statistically meaningful but modest level of discrimination. Using the standard 0.50 threshold, the model correctly classified 90.0 percent of non-adopters but only 17.0 percent of adopters, reflecting the conservative, imbalanced classification behaviour typical of single-predictor models applied to moderately imbalanced binary outcomes. With only one predictor, VIF = 1.00, ruling out multicollinearity by construction.

Model 2: Adding Business Sentiment

Introducing Business Sentiment alongside AI Maturity produced a statistically significant model ($\chi^2 = 15.56$, df = 2, $p < 0.001$), with only a marginal increase in explanatory power (Nagelkerke $R^2 = 0.069$). AI Maturity remained a highly significant predictor ($\beta = 0.726$, $p = 0.0005$; OR = 2.07), while Business Sentiment was not statistically significant once AI Maturity was controlled for ($\beta = -0.226$, $p = 0.261$; OR = 0.80). This pattern is consistent with substantial shared explanatory variance between the two constructs rather than with managerial sentiment being irrelevant: organisations with higher AI Maturity also tend to report more favourable sentiment, so that, in a two-predictor model, sentiment contributes comparatively little unique information. AUC (0.632) and classification accuracy (91.1 percent for non-adopters, 16.1 percent for adopters) were similar to Model 1. Both predictors showed identical VIF (1.77), well below concerning thresholds.

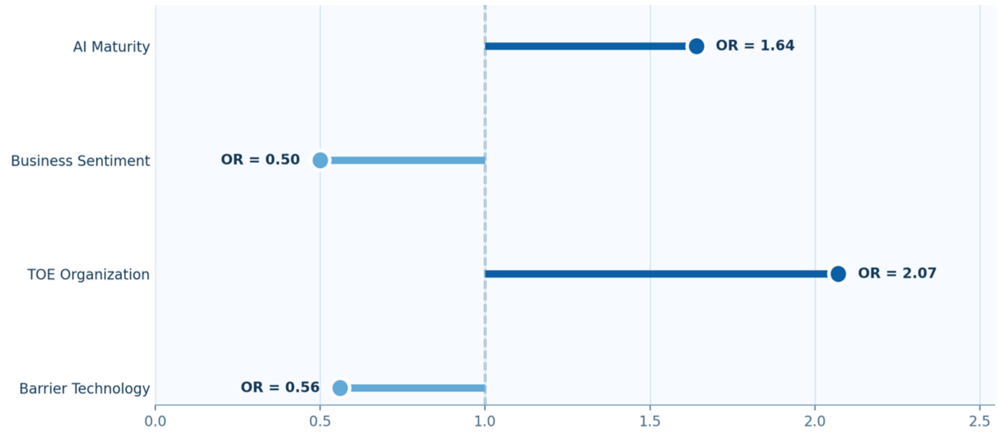
Model 3: Extended TOE model

Introducing the seven TOE dimensions produced the largest single increase in explanatory power observed across the hierarchical sequence ($\chi^2 = 26.46$, df = 9, $p = 0.002$; Nagelkerke $R^2 = 0.115$, up from 0.069). Within this specification, AI Maturity's coefficient decreased and became only marginally significant ($\beta = 0.444$, $p = 0.060$; OR = 1.56), consistent with part of its explanatory content being redistributed to the more specific TOE dimensions. Business Sentiment became statistically significant ($\beta = -0.634$, $p = 0.015$; OR = 0.53) once the TOE variables were controlled for - a finding the source report attributes to the coding direction of the sentiment scale (with higher values plausibly representing greater scepticism) rather than to a substantive reversal of the expected relationship. TOE Organization emerged as the strongest predictor in the model ($\beta = 0.663$, $p = 0.019$; OR = 1.94). None of the remaining TOE dimensions - AI Benefits, AI Complexity, Technology Readiness, Public Support, Market Pressure, or Regulatory Risk - reached conventional significance levels. AUC improved to 0.665, and classification accuracy was 86.3 percent for non-adopters and 29.5 percent for adopters. VIF values ranged from 1.14 to 3.33 (highest for TOE Organization), remaining within acceptable limits.

Model 4: Full model (TOE and barrier dimensions)

The full model, adding the three barrier dimensions to Model 3, achieved the highest overall likelihood-ratio statistic ($\chi^2 = 31.57$, df = 12, $p = 0.002$) and the highest explanatory power across all specifications (Nagelkerke $R^2 = 0.136$). Four predictors remained statistically significant: AI Maturity ($\beta = 0.497$, $p = 0.044$; OR = 1.64), Business Sentiment ($\beta = -0.687$, $p = 0.010$; OR = 0.50), TOE Organization ($\beta = 0.727$, $p = 0.012$; OR = 2.07), and Barrier Technology ($\beta = -0.581$, $p = 0.049$; OR = 0.56). The remaining TOE dimensions and the Barrier Organization and Barrier External constructs did not reach statistical significance. Public Support approached but did not reach significance ($\beta = -0.299$, $p = 0.096$). Predictive performance reached its highest level in this specification (AUC = 0.684), with classification accuracy of 87.9 percent for non-adopters and 29.5 percent for adopters. VIF values ranged from 1.20 to 3.43 (highest for TOE Organization), within accepted methodological limits.

Figure 2
Odds ratios of the four statistically significant predictors



Source: authors' own elaboration

Model 5: Parsimonious (robustness) model

The final parsimonious model retained only AI Maturity, Business Sentiment, TOE Organization and Barrier Technology. The model remained highly significant ($\chi^2 = 26.07$, df = 4, $p < 0.001$) and preserved approximately 83 percent of the explanatory power of the full model (Nagelkerke $R^2 = 0.113$ versus 0.136) while using only one-third of the predictors, and achieved the lowest AIC (382.21) and BIC (400.77) among all five models. AI Maturity remained positive but only marginally significant ($\beta = 0.441$, $p = 0.058$; OR = 1.55); Business Sentiment remained significant ($\beta = -0.539$, $p = 0.023$; OR = 0.58); TOE Organization remained the strongest and most stable predictor ($\beta = 0.657$, $p = 0.008$; OR = 1.93); and Barrier Technology narrowly missed conventional significance ($\beta = -0.385$, $p = 0.077$; OR = 0.68) while retaining a stable direction and magnitude consistent with the full model. AUC was 0.667, with classification accuracy of 88.4 percent for non-adopters and 27.7 percent for adopters. VIF values ranged from 1.00 to 2.55, the lowest range observed across the five models.

Table 3
Summary of hypothesis testing across the hierarchical models

Hypothesis	Main result	Decision
H1: AI Maturity is positively associated with AI adoption odds	Positive and significant in Models 1-2 and 4; positive but only marginally significant in Models 3 and 5 (OR 1.55-2.07 throughout)	Supported (attenuates once TOE Organization is controlled for)
H2: Business Sentiment is positively associated with AI adoption odds after controlling for AI Maturity	Not significant in Model 2; significant with a negative coefficient in Models 3-5	Not supported as originally directional; a significant association emerges, but its sign requires cautious interpretation given coding-direction ambiguity (Section 4.4)
H3: TOE Organization is positively associated with AI adoption odds independently of AI Maturity and Business Sentiment	Positive and significant in Models 3-5 (OR 1.93-2.07), the strongest and most stable predictor overall	Supported
H4: Perceived technological barriers are negatively associated with AI adoption odds	Negative and significant in Model 4 (OR = 0.56); negative but marginal in Model 5 (p = 0.077)	Partially supported

Source: authors' own elaboration

5 Discussion

The results indicate that internal organisational capability, rather than the availability of technology itself or external environmental conditions, is the correlate most consistently associated with AI adoption among the surveyed Slovak enterprises. Across all specifications in which it was included, TOE Organization - reflecting governance structures, managerial commitment and internal coordination capacity - was the strongest and most stable predictor, a finding that directly supports the central TOE proposition that organisational context is at least as important as technological characteristics in shaping adoption outcomes (Tornatzky & Fleischer, 1990).

The behaviour of the AI Maturity construct across the hierarchical sequence is informative in its own right. Its coefficient remained positive throughout but weakened as more specific TOE dimensions were introduced, consistent with AI Maturity representing a higher-order organisational capability whose explanatory content is partly captured by, and partly distinct from, the more granular organisational readiness measured by TOE Organization (Mikalef & Gupta, 2021). This pattern illustrates a general risk in explanatory modelling of organisational capability: broad composite constructs and their more specific components can compete for the same explanatory variance, so that apparent changes in significance across nested models should be interpreted structurally rather than as evidence that a predictor has become unimportant. As discussed further in Section 6.1, this attenuation pattern is also the classic statistical signature of mediation, and is best confirmed formally rather than inferred solely from the sequence of nested models.

The behaviour of Business Sentiment is more difficult to interpret with confidence. Its non-significance in Model 2 and significant negative coefficient in Models 3-5 is consistent with the source report's own caveat that the direction of this result may reflect the coding of the sentiment scale (with higher scores potentially indicating greater scepticism) rather than a substantive finding that positive attitudes reduce adoption odds. This is compounded by the broader observation that AI-related organisational discourse and actual implementation do not always progress in a simple linear sequence, with automation and augmentation applications of AI creating persistent rather than transitional organisational tensions (Raisch & Krakowski, 2021). Given this ambiguity, the present study reports the association but explicitly declines to draw a substantive directional conclusion about managerial sentiment beyond noting that it retains independent explanatory content once organisational readiness is controlled for.

The independent, significant association between perceived technological barriers and lower adoption odds in the full model - alongside the non-significance of organisational and external barriers - suggests that, once organisational capability is accounted for, the remaining constraint most closely tied to non-adoption is specifically technological (infrastructure, technical expertise, integration difficulty) rather than organisational or external in a broader sense. This is consistent with resource-based arguments that AI contributes to firm outcomes mainly when embedded within a wider set of complementary organisational resources, so that technological gaps not compensated by organisational capability remain a binding constraint (Chen et al., 2022).

The comparatively modest explanatory power (maximum Nagelkerke $R^2 = 0.136$) and discrimination (maximum AUC = 0.684) observed across all models should not be read as a failure of the modelling strategy; pseudo-R^2 and AUC values of this magnitude are common in organisational technology-adoption research, where adoption decisions are shaped by numerous strategic, economic and behavioural factors that cannot be fully captured within a single questionnaire-based model. The consistent, theoretically coherent pattern of improvement from Model 1 to Model 4, and the retention of about 83 percent of that explanatory power in the four-predictor Model 5, together provide reasonably robust evidence that a small number of organisational constructs - overall maturity, organisational readiness and technological barriers, together with managerial sentiment - capture most of the systematic organisational variation associated with AI adoption in this population.

For enterprise managers, the results suggest that investment in AI-specific technology alone is unlikely to be sufficient for successful adoption unless accompanied by organisational capability-building. Concrete implications include: (a) prioritising governance structures, clear organisational responsibility and internal coordination mechanisms for AI initiatives, given that TOE Organization was the most robust predictor across all specifications; (b) treating overall AI maturity - spanning strategy, culture, data governance and ethics - as a cumulative organisational asset built over time rather than as a by-product of acquiring AI tools; and (c) directly addressing technological implementation barriers such as infrastructure gaps and technical-skill shortages, since these retained an independent negative association with adoption even after organisational readiness was controlled for.

From a policy perspective, the results suggest that national support measures aimed at accelerating AI diffusion should not rely primarily on technology-focused subsidies or awareness campaigns. Instead, the consistent importance of organisational readiness (TOE Organization) and technological implementation barriers points towards support for organisational capability development - managerial training, AI governance guidance, and structured technical assistance targeting infrastructure and skills gaps - as potentially more effective levers for increasing the share of enterprises that translate AI awareness into actual adoption. Given that the underlying sample corresponds to enterprises already engaged with AI (Section 3.2), such measures may be particularly relevant for supporting this population's transition from experimentation to broader implementation, while further research is needed to determine whether the same associations hold in the wider population of Slovak enterprises that have not yet engaged with AI at all.

6 Conclusions

This paper examined the organisational factors associated with AI adoption among Slovak enterprises using five hierarchical binary logistic regression models estimated on composite indicators of AI maturity, managerial sentiment, TOE dimensions and perceived implementation barriers. The results show that organisational readiness (TOE Organization) is the most robust and stable correlate of AI adoption, followed by overall AI maturity, while managerial sentiment and technological barriers retain independent, though more sensitive, associations once other organisational characteristics are controlled for. Explanatory power and predictive discrimination improved consistently as organisational-level predictors were added, and a parsimonious four-predictor model preserved most of the explanatory capacity of the full specification.

In answer to the research questions: (RQ1) AI Maturity is positively associated with adoption odds, though the strength of this association attenuates once more specific organisational readiness measures are introduced (H1 supported); (RQ2) Business Sentiment contributes independent explanatory content once TOE dimensions are controlled for, but the direction of this association is ambiguous given a possible scale-coding issue flagged in the source data, so H2 is not supported in its originally hypothesised positive direction; (RQ3) among the TOE dimensions, only TOE Organization retains a robust independent association with adoption, strongly supporting H3; and (RQ4) perceived technological barriers are negatively associated with adoption odds in the full model, partially supporting H4, while organisational and external barriers do not retain independent significance.

The hierarchical results reported in Section 4 display a pattern that is characteristic of statistical mediation rather than pure suppression or redundancy: the association between AI Maturity and AI adoption is strong and significant when AI Maturity is the sole predictor (Model 1, OR = 1.78), but it attenuates once TOE Organization is introduced (Model 3, OR falls to 1.56 and loses conventional significance), while TOE Organization itself emerges as the strongest and most stable predictor in every specification in which it appears. This is precisely the coefficient pattern that formal mediation analysis is designed to test, and the present nested-model comparison, while suggestive, does not by itself establish mediation because it does not decompose the total association into direct and indirect components or provide a significance test for the indirect path.

A methodologically stronger next step would therefore be to complement the hierarchical logistic regression with a formal mediation model - for example, a structural equation model (SEM) with a binary or probit-linked outcome, or a Karlson-Holm-Breen (KHB) decomposition designed specifically for comparing nested nonlinear probability models, together with bootstrapped confidence intervals (e.g., 5,000 resamples) for the indirect effect of AI Maturity on AI adoption operating through TOE Organization. Unlike the simple comparison of coefficients across nested logistic models used here, the KHB approach and SEM-based mediation explicitly correct for the rescaling of logistic coefficients that occurs whenever predictors are added to a nonlinear model, which can otherwise create the appearance of attenuation even in the absence of true mediation. Confirming or disconfirming mediation formally would clarify whether AI Maturity's association with adoption operates primarily indirectly, through the organisational readiness captured by TOE Organization, or whether the two constructs make more genuinely separable contributions - a distinction with direct managerial relevance, since it would indicate whether efforts to raise general AI maturity are expected to translate into adoption mainly by strengthening organisational governance specifically, or through other, more independent channels.

A second, complementary refinement concerns model estimation rather than model structure. With an inferred analytic sample of roughly n = 312 and up to twelve candidate predictors in Model 4, the ratio of events (adopters) to predictors is relatively low, and several odds ratios in Sections 4.4-4.6 sit close to conventional significance thresholds (e.g., $p = 0.049$, $p = 0.058$, $p = 0.077$). Under these conditions, standard maximum-likelihood logistic regression is known to be vulnerable to small-sample bias and, in more extreme cases, to quasi-separation. Firth's penalised (bias-reduced) logistic regression - which adds a Jeffreys-prior penalty to the likelihood function - provides a more robust alternative for the full and parsimonious models, and would also allow exact or profile-likelihood confidence intervals to be reported for the borderline predictors, rather than relying solely on Wald-based p-values. Re-estimating Models 4 and 5 with Firth's correction, alongside the proposed mediation analysis, would strengthen confidence in which associations are genuinely robust before the findings are used to inform managerial or policy recommendations. Both extensions would require direct access to the underlying microdata and could not be performed within the scope of the present paper, which relies on the aggregate model outputs reported in Deliverable 5.2; they are therefore proposed here as a concrete next analytical step rather than presented as completed analyses.

The study is subject to several important limitations. First, and most significantly, the source econometric report does not explicitly state the exact sample size used in the regression models; based on the correspondence of the composite variables with the CAWI questionnaire sections described in a companion project report, the analytic sample is inferred to be the n = 312 CAWI population, but this could not be independently verified and should be confirmed before the findings are used for generalisation. Second, the CAWI sample comprises enterprises already engaged with AI-related activities rather than a random cross-section of Slovak enterprises, limiting the generalisability of the findings to the broader enterprise population. Third, the cross-sectional design and self-reported nature of all measures mean that the reported associations cannot be interpreted causally, despite the explanatory framing of the underlying logistic regression models; reverse causality (for example, enterprises that adopt AI subsequently reporting higher organisational maturity or more favourable sentiment) cannot be excluded. Fourth, the ambiguity regarding the coding direction of the Business Sentiment scale limits confidence in the substantive interpretation of that specific finding. Fifth, although the project's research framework describes a complementary Principal Component Analysis (PCA) and JointSpace mapping of organisational perceptions, no PCA results (eigenvalues, loadings, or explained variance) are reported in the source document, and this study therefore does not present PCA findings; readers should not assume that such an analysis was completed within the reviewed deliverable.

Future research should prioritise: formally testing TOE Organization as a mediator of the AI Maturity - AI adoption association using SEM-based or KHB decomposition methods with bootstrapped indirect-effect confidence intervals, as outlined in Section 6.1; re-estimating the full and parsimonious models using Firth's penalised logistic regression to address small-sample and borderline-significance concerns; confirming the exact analytic sample size and, ideally, obtaining access to the underlying microdata to verify the coding direction of the Business Sentiment scale; extending the analysis to a broader, more representative sample of Slovak enterprises including those with no prior AI engagement; incorporating firm-size, sector and regional controls, which were not available in the reviewed report; conducting the planned PCA and JointSpace analysis to complement the explanatory logistic regression results with a strategic, dimension-reduction perspective on organisational perceptions; and, where feasible, adopting longitudinal designs capable of addressing the direction of causality between organisational readiness, sentiment and AI adoption suggested, but not established, by the present cross-sectional models.

Acknowledgement

This paper is based on data collected within the AI-impactSK project, funded by the European Union through the NextGenerationEU instrument under the Recovery and Resilience Plan for Slovakia, project No. 09I05-03-V02-00003/2025/VA. The authors wish to acknowledge the contribution of Matej Černý to the underlying data collection and statistical analysis on which this paper draws.

References

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F. & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. International Journal of Information Management. Vol. 57, 102225. ISSN 0268-4012.

Chen, D., Esperança, J. P. & Wang, S. (2022). The Impact of Artificial Intelligence on Firm Performance: An Application of the Resource-Based View to e-Commerce Firms. Frontiers in Psychology. Vol. 13, 884830. ISSN 1664-1078. DOI 10.3389/fpsyg.2022.884830.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika. Vol. 16, Issue 3, pp. 297-334. ISSN 0033-3123.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly. Vol. 13, Issue 3, pp. 319-340. ISSN 0276-7783. DOI 10.2307/249008.

Karlson, K. B., Holm, A. & Breen, R. (2012). Comparing Regression Coefficients Between Same-sample Nested Models Using Logit and Probit: A New Method. Sociological Methodology. Vol. 42, Issue 1, pp. 286-313. ISSN 0081-1750. DOI 10.1177/0081175012444861.

Kaplan, A. & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. Business Horizons. Vol. 63, Issue 1, pp. 37-50. ISSN 0007-6813. DOI 10.1016/j.bushor.2019.09.003.

Kádárová, J., Fiľo, M., Sukopová, D. & Dúlová, M. (2026). Artificial Intelligence Adoption and Labour Productivity in Slovakia and the EU27: Implications for Sustainable Economic Growth. Sustainability. Vol. 18, Issue 4, 2135. ISSN 2071-1050. DOI 10.3390/su18042135.

Mikalef, P. & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management. Vol. 58, Issue 3, 103434. ISSN 0378-7206. DOI 10.1016/j.im.2021.103434.

Raisch, S. & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. Academy of Management Review. Vol. 46, Issue 1, pp. 192-210. ISSN 0363-7425. DOI 10.5465/amr.2018.0072.

Stovíček, F., Hanák, R., Hajduová, Z. & Černý, M. (2026a). Statistical Analysis Report 3.3 (Deliverable 3.3, AI-impactSK project). Bratislava: Bratislava University of Economics and Business.

Stovíček, F., Hanák, R., Hajduová, Z. & Černý, M. (2026b). Econometric Model Outcomes (Deliverable 5.2, AI-impactSK project). Bratislava: Bratislava University of Economics and Business.

Tornatzky, L. G. & Fleischer, M. (1990). The Processes of Technological Innovation. Lexington, MA: Lexington Books. ISBN 0-669-20348-3.

Pozícia Slovenska v ekosystéme podnikovej adopcie umelej inteligencie v rámci krajín EÚ

Slovakia's Position in the Enterprise Artificial Intelligence Adoption Ecosystem within EU Countries

Slavka Šagátová, Nora Grisáková, Vladimír Hojdík

Abstract

This paper examines Slovakia's position in the empirically comparable part of the enterprise artificial intelligence adoption ecosystem within the European Union. The analysis applies a rank-based weighted linear aggregation model combining institutional AI readiness, GAIRI Development & Diffusion, digital absorptive conditions and direct enterprise AI adoption. The main adoption-oriented scenario S1 is examined in detail, while control scenarios S2–S5 test the stability of results under alternative weighting and robustness settings, including a renormalised scenario without the GAIRI Development & Diffusion criterion. Microsoft AI Diffusion is used only as an external robustness control. The results show that Slovakia ranks 22nd in S1 and remains outside the group of EU AI adoption leaders. Its position is stable across all control scenarios, varying between 21st and 24th place, and high Spearman rank correlations confirm the robustness of the overall ordering. The dynamic perspective identifies Slovakia as a rapidly catching-up economy, but this interpretation is qualified by a low initial adoption base and weak institutional, diffusion and digital absorptive conditions. The paper contributes by distinguishing direct adoption, institutional readiness, digital absorptive capacity and AI development and diffusion, and by linking the static EU ranking with adoption dynamics and the interpretation of Slovakia as a rapidly catching-up but systemically constrained AI adoption economy.

***JEL classification**: O33, O38*
***Keyword**: artificial intelligence adoption; Slovakia; composite indicator*

1 Úvod

Adopcia umelej inteligencie sa stala jedným z kľúčových prejavov digitálnej transformácie podnikov a zároveň dôležitým ukazovateľom digitálnej pripravenosti ekonomík. AI už nepredstavuje iba technológiu spojenú s výskumom a vývojom modelov, ale čoraz viac vstupuje do podnikových procesov, rozhodovania, automatizácie, marketingu, zákazníckej komunikácie, controllingu a riadenia výkonnosti. Z vedeckého hľadiska preto nestačí sledovať len podiel podnikov, ktoré AI používajú. Potrebné je rozlišovať medzi priamou adopciou, inštitucionálnou pripravenosťou, digitálnou absorpčnou kapacitou a rozvojovo-difúznymi podmienkami, ktoré umožňujú širšie a produktívnejšie využitie AI.

2 Súčasný stav riešenej problematiky doma a v zahraničí

Hodnotenie pozície jednotlivých krajín v oblasti umelej inteligencie si vyžaduje rozlíšenie medzi samotným používaním AI a podmienkami, ktoré umožňujú jej širšie rozšírenie. Teoretické východiská preto prepájajú literatúru o technologickej adopcii, inováciách, absorpčnej kapacite a technologickom dobiehaní s konceptom ekosystému podnikovej adopcie digitálnych technológií.

2.1 Teoretické rámce technologickej adopcie

Teoretické vysvetlenie adopcie AI možno opierať o difúziu inovácií a rámec Technology-Organization-Environment (TOE). Teória difúzie inovácií vysvetľuje, že nové technológie sa medzi organizáciami nešíria rovnomerne, nakoľko ich prijatie závisí od vnímanej relatívnej výhody, kompatibility, komplexnosti, možnosti experimentovania a pozorovateľnosti výsledkov (Rogers, 2003). Pri AI je tento rámec relevantný najmä preto, že podniky často postupujú od experimentovania k pilotným riešeniam a až následne k širšiemu zakoreneniu technológie v procesoch. Rámec TOE dopĺňa tento pohľad tým, že vysvetľuje adopciu technológií ako výsledok technologických, organizačných a environmentálnych faktorov (Tornatzky & Fleischer, 1990).

V technologickej dimenzii je kľúčová dátová pripravenosť, interoperabilita, cloud, kybernetická bezpečnosť a digitálna infraštruktúra. V organizačnej dimenzii ide o veľkosť podniku, manažérsku podporu, interné zručnosti a schopnosť meniť procesy. Environmentálna dimenzia zahŕňa regulačný rámec, konkurenciu, dostupnosť externých dodávateľov, verejné politiky a inovačný ekosystém. Novšie štúdie potvrdzujú, že tento rámec je vhodný aj pre analýzu AI, pretože AI adopcia je podmienená súbežným pôsobením technologických, organizačných a inštitucionálnych faktorov (Ayinaddis, 2025; Dwivedi et al., 2021). Adopciu AI je pritom dôležité vnímať aj v kontexte konceptu absorpčnej kapacity. Tento koncept upozorňuje na skutočnosť, že schopnosť využívať nové poznatky a technológie závisí od existujúcich znalostí, zručností a organizačných kapacít (Cohen & Levinthal, 1990; Zahra & George, 2002).

Súčasná literatúra zároveň zdôrazňuje, že AI sa odlišuje od tradičných informačných technológií tým, že zasahuje do rozhodovania, automatizuje kognitívne úlohy a vyžaduje nové formy riadenia rizík, transparentnosti a zodpovednosti. Dlhodobý vplyv AI na produktivitu preto nebude závisieť len od počtu podnikov, ktoré AI používajú, ale najmä od kvality jej integrácie, podnikových procesov a od komplementárnych organizačných zmien (Filippucci et al., 2024).

2.2 Zavádzanie AI do praxe

Pri skúmaní zavádzania AI do podnikovej praxe je potrebné odlišovať adopciu, pripravenosť a kapacitu implementácie. Adopcia AI označuje reálne používanie AI technológií podnikmi. Podľa údajov Eurostatu používalo v roku 2025 aspoň jednu AI technológiu približne 20 % podnikov v EÚ. Miera adopcie sa pritom výrazne líšila podľa veľkosti podniku, pričom aspoň jednu technológiu AI používala viac ako polovica veľkých podnikov, zatiaľ čo medzi malými a strednými podnikmi bol tento podiel nižší (Eurostat, 2026). Tento ukazovateľ je najpriamejšou mierou podnikovej adopcie, ale sám osebe nevysvetľuje, prečo niektoré krajiny dokážu AI zavádzať rýchlejšie a širšie.

Dôležitými faktormi, ktoré umožňujú posudzovať podmienky adopcie sú: pripravenosť na AI, kapacita AI a difúzia AI. Pripravenosť na AI vyjadruje schopnosť štátu a inštitucionálneho prostredia vytvárať podmienky na bezpečné a efektívne využívanie AI. Government AI Readiness Index (GAIRI) hodnotí pripravenosť vlád prostredníctvom rozsiahleho súboru indikátorov v oblasti policy capacity, governance, infraštruktúry, verejnej adopcie, vývoja, difúzie a odolnosti (Oxford Insights, 2025). Tento index preto nemeria priamo podnikovú adopciu, ale širšie verejno-politické a inštitucionálne predpoklady. Kapacita AI zahŕňa širšie zdroje potrebné na vývoj, implementáciu a škálovanie umelej inteligencie vrátane infraštruktúry, dátových zdrojov, zručností a verejných politík. OECD zdôrazňuje, že národné AI ekosystémy nemožno redukovať na jeden indikátor, pretože zahŕňajú výskum, infraštruktúru, pracovné miesta, zručnosti, investície a verejné politiky (OECD, 2026). Difúzia AI vyjadruje proces šírenia AI naprieč podnikmi, sektormi a krajinami. Tento proces je nerovnomerný a býva koncentrovaný vo veľkých podnikoch, znalostne intenzívnych službách a technologicky vyspelejších regiónoch (Kergroach & Héritier, 2025).

2.3 Determinanty a príležitosti adopcie AI

Podobne ako pri iných typoch inovácií aj pri implementácii AI je jedným z najstabilnejších empirických zistení veľkostná diferenciácia jej adopcie. Veľké podniky disponujú väčšími dátovými zdrojmi, investičnou kapacitou, špecializovanými IT tímami a formálnejšími procesmi riadenia zmien. Malé a stredné podniky častejšie narážajú na nedostatok kapitálu, zručností, dátovej infraštruktúry a implementačnej podpory (OECD, 2025). Preto veľké podniky často pôsobia ako systémoví nositelia AI difúzie v hodnotových reťazcoch.

Pojem etablovanie AI do podnikových procesov označuje mieru, v akej je AI integrovaná do základných podnikových funkcií, rozhodovania, interného vývoja, riadenia výkonnosti a tvorby hodnoty. Tento pohľad nadväzuje na literatúru, podľa ktorej účinky AI nezávisia iba od samotného používania technológie, ale aj od kvality jej integrácie do podnikových procesov a od komplementárnych organizačných zmien (Filippucci et al., 2024). Zjednodušená adopcia, napríklad používanie generatívnych nástrojov na jednoduché textové úlohy, nemusí znamenať systémovú transformáciu. Pre dobiehajúce ekonomiky je preto kľúčové prejsť od izolovaných experimentov k produktívnej a procesne integrovanej adopcii. Pozíciu Slovenska je v tejto súvislosti potrebné interpretovať z pohľadu technologického dobiehania. Pre dobiehajúce ekonomiky je podstatná nielen schopnosť vyvíjať vlastné špičkové AI riešenia, ale aj schopnosť adaptovať existujúce technológie a premeniť ich na produktívnu podnikovú schopnosť (Fagerberg & Godinho, 2005; Fagerberg & Srholec, 2008). Vysoká dynamika rastu adopcie preto nemusí automaticky znamenať konvergenciu k vedúcim ekonomikám, ak nie je sprevádzaná zlepšením inštitucionálnych, difúznych a digitálnych predpokladov

Z uvedených východísk vyplýva štruktúra empirického modelu článku. Priama podniková adopcia AI zodpovedá pozorovanému používaniu technológie v podnikoch. Inštitucionálne prostredie reflektuje environmentálnu dimenziu technologickej adopcie v rámci TOE prístupu (Tornatzky & Fleischer, 1990; Jöhnk et al., 2021). Rozvojovo-difúzna dimenzia zachytáva širšie šírenie AI v ekonomike v súlade s teóriou difúzie inovácií, podľa ktorej sa nové technológie medzi organizáciami a ekonomikami šíria nerovnomerne (Rogers, 2003). Digitálne absorpčné predpoklady nadväzujú na koncept absorpčnej kapacity, podľa ktorého schopnosť využívať nové technológie závisí od existujúcich znalostí, zručností, dátovej a technologickej základne (Cohen & Levinthal, 1990; Zahra & George, 2002).

3 Výskumný dizajn

Hodnotenie pozície krajín v oblasti podnikovej adopcie umelej inteligencie nemožno založiť na jedinom ukazovateli, pretože priama adopcia, digitálne predpoklady, inštitucionálne prostredie a rozvojovo-difúzna dimenzia zachytávajú odlišné, ale vzájomne prepojené časti toho istého procesu. Výskumný dizajn článku preto vychádza z konštrukcie kompozitného poradového hodnotenia krajín EÚ27. Tento prístup nadväzuje na metodickú literatúru o kompozitných indikátoroch, podľa ktorej tvorba súhrnného hodnotenia zahŕňa výber ukazovateľov, úpravu alebo transformáciu vstupných údajov, váženie, agregáciu a overovanie citlivosti výsledkov (OECD – European Commission, Joint Research Centre, 2008; Greco et al., 2019). Hlavným cieľom článku je zhodnotiť pozíciu Slovenska v empiricky porovnateľnej časti ekosystému podnikovej adopcie AI v rámci krajín EÚ27. Čiastkovými cieľmi sú zostaviť kompozitné poradie krajín EÚ, vyhodnotiť pozíciu Slovenska, doplniť statické poradie o dynamiku rastu adopcie AI, porovnať Slovensko so susednými krajinami a overiť stabilitu výsledkov. Na základe identifikovaných teoretických východísk a stanoveného cieľa boli sformulované nasledovné výskumné otázky: O1: Akú pozíciu dosahuje Slovensko v EÚ27 pri hodnotení podmienok a prejavov podnikovej adopcie AI? O2: Je pozícia Slovenska v procese adopcie AI stabilná pri rôznych váhových scenároch a robustnostných kontrolách? O3: Mení sa interpretácia pozície Slovenska po zohľadnení dynamiky rastu adopcie AI?

V nadväznosti na stanovené ciele možno ako objekt skúmania identifikovať krajiny EÚ27, s dôrazom na Slovenskú republiku. Dátový rámec spája indikátory s úplným alebo metodicky kontrolovaným pokrytím krajín EÚ27. Výsledné poradie sa interpretuje ako kompozitný prierezový profil, nie ako presné synchrónne meranie jedného kalendárneho roka. Hlavný model je obmedzený na dostupné a empiricky porovnateľné podmienky a prejavy podnikovej adopcie AI. Nemožno ho preto interpretovať ako celkové poradie národnej AI kapacity, ale ako hodnotenie vybraných dimenzií adopčného ekosystému, ktoré sú empiricky porovnateľné naprieč krajinami EÚ27.

3.1 Operacionalizácia konceptu podnikovej adopcie AI

Na účely empirického hodnotenia je koncept podnikovej adopcie AI prevedený do štyroch statických výpočtových dimenzií: inštitucionálnej AI pripravenosti, rozvoja a difúzie AI, digitálnych absorpčných predpokladov a priamej podnikovej adopcie. Ide o model adopčného ekosystému v rámci EÚ, nie o úplné meranie národnej AI kapacity. Dynamika adopcie je zachytená samostatným ukazovateľom E, ktorý je v texte interpretovaný ako priemerné ročné tempo rastu adopcie AI v období 2021–2025. Tento ukazovateľ nevstupuje do výpočtu hlavného agregovaného skóre, pretože vyjadruje zmenu v čase, nie statickú úroveň adopčného ekosystému. Používa sa však pri interpretácii rastovej trajektórie krajín a pri odlíšení krajín s nízkou statickou úrovňou, ale vyšším tempom dobiehania.

Tabuľka 1
Operacionalizácia konceptu podnikovej adopcie AI v empirickom modeli

Teoretická dimenzia	Empirické kritérium	Funkcia v modeli
Inštitucionálne prostredie	A - Indexu pripravenosti vlád na AI	verejno-politická, regulačná a verejno-sektorová pripravenosť
Rozvoj a difúzia AI	B - Rozvoj a difúzia	širší rozvoj, ľudský kapitál, AI sektor a šírenie AI
Digitálna absorpčná kapacita	C – Digitalizácia ekonomiky a spoločnosti	digitálne absorpčné predpoklady adopcie AI
Priama podniková adopcia	D - Eurostat - Adopcia AI v podnikoch	jadro skúmaného javu
Dynamika adopcie	E – Priemerné ročné tempo rastu adopcie AI , v rokoch 2021–2025	interpretačný ukazovateľ rastu, nie vstup do hlavného agregovaného skóre
Robustnostná kontrola	M - Microsoft AI Diffusion	externý difúzny ukazovateľ, nie hlavné kritérium

Zdroj: vlastné spracovanie na základe vstupných údajov empirických kritérií (Oxford Insights, 2025; European Commission, 2025; Eurostat, 2026; Microsoft AI Economy Institute, 2025)

Tabuľka 1 ukazuje logiku prechodu od konceptuálnych dimenzií k empirickým kritériám. Kritérium D predstavuje jadro skúmaného javu, pretože priamo zachytáva podnikovú adopciu AI. Kritériá A, B a C vyjadrujú širšie systémové, difúzne a absorpčné podmienky, ktoré môžu ovplyvňovať rozsah a kvalitu podnikovej adopcie. Kritérium E a ukazovateľ M nevstupujú do hlavného agregovaného skóre, používajú sa iba na interpretačné a robustnostné doplnenie výsledkov.

3.2 Dátové zdroje a výber ukazovateľov

Kritériá boli vybrané na základe troch podmienok: vecnej relevancie pre ekosystém podnikovej adopcie AI, pokrytia krajín EÚ27 a dostupnosti číselných údajov vhodných na poradové porovnanie. Priama podniková adopcia tvorí jadro hodnotenia, zatiaľ čo inštitucionálna pripravenosť, rozvoj a difúzia AI a digitálne absorpčné predpoklady zachytávajú podmienky, ktoré umožňujú adopciu rozvíjať, škálovať a zakoreniť v podnikovej praxi.

Kritérium A bolo vypočítané ako aritmetický priemer troch pilierov Indexu pripravenosti vlád na umelú inteligenciu pre rok 2025 (GAIRI 2025) (Oxford Insights, 2025): Kapacita verejných politík, Správa a Zavádzanie AI vo verejnom sektore. Tým sa nahrádza celkové skóre GAIRI a znižuje sa riziko prekryvu s infraštruktúrnou a difúznou dimenziou. Kritérium B tvorí samostatný pilier GAIRI 2025 Rozvoj a difúzia, ktorý zachytáva širší rozvoj a šírenie AI v ekonomike. Kritérium C bolo vypočítané ako aritmetický priemer poradí krajiny v štyroch subindikátoroch DESI (Indexu digitálnej ekonomiky a spoločnosti) (European Commission, 2025): cloud, analýza veľkých dát / dátová analytika, digitálna intenzita MSP a podiel IKT špecialistov. Kritérium C sa od kritérií A, B a D líši tým, že nevychádza z jedného pôvodného skóre, ale z priemerného poradia krajiny v štyroch digitálnych subindikátoroch. Z tohto dôvodu sa pri kritériu C nižšia hodnota interpretuje ako priaznivejšia pozícia. Všetkým štyrom indikátorom boli priradené rovnaké váhy významnosti, pretože slúžia ako subindex digitálnej absorpčnej kapacity, nie ako samostatný oficiálny index.

Vzhľadom na rozdielne referenčné roky vstupných zdrojov sa výsledné poradie interpretuje ako kompozitný prierezový profil. Tento postup je v súlade s odporúčaniami literatúry o kompozitných indikátoroch, ktorá upozorňuje, že výsledok kompozitného hodnotenia závisí nielen od vstupných údajov, ale aj od spôsobu transformácie, váženia a agregácie ukazovateľov (OECD – European Commission, Joint Research Centre, 2008; Greco et al., 2019).

Tabuľka 2
Dátové zdroje a ukazovatele použité v multikriteriálnej analýze

Kód / Kritérium	Ukazovateľ	Zdroj	Rok	Funkcia v analýze
A	Inštitucionálna AI pripravenosť	Oxford Insights GAIRI 2025; priemer Kapacita verejných politík, správa a zavádzanie AI vo verejnom sektore	2025	inštitucionálne prostredie
B	Rozvoj a difúzia AI	Oxford Insights GAIRI 2025; pilier Rozvoj a difúzia	2025	difúzna a rozvojová dimenzia
C	Digitálne absorpčné predpoklady	DESI/digitálna dekáda - cloudové služby, veľké dáta, digitálna intenzita MSP, odborníci v IKT.	2023	digitálne absorpčné predpoklady
D	Podniky využívajúce AI	Eurostat - isoc_eb_ai (% podnikov nad 10 zamestnancov, používajúce aspoň jednu AI technológiu)	2025	priama adopcia
E	Dynamika rastu AI	Eurostat - isoc_eb_ai (% podnikov nad 10 zamestnancov, používajúce aspoň jednu AI technológiu)	2021–2025	dynamika, nie hlavné agregované skóre
M	Microsoft AI Diffusion	Microsoft AI Economy Institute	2025	robustnostná kontrola, nie hlavný model

Zdroj: vlastné spracovanie podľa Oxford Insights, 2025; European Commission, 2025; Eurostat, 2026; Microsoft AI Economy Institute, 2025)

Poznámka: Microsoft AI Diffusion nie je súčasťou hlavného modelu; používa sa iba ako kontrola. Investičné, výskumné a talentové ukazovatele nie sú zahrnuté do hlavného výpočtu, pretože nezachytávajú priamo podnikovú adopciu AI v EÚ27 alebo nemajú dostatočne harmonizované pokrytie pre účely hlavného modelu.

3.3 Poradovo založená vážená lineárna agregácia a hodnotenie dynamiky adopcie AI

Na agregované hodnotenie krajín bola použitá poradovo založená vážená lineárna agregácia. Ide o postup využívaný pri konštrukcii kompozitných indikátorov a rebríčkov, v ktorom sa pôvodné hodnoty jednotlivých ukazovateľov najprv transformujú na poradia a následne sa tieto poradia agregujú pomocou vopred stanovených váh významnosti. Takýto prístup nadväzuje na metodickú literatúru o kompozitných indikátoroch, podľa ktorej sú váženie, agregácia a testovanie robustnosti výsledkov kľúčovými krokmi konštrukcie súhrnných hodnotení (OECD – European Commission, Joint Research Centre, 2008; Greco et al., 2019). Poradová transformácia znižuje citlivosť výsledku na mierku pôvodných údajov a umožňuje spojiť analyzované ukazovatele do jedného transparentného porovnávacieho rámca. Poradová transformácia bola zvolená vzhľadom na rozdielnu mierku, zdrojovú heterogenitu a koncepčnú odlišnosť vstupných ukazovateľov; jej cieľom je porovnať relatívnu pozíciu krajín v jednotnom rámci, nie merať absolútnu vzdialenosť medzi nimi.

Pri každom kritériu sa krajinám priradilo poradie, pričom hodnota 1 označuje najlepšiu pozíciu. Všetky kritériá boli orientované ako benefitné, teda vyššia pôvodná hodnota indikátora znamená priaznivejšiu pozíciu krajiny. Pri rovnosti hodnôt bolo použité priemerné poradie. V hlavnom modeli A-B-C-D sa pracuje s úplným poradovým porovnaním krajín EÚ27. Osobitné metodické zaobchádzanie si vyžaduje iba robustnostný scenár S4, v ktorom je namiesto kritéria B použitý ukazovateľ Microsoft AI Diffusion. Tento zdroj nepokrýva Cyprus, Estónsko, Lotyšsko, Luxembursko a Maltu. Týmto krajinám bolo v scenári S4 konzervatívne priradené priemerné poradie 25, ktoré zodpovedá priemeru dolnej skupiny chýbajúcich poradí 23 až 27. Tento postup nezvyšuje ich pozíciu umelo a umožňuje zachovať porovnanie všetkých krajín EÚ27 v robustnostnom teste. Keďže ukazovateľ Microsoft AI Diffusion nepokrýva všetky krajiny EÚ27, scenár S4 má charakter doplnkového robustnostného testu a jeho výsledky sa interpretujú opatrnejšie než výsledky scenárov S1 až S3.

Výsledné agregované skóre krajiny je vypočítané ako:

$$S_i = \sum_{j=1}^{k} (w_j r_{ij}) \tag{1}$$

kde Si - agregované poradové skóre krajiny i,
r_{ij} - poradie krajiny i v kritériu j,
w_j -váha kritéria j
k - počet kritérií.

Keďže váhy sú v jednotlivých scenároch normalizované tak, že ich súčet je rovný 1, výsledné agregované skóre možno interpretovať ako vážený priemer poradí. Nižšia hodnota agregovaného skóre znamená lepšiu výslednú pozíciu krajiny.

Váhové scenáre nepredstavujú empiricky odhadnuté parametre, ale štruktúrované analytické predpoklady slúžiace na overenie citlivosti výsledkov. Scenárový prístup je v súlade s literatúrou o kompozitných indikátoroch, ktorá zdôrazňuje potrebu testovať, či výsledné poradie nie je neprimerane závislé od jednej voľby váh alebo agregácie (OECD – European Commission, Joint Research Centre, 2008; Greco et al., 2019). Váha kritéria D je v hlavnom scenári zvýšená, pretože priama podniková adopcia predstavuje jadro skúmaného javu, ale nie je nastavená dominantne. Získaný výsledok tak neznižuje adopčný ekosystém na jediný ukazovateľ a zachováva význam inštitucionálnych, difúznych a digitálnych predpokladov.

Tabuľka 3
Váhové scenáre použité v analýze

Scenár	Charakter scenára	Váhy	Funkcia v analýze
S1	hlavný adopčne orientovaný scenár	A=0,20; B=0,20; C=0,25; D=0,35	hlavné hodnotenie pozície krajín
S2	neutrálny benchmark	A=0,25; B=0,25; C=0,25; D=0,25	kontrola pri rovnakých váhach
S3	kapacitný scenár	A=0,35; B=0,25; C=0,30; D=0,10	vyšší dôraz na systémové a digitálne predpoklady
S4	externý difúzny ukazovateľ	A=0,20; M=0,20; C=0,25; D=0,35	kontrola s Microsoft AI Diffusion namiesto B
S5	scenár bez B	A=0,2500; C=0,3125; D=0,4375	kontrola bez GAIRI Development & Diffusion; renormalizácia váh S1

Zdroj: vlastné spracovanie

Scenár S1 je hlavným analytickým scenárom, pretože najvyššiu váhu priraďuje priamej podnikovej adopcii AI. Scenár S2 slúži ako neutrálny benchmark pri rovnakých váhach. Scenár S3 testuje citlivosť výsledkov pri vyššom dôraze na inštitucionálne a digitálne predpoklady. Scenár S4 nahrádza kritérium B externým ukazovateľom Microsoft AI Diffusion. Scenár S5 slúži ako kontrola bez rozvojovo-difúzneho kritéria B; po jeho vylúčení boli zostávajúce váhy hlavného scenára S1 renormalizované tak, aby ich súčet bol rovný 1. V kapitole výsledkov sú preto samostatne uvedené výsledky hlavného scenára S1 a následne súhrnné výsledky kontrolných scenárov S2 až S5. Tento postup umožňuje oddeliť hlavný analytický výsledok od robustnostných kontrol.

Okrem statickej úrovne adopčného ekosystému bola vyhodnotená aj jeho dynamika. Dynamika adopcie AI sa hodnotí samostatne prostredníctvom priemerného ročného tempa rastu adopcie AI za obdobie 2021–2025. Ukazovateľ E nie je zahrnutý do hlavného agregovaného skóre, pretože úroveň adopcie a tempo rastu predstavujú koncepčne odlišné veličiny. Vysoké tempo rastu z nízkej východiskovej bázy nemusí znamenať skutočnú konvergenciu k lídrom, preto sa tento ukazovateľ používa iba ako interpretačný ukazovateľ rastovej trajektórie krajiny.

4 Výsledky výskumu

Výsledky uvedené v tejto kapitole sú vlastným výpočtom na základe metodiky opísanej v kapitole 3. Východiskom sú pôvodné hodnoty ukazovateľov Inštitucionálna AI pripravenosť (A), Rozvoj a difúzia AI (B), Digitálne absorpčné predpoklady (C), Podniky využívajúce AI (D) a Microsoft AI Diffusion (M), ich transformácia na poradia krajín EÚ27 a následná agregácia podľa váh scenárov S1 až S5. Hodnota agregovaného skóre preto nepredstavuje samostatne prevzatý externý index, ale výsledok výpočtu z čiastkových poradí analyzovaných indikátorov. Nižšia hodnota agregovaného skóre znamená lepšiu pozíciu krajiny.

4.1 Výpočet a výsledky hlavného adopčne orientovaného scenára S1

Scenár S1 predstavuje hlavné adopčne orientované hodnotenie, pretože najvyššiu váhu priraďuje priamej podnikovej adopcii AI, ale zároveň zachováva význam inštitucionálnych, rozvojovo-difúznych a digitálnych absorpčných predpokladov. Výsledné skóre S1 je vypočítané z poradí krajín v kritériách A, B, C a D pri váhach uvedených v kapitole 3. Pred samotnou interpretáciou agregovaného poradia je potrebné vypočítať umiestnenie jednotlivých krajín v kritériách, ktoré sú odvodené z viacerých vstupných faktorov (v tabuľke 4 je uvedený príklad výpočtu pre Slovensko). Ide najmä o kritérium A, ktoré je vypočítané ako priemer troch pilierov GAIRI, a kritérium C, ktoré predstavuje priemerné poradie v štyroch digitálnych subindikátoroch.

Tabuľka 4
Vstupné a odvodené hodnoty agregovaných kritérií A a C pre Slovensko

Kritérium	Čiastkové vstupy	Výsledné skóre za SR	Poradie / hodnota v modeli
A - inštitucionálna AI pripravenosť	Kapacita tvorby verejných politík = 19,00; riadenie = 72,50; adopcia vo verejnom sektore = 62,12.	A = 51,21	27. miesto
C - digitálne absorpčné predpoklady	Cloudové služby = 32 % (21. miesto); veľké dáta = 16 % (21. miesto); digitálna intenzita malých a stredných podnikov = 55 % (21,5. miesto); odborníci v oblasti informačných a komunikačných technológií = 4,2 % (21,5. miesto).	C = 21,25	priemerné poradie 21,25

Zdroj: vlastné výpočty na základe(Oxford Insights, 2025; European Commission, 2025)

Poznámka: Kritérium A je aritmetický priemer troch pilierov GAIRI. Kritérium C je aritmetický priemer poradí v štyroch digitálnych subindikátoroch; preto je vyjadrené ako priemerné poradie.

Tabuľka 5
Výpočet údajov hlavného adopčne orientovaného scenára S1

Krajina	A skóre	A poradie	B skóre	B poradie	C priemer	C poradie	D skóre	D poradie	S1 celkové skóre	S1 celkové poradie
Dánsko	90,59	3	58,91	7	3,88	4	42,03	1	3,32	1
Fínsko	82,16	10	63,01	3	1,00	1	37,82	2	3,55	2
Holandsko	93,40	2	62,50	4	4,25	5	33,21	6	4,36	3
Švédsko	81,46	11	57,03	9	2,12	2	35,04	3	5,58	4
Nemecko	86,19	5	66,24	2	11,25	10	25,97	8	7,01	5
Luxembursko	79,33	13	46,26	15	3,75	3	33,61	5	8,29	6
Estónsko	95,21	1	46,01	16	7,75	8	23,40	9	8,49	7
Belgicko	79,00	14	49,84	13	9,00	9	34,54	4	9,05	8
Francúzsko	88,23	4	68,20	1	12,12	12	18,16	15	9,28	9
Španielsko	86,06	6	61,98	5	11,62	11	20,27	13	9,66	10
Írsko	85,73	7	56,91	10	6,00	6	19,64	14	9,80	11
Rakúsko	78,20	16	58,06	8	12,50	13,5	29,95	7	10,38	12
Litva	85,49	8	45,56	17	15,38	15	21,30	12	13,04	13
Malta	77,12	19	44,16	20	7,25	7	21,51	11	13,46	14
Slovinsko	77,65	17	45,52	18	17,50	17	21,61	10	14,88	15
Taliansko	75,17	22	61,38	6	17,88	18	16,40	18	16,37	16
Portugalsko	77,64	18	52,86	12	12,50	13,5	11,54	21	16,48	17
Česko	74,82	23	54,04	11	16,25	16	17,60	17	16,81	18
Lotyšsko	78,76	15	37,18	24	19,50	20	12,21	20	19,68	19
Maďarsko	80,64	12	45,24	19	23,12	23	10,37	22	19,68	20
Poľsko	85,28	9	47,18	14	25,00	25	8,36	26	19,95	21
Slovensko	**51,21**	**27**	**31,39**	**26**	**21,25**	**21**	**18,00**	**16**	**21,51**	**22**
Cyprus	76,94	20	36,07	25	18,50	19	9,27	23	21,67	23
Chorvátsko	58,94	26	29,92	27	21,88	22	15,19	19	22,72	24
Grécko	76,93	21	41,50	21	23,75	24	8,93	24	22,74	25
Bulharsko	66,97	25	39,78	22	26,00	26	8,55	25	24,65	26
Rumunsko	70,46	24	38,06	23	27,00	27	5,21	27	25,60	27

Zdroj: vlastné výpočty na základe Oxford Insights, 2025; European Commission, 2025; Eurostat, 2026)

Poznámka: A je aritmetický priemer vybraných pilierov GAIRI; B je hodnota piliera GAIRI Development & Diffusion; C je priemerné poradie štyroch digitálnych subindikátorov; D je podiel podnikov využívajúcich AI v roku 2025. Pri A, B a D vyššia pôvodná hodnota znamená lepšiu pozíciu; pri C a S1 nižšia hodnota znamená lepšiu pozíciu.

Výsledky ukazujú, že najslabšou dimenziou Slovenska je inštitucionálna pripravenosť. Kritérium A dosahuje hodnotu 51,21, čo Slovensko zaraďuje na 27. miesto v EÚ27. Slabé je aj postavenie v digitálnych absorpčných predpokladoch. Všetky štyri subindikátory kritéria C sa pohybujú približne okolo 21. miesta, čo vedie k priemernému poradiu C = 21,25. Slovensko preto nevstupuje do hlavného scenára S1 len ako krajina so strednou priamou adopciou AI, ale zároveň ako krajina so slabším systémovým a digitálnym zázemím.

Výsledky hlavného adopčného scenára S1 v Tabuľke 5 ukazujú, že vedúce krajiny majú spravidla vyváženejší profil naprieč viacerými dimenziami. Slovensko sa nachádza za Poľskom a pred Cyprom, Chorvátskom, Gréckom, Bulharskom a Rumunskom. Jeho umiestnenie podporuje interpretáciu, že slovenská pozícia nie je daná iba úrovňou priamej adopcie, ale najmä slabším systémovým a absorpčným zázemím.

Regionálne porovnanie ukazuje, že Slovensko zaostáva za všetkými susediacimi krajinami. Rakúsko dosahuje v scenári S1 skóre 10,38 a 12. miesto, Česko skóre 16,81 a 18. miesto, Maďarsko skóre 19,68 a 20. miesto a Poľsko skóre 19,95 a 21. miesto. Slovensko dosahuje skóre 21,51 a 22. miesto. Najväčší odstup má teda voči Rakúsku, zatiaľ čo najbližšie je Slovensko k Poľsku a Maďarsku. Regionálna pozícia podporuje záver, že problém Slovenska nespočíva iba v nižšej priamej adopcii, ale najmä v slabšom systémovom ukotvení AI. V porovnaní s Rakúskom a Českom má Slovensko menej priaznivé inštitucionálne a rozvojovo-difúzne predpoklady. V porovnaní s Maďarskom a Poľskom je rozdiel menší, ale Slovensko zostáva aj v tomto užšom regionálnom rámci.

4.2 Kontrolné scenáre S2 až S5 a stabilita výsledkov

Scenáre S2 až S5 slúžia na overenie, či pozícia Slovenska závisí od konkrétneho váhového nastavenia hlavného scenára S1. Výsledky týchto scenárov nevychádzajú z nových externých zdrojov, ale z vstupných ukazovateľov, ktoré boli definované v kapitole 3. V scenároch S2 a S3 sa používajú poradia krajín v kritériách A, B, C a D, pričom sa mení iba váhová štruktúra. Scenár S4 nahrádza kritérium B externým difúznym ukazovateľom Microsoft AI Diffusion, zatiaľ čo kritériá A, C a D zostávajú zachované. V scenári S5 je vylúčené kritérium B a zostávajúce váhy hlavného scenára S1 sa renormalizujú na A = 0,2500; C = 0,3125; D = 0,4375.

Výsledky kontrolných scenárov v tabuľke 6 potvrdzujú stabilitu hlavného zistenia. Slovensko sa ani v jednom kontrolnom scenári neposúva medzi vedúce adopčné ekonomiky EÚ. V neutrálnom benchmarku S2 a v kapacitnom scenári S3 sa nachádza na 24. mieste. V scenári S4 zostáva na 22. mieste a v scenári S5, v ktorom je vylúčené rozvojovo-difúzne kritérium B, sa posúva na 21. miesto. Porovnanie s ostatnými krajinami ukazuje, že slovenská pozícia je citlivá najmä na zahrnutie systémových a difúznych predpokladov, ale základný záver zostáva stabilný: Slovensko patrí medzi dobiehajúce krajiny s relatívne lepšou priamou adopciou než systémovým ukotvením AI.

Tabuľka 6
Výsledky kontrolných scenárov S2 až S5

Krajina	S2 skóre	S2 poradie	S3 skóre	S3 poradie	S4 skóre	S4 poradie	S5 skóre	S5 poradie
Dánsko	**3,72**	**1**	**4,06**	**2**	**3,72**	**1**	**2,40**	**1**
Fínsko	4,00	2	4,75	3	5,75	4	3,69	2
Holandsko	4,06	3	3,57	1	4,36	2	4,45	3
Švédsko	6,28	4	7,04	6	4,98	3	4,73	4
Nemecko	6,56	5	6,42	4	8,61	7	8,27	8
Luxembursko	9,19	9	9,93	10	10,29	11	6,61	5
Estónsko	8,44	7	7,57	7	10,29	11	6,61	5
Belgicko	10,00	11	11,25	11	7,45	5	8,06	7
Francúzsko	8,03	6	6,79	5	9,48	9	11,35	12
Španielsko	8,91	8	8,14	8	9,26	8	10,82	10
Írsko	9,25	10	8,15	9	8,00	6	9,75	9
Rakúsko	10,88	12	12,05	12	10,18	10	10,97	11
Litva	13,09	13	12,86	13	13,64	13	12,05	14
Malta	14,31	14	14,92	14	14,46	14	11,83	13
Slovinsko	15,62	15	16,70	17	14,48	15	14,09	15
Taliansko	15,97	17	16,36	16	17,77	19	18,96	19
Portugalsko	15,88	16	15,15	15	17,48	17	17,59	16
Česko	16,81	18	17,38	19	17,01	16	18,27	17
Lotyšsko	19,62	21	19,10	21	19,88	21	18,59	18
Maďarsko	19,03	20	18,09	20	17,48	18	19,85	20
Poľsko	18,50	19	16,75	18	19,35	20	21,44	23
Slovensko	**22,56**	**24**	**23,93**	**24**	**19,91**	**22**	**20,39**	**21**
Cyprus	21,62	22	21,10	22	21,67	24	20,84	22
Chorvátsko	23,47	25	24,31	25	21,12	23	21,65	24
Grécko	22,44	23	22,12	23	22,74	25	23,17	25
Bulharsko	24,50	26	24,55	26	23,25	26	25,31	26
Rumunsko	25,25	27	24,95	27	25,40	27	26,25	27

Zdroj: vlastné výpočty Oxford Insights, 2025; European Commission, 2025; Eurostat, 2026; Microsoft AI Economy Institute, 2025)

Poznámka: S2 = neutrálny benchmark; S3 = kapacitný scenár; S4 = scenár s Microsoft AI Diffusion namiesto kritéria B; S5 = scenár bez kritéria B s renormalizovanými váhami hlavného scenára S1. Nižšia hodnota poradia znamená lepšiu pozíciu krajiny.

Tabuľka 7
Spearmanova korelácia poradí kontrolných scenárov voči hlavnému scenáru S1

Porovnávané scenáre	Spearmanovo ρ voči S1	Interpretácia
S1–S2	0,984	veľmi vysoká stabilita poradia
S1–S3	0,972	veľmi vysoká stabilita poradia
S1–S4	0,961	vysoká stabilita aj pri použití Microsoft AI Diffusion
S1–S5	0,986	veľmi vysoká stabilita po vylúčení kritéria B

Zdroj: vlastné výpočty

Poznámka: Spearmanovo ρ porovnáva poradie všetkých 27 krajín voči hlavnému scenáru S1.

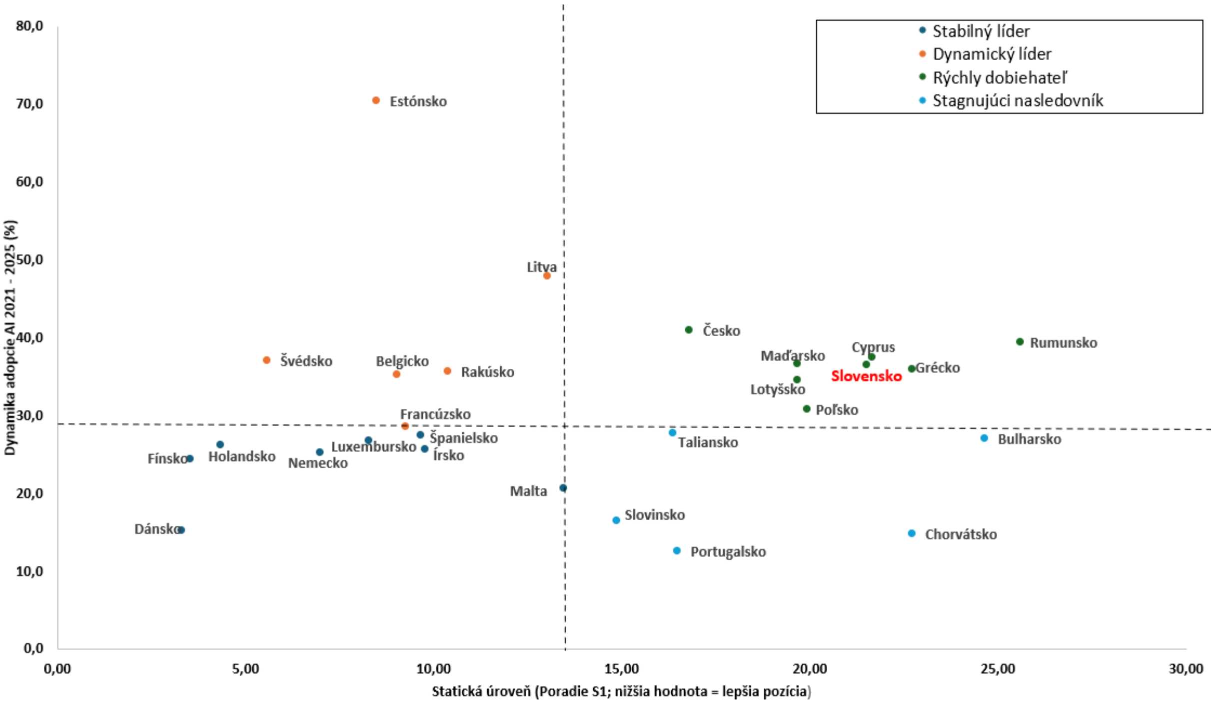
Vysoké hodnoty Spearmanovej korelácie potvrdzujú, že záver o pozícii Slovenska je stabilný nielen z pohľadu jeho umiestnenia, ale aj z pohľadu celkovej štruktúry poradia krajín EÚ27.

4.3 Dynamika adopcie AI a typologická interpretácia krajín

Okrem statickej pozície v hlavnom scenári S1 bola vyhodnotená aj dynamika adopcie AI. Vzťah vývoja adopcie v čase a jeho statickej pozície v rámci krajín EÚ je zachytený v obrázku 1. Tento obrázok bol zostavený na základe dvoch premenných: agregovaného skóre S1 a priemerného ročného tempa rastu adopcie AI v období 2021–2025. Deliace línie predstavujú mediány oboch premenných. Takto vytvorená matica umožňuje odlíšiť krajiny s priaznivou statickou pozíciou, krajiny s vyššou dynamikou rastu a krajiny, ktoré zostávajú v slabšej statickej aj dynamickej pozícii. V prípade Slovenska vzrástol podiel podnikov využívajúcich AI z 5,19 % v roku 2021 na 18,00 % v roku 2025. Ide o absolútnu zmenu 12,81 percentuálneho bodu a priemerné ročné tempo rastu 36,5 %.

Obrázok 1 ukazuje, že Slovensko sa nachádza v kvadrante rýchlych dobiehateľov, teda medzi krajinami s horšou statickou pozíciou, ale vyššou dynamikou rastu adopcie AI. Táto poloha je priaznivejšia než zaradenie medzi stagnujúcich nasledovníkov, ale neznamená automatickú konvergenciu k vedúcim krajinám. Keďže rast vychádza z nízkej východiskovej bázy, Slovensko treba interpretovať ako rýchlo dobiehajúcu, ale systémovo obmedzenú adopčnú ekonomiku.

Obrázok 1
Matica statickej úrovne a dynamiky adopcie AI v krajinách EÚ27



Zdroj: vlastné spracovanie na základe agregovaného skóre S1 a priemerného tempa rastu adopcie AI za obdobie 2021–2025.

Poznámka: Deliace hodnoty sú mediány agregovaného skóre S1 = 13,46 a priemerného tempa rastu adopcie = 28,45.

Na základe výsledkov realizovaných analýz možno odpovedať na položené výskumné otázky. Po prvé, Slovensko dosahuje v hlavnom adopčne orientovanom scenári S1 22. miesto v EÚ27. Po druhé, jeho pozícia je stabilná, pretože v scenároch S1 až S5 sa pohybuje iba medzi 21. a 24. miestom a vysoké hodnoty Spearmanovej korelácie potvrdzujú stabilitu celého poradia krajín. Po tretie, dynamika rastu adopcie umožňuje interpretovať Slovensko ako rýchleho dobiehateľa. Dôvodom nezaradenia krajiny medzi vedúce adopčné ekonomiky EÚ, sú predovšetkým slabšie inštitucionálne, rozvojovo-difúzne a digitálne absorpčné predpoklady.

5 Diskusia

Hlavným zistením predchádzajúcej kapitoly je rozdiel medzi rastom priameho používania AI a slabším systémovým ukotvením jej adopcie. Slovensko preto nemožno interpretovať ako stabilného lídra, ale ani ako stagnujúceho nasledovníka, jeho pozícia zodpovedá rýchlo dobiehajúcej ekonomike s obmedzenými systémovými predpokladmi. V nadväznosti na literatúru o technologickom dobiehaní, ktorá zdôrazňuje význam sociálnych, inštitucionálnych, technologických a inovačných kapacít pre udržateľnú konvergenciu (Fagerberg & Godinho, 2005), ako aj na literatúru o absorpčnej kapacite a pripravenosti na adopciu AI (Cohen & Levinthal, 1990) výsledky článku ukazujú, že rast priameho používania AI nemusí byť sprevádzaný rovnako intenzívnym rozvojom systémových predpokladov. Prípad Slovenska preto rozširuje diskusiu o technologickom dobiehaní o situáciu, v ktorej aplikačné dobiehanie prebieha rýchlejšie než budovanie inštitucionálnych, difúznych a digitálnych absorpčných kapacít. Zároveň je potrebné upozorniť na skutočnosť, že vysoká dynamika adopcie z nízkeho základu nemusí nutne znamenať kvalitatívnu konvergenciu k lídrským ekonomikám.

Zistenia sú v súlade s rámcom TOE, podľa ktorého adopcia technológií nezávisí iba od dostupnosti samotnej technológie, ale aj od organizačných a environmentálnych podmienok jej využitia (Tornatzky & Fleischer, 1990; Jöhnk et al., 2021). Slovensko dosahuje priaznivejšie postavenie v priamej adopcii než v inštitucionálnych a difúznych podmienkach. To naznačuje, že samotné používanie AI nástrojov nie je sprevádzané rovnako silným systémovým a inštitucionálnym ukotvením. Výsledky zároveň podporujú literatúru o absorpčnej kapacite. Slabšie postavenie Slovenska v digitálnych absorpčných predpokladoch naznačuje, že schopnosť podnikov využívať AI závisí od predchádzajúcej digitálnej vybavenosti, práce s dátami, dostupnosti IKT špecialistov a úrovne digitálnej intenzity podnikov (Cohen & Levinthal, 1990; Zahra & George, 2002). AI adopcia tak môže rásť aj pri slabšom systémovom zázemí, ale bez posilnenia absorpčnej kapacity môže zostať povrchová, fragmentovaná alebo obmedzená na jednoduché aplikačné využitie. Z pohľadu literatúry o technologickom dobiehaní článok ukazuje rozdiel medzi rýchlosťou rastu a kvalitou konvergencie. Vysoká dynamika adopcie AI na Slovensku naznačuje dobiehanie, ale nízka východisková báza a slabšie systémové predpoklady ukazujú, že nejde automaticky o prechod medzi vedúce adopčné ekonomiky (Fagerberg & Godinho, 2005; Fagerberg & Srholec, 2008). Prínos článku voči existujúcej literatúre spočíva v tom, že ukazuje rozdiel medzi rastom priamej adopcie AI a štrukturálnou pripravenosťou na jej produktívne zakorenenie v podnikovej praxi.

Politické a manažérske implikácie vyplývajú najmä z rozdielu medzi priamou adopciou a systémovými predpokladmi. Keďže Slovensko dosahuje priaznivejšie poradie v priamej adopcii než v inštitucionálnej a rozvojovo-difúznej dimenzii, verejná politika by sa nemala sústrediť iba na podporu nákupu alebo používania AI nástrojov. Dôležitejšie je posilňovať podmienky ich produktívneho škálovania, ako je: dátová pripravenosť, dostupnosť odborných služieb pre MSP, testovacie prostredia, sprostredkovateľské inštitúcie, cloudovú infraštruktúru a IKT zručnosti. Z manažérskeho hľadiska zistenia naznačujú, že AI adopcia si vyžaduje dátovú stratégiu, interné kompetencie, procesnú integráciu, riadenie rizík a meranie prínosov, nie iba izolované zavádzanie softvérových nástrojov. Výsledky preto ukazujú, že Slovensko nemožno interpretovať ani ako stabilného lídra, ale ani ako stagnujúceho nasledovníka. Jeho pozícia lepšie zodpovedá rýchlo dobiehajúcej ekonomike so slabším systémovým ukotvením AI.

Vzhľadom na obmedzenú dostupnosť dát má článok niekoľko limitov. Po prvé, kombinuje zdroje s rozdielnymi referenčnými rokmi, preto výsledné poradie predstavuje kompozitnú prierezovú aproximáciu. Limitujúca je tiež skutočnosť, že dve hlavné kritériá, A a B, vychádzajú z rovnakého zdroja GAIRI 2025. Rozdelenie celkového GAIRI skóre na užší inštitucionálny subindex zameraný na verejnú správu a samostatný pilier Rozvoj a difúzia znižuje riziko vecného prekrývania, ale zároveň ponecháva časť modelu závislú od jednej metodiky. Robustnostné scenáre S4 a S5 preto slúžia aj ako kontrola tejto zdrojovej závislosti.

Dôležité je tiež upozorniť, že Microsoft AI Diffusion nie je súčasťou hlavného modelu, pretože nepokrýva všetky krajiny EÚ27, ale používa sa iba ako robustnostná kontrola. Vzhľadom na neúplné pokrytie tohto zdroja treba výsledky scenára S4 interpretovať opatrnejšie než výsledky scenárov S1 až S3. Výsledné poradie preto nemožno chápať ako celkové poradie národnej AI kapacity, ale ako poradie vybraných merateľných podmienok a prejavov podnikovej adopcie AI. Ďalším limitom je skutočnosť, že váhy priradené jednotlivým ukazovateľom sú analytické scenáre, nie empiricky odhadnuté parametre. Poradová agregácia zároveň stráca informáciu o veľkosti rozdielov medzi krajinami. Výsledky sú preto interpretované ako transparentné porovnávacie poradie, nie ako presné meranie vzdialenosti medzi krajinami. Budúci výskum by mal túto časť modelu overiť s alternatívnymi zdrojmi pre inštitucionálnu a difúznu dimenziu AI a doplniť sektorové a veľkostné analýzy podnikovej adopcie AI.

6 Záver

Podľa získaných výsledkov sa Slovensko, v hlavnom adopčne orientovanom scenári S1, nachádza na 22. mieste v EÚ27. Výsledok vychádza z kombinácie priamej podnikovej adopcie AI, inštitucionálneho prostredia, rozvojovo-difúznej dimenzie a digitálnych absorpčných predpokladov. Slovensko dosahuje priaznivejšie postavenie v priamej adopcii než v systémových podmienkach, čo podporuje záver o slabšom ukotvení AI v širšom adopčnom ekosystéme. Stabilitu hlavného zistenia podporujú aj kontrolné scenáre S2 až S5. Pozícia Slovenska sa pri alternatívnych váhach, použití externého difúzneho ukazovateľa Microsoft AI Diffusion aj pri vylúčení kritéria B pohybuje medzi 21. a 24. miestom. Slovensko preto nemožno zaradiť medzi lídrov podnikovej adopcie AI, hoci zároveň nejde o krajinu bez rastovej dynamiky.

Dynamická analýza ukazuje relatívne vysoké tempo rastu adopcie AI, ktoré však vychádza z nízkej východiskovej hodnoty a neznamená automatickú konvergenciu k európskym lídrom. Slovensko dokonca zaostáva aj za najbližšími susedmi. Závery článku sa však nevzťahujú na celkovú národnú AI kapacitu Slovenska, ale na podmienky a prejavy podnikovej adopcie AI merané dostupnými indikátormi.

Poznámka o riešenom projekte

Táto práca bola podporená Európskou úniou – NextGenerationEU prostredníctvom Plánu obnovy a odolnosti pre Slovensko v rámci projektu č. 09I05-03-V02-00003/2025/VA (AI-impactSK); 100% podiel.

Použitá literatúra (References)

Ayinaddis, S. G. (2025). Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: A systematic review and bibliometric analysis. *Journal of Innovation & Knowledge,* 10(3), 100682. ISSN 2444-569X. DOI 10.1016/j.jik.2025.100682.

Cohen, W. M. & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, 35(1), 128–152. ISSN 0001-8392. DOI 10.2307/2393553.

Dwivedi, Y. K. et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, 101994. ISSN 0268-4012. DOI 10.1016/j.ijinfomgt.2019.08.002.

European Commission. (2025). Digital Decade 2025 - Country reports. https//digital-strategy.ec.europa.eu/en/library/digital-decade-2025-country-reports. [accessed 7.6.2026].

Eurostat. (2026). *Artificial intelligence by size class of enterprise.*

https://doi.org/10.2908/ISOC_EB_AI [accessed 7.7.2026].

Fagerberg, J. & Godinho, M. M. (2005). Innovation and catching-up. In Fagerberg, J., Mowery, D. C. & Nelson, R. R. (eds.), *The Oxford Handbook of Innovation*. Oxford: Oxford University Press, pp. 514–542. ISBN 978-0-19-157731-4. DOI 10.1093/oxfordhb/9780199286805.003.0019.

Fagerberg, J. & Srholec, M. (2008). National innovation systems, capabilities and economic development. *Research Policy*, 37(9), 1417–1435. ISSN 0048-7333. DOI https://doi.org/10.1016/j.respol.2008.06.003.

Filippucci, F., Gal, P., Jona-Lasinio, C., Leandro, A. & Nicoletti, G. (2024). *The impact of artificial intelligence on productivity, distribution and growth.* Paris: OECD Publishing. DOI 10.1787/8d900037-en.

Greco, S., Ishizaka, A., Tasiou, M. & Torrisi, G. (2019). On the methodological framework of composite indices: A review of the issues of weighting, aggregation, and robustness. *Social Indicators Research,* 141(1), 61–94. eISSN 1573-0921, DOI 10.1007/s11205-017-1832-9.

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20. eISSN 1867-0202, https://doi.org/10.1007/s12599-020-00676-7.

Kergroach, S. & Héritier, J. (2025). *Emerging divides in the transition to artificial intelligence.* Paris: OECD Publishing. DOI 10.1787/7376c776-en.

Microsoft AI Economy Institute. (2025). *AI Diffusion Report: Where AI is most used, developed, and built. Redmond: Microsoft Research*. https://www.microsoft.com/en-us/research/wp-content/uploads/2025/10/Microsoft-AI-Diffusion-Report.pdf, [accessed 7.6.2026].

OECD. (2025). *AI adoption by small and medium-sized enterprises*. Paris: OECD Publishing. DOI 10.1787/426399c1-en. [accessed 7.6.2026].

OECD. (2026). *The OECD.AI Index: Technical paper.* Paris: OECD Publishing. https://www.oecd.org/en/publications/2026/02/oecd-ai-observatory-index_8f5fa0f2.html, [accessed 2.7.2026].

OECD – European Commission, Joint Research Centre. (2008). *Handbook on Constructing Composite Indicators: Methodology and User Guide.* Paris: OECD Publishing. DOI 10.1787/9789264043466-en. [accessed 2.7.2026].

Oxford Insights. (2025). *Government AI Readiness Index 2025*. Oxford: Oxford Insights. https://oxfordinsights.com/ai-readiness/government-ai-readiness-index-2025, [accessed 7.6.2026].

Rogers, E. M. (2003). *Diffusion of Innovations*. 5th ed. New York: Free Press. ISBN 0-7432-5823-1.

Tornatzky, L. G. & Fleischer, M. (1990). *The Processes of Technological Innovation*. Lexington: Lexington Books. ISBN 0-669-20348-3.

Zahra, S. A. & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review*, 27(2), 185–203. ISSN(online) 1930-3807. DOI 10.5465/amr.2002.6587995.

Project overview

Futurepreneurs and SMEs for a sustainable Central Europe | Certification Scheme

Futurepreneurs are professionals that are driven by purpose and impact. They take on societal challenges and climate change with an entrepreneurial mindset and want to improve our lives. The GREENPACT project sets up partnerships between companies and futurepreneurs. The aim is to develop a certification scheme for a new generation of impact-driven top executives. To this end, the project develops joint action plans, pilot actions and a self-assessment tool.

1,78 m €
Project Budget

80%
of the Budget is funded by ERDF

5
Countries

6
Regions

9
Partners

1
Pilots

Duration

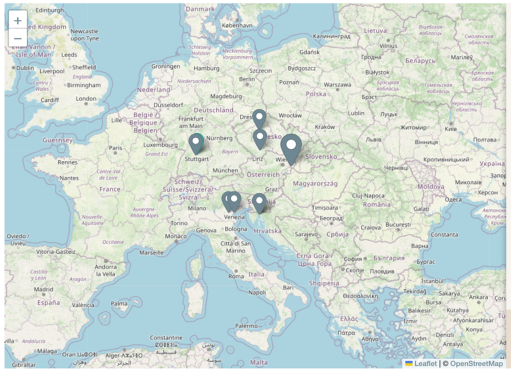
Start date 04.2023

End date 03.2026

Project progress

20%

Project partnership



Project partner

University of Economics in Bratislava

Faculty of Business management

Address
Dolnozemská cesta 1
85235 Bratislava

Country
Slovakia (SK)

Web
www.euba.sk

Total partner budget
207 200 €

Project partners

Lead partner
Stuttgart Media University

Startup Center

Address
Nobelstr. 10
740569 Stuttgart

Country
Germany (DE)

Web
https://www.hdm-stuttgart.de/en

Project partner

- Stuttgart Region Economic Development Corporation
- ENAIP Veneto Social Enterprise
- Region of Veneto - Department of Labour
- STEP RI Science and Technology Park of the University of Rijeka Ltd
- City of Rijeka
- Czech Chamber of Commerce
- Institute of Technology and Business in České Budějovice
- University of Economics in Bratislava

Interreg CENTRAL EUROPE Co-funded by the European Union

About us Projects Apply Implement Library Contacts

VReduMED

Project partners

Lead partner
South Bohemian Science and Technology Park, corp.

Address
Lipová 1789/9
37005 České Budějovice

Country
Czechia (CZ)

Web
www.jvtp.cz

Project partner

- University of South Bohemia in České Budějovice
- Business Upper Austria
- Education Group
- University of Economics in Bratislava
- National Institute of Children's Diseases
- Strategic Partnership for Sensor Technologies
- Ostbayerische Technische Hochschule Regensburg
- Innoskart Business Development Nonprofit Ltd.
- Széchenyi István University

Project overview

Virtual Reality Education and Training Solutions for Medicine Sector

Medical interventions are increasingly digitalised but training of health care staff is still lagging behind. The VReduMED project helps to untap the potential of virtual and augmented reality for their education. The partnership develops a roadmap for virtual reality training products and services and will publish a handbook on the integration of virtual reality into health care education. They also set up three regional virtual reality labs to test different virtual reality use cases.

2,20 m €
Project Budget

80%
of the Budget is funded by ERDF

5
Countries

6
Regions

10
Partners

3
Pilots

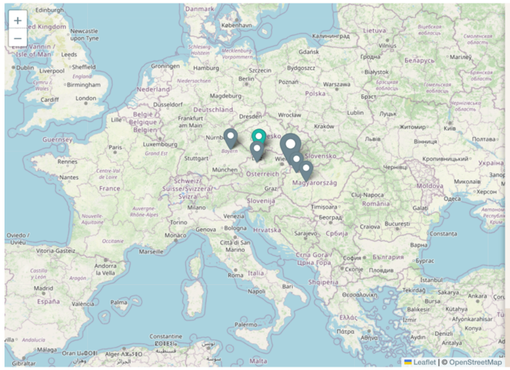
Duration

Start date 04.2023
End date 03.2026

Project progress

20%

Project partnership



Project partner
University of Economics in Bratislava

Faculty of Business Management

Address
Dolnozemská cesta 1/A
852 35 Bratislava

Country
Slovakia (SK)

Web
www.euba.sk

Total partner budget
220 900 €

Interreg
Danube Region

Co-funded by
the European Union

SReST

Project overview

Start date:

01 January 2024

Status: ongoing

End date:

30 June 2026

€1,540,470 budget

80.00 % funded by Interreg Funds

7 countries

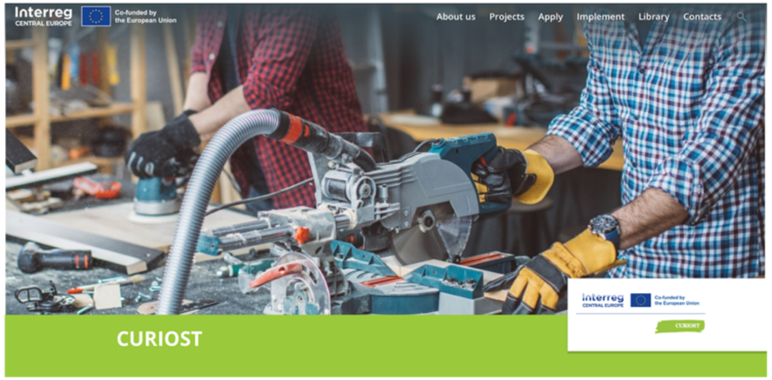
10 partners

SOCIALLY RESPONSIBLE SLOW FOOD TOURISM IN THE DANUBE REGION

The main objective of the SReST project is to promote “slow food” tourism in the Danube region and enhance the employability of vulnerable groups by providing solutions that enable the valorisation of agrobiodiversity and gastronomic heritage and a fair distribution of generated benefits, including the well-being of the host communities.

By focusing on agro-biodiversity, food heritage and local identity, the goal is to broaden the socially responsible sustainable tourism offer and promote "slow food" tourism based on the exploration of gastronomic traditions and the local communities that preserve them. The project will help enhance local agricultural high-value chains while appreciating natural and cultural diversity of partner regions.

SReST will develop joint solutions to enhance socio-economic development and promote alternative models and competitive new tourism products of “slow food” itineraries grounded in agrobiodiversity and food heritage, tested in different territorial contexts of pilot regions. These solutions will not be limited to the local level, but will have a wider impact in the Danube area. Therefore, the success of the project will be based on close cooperation between partners from different countries and regions. You can learn more about the project partners here.

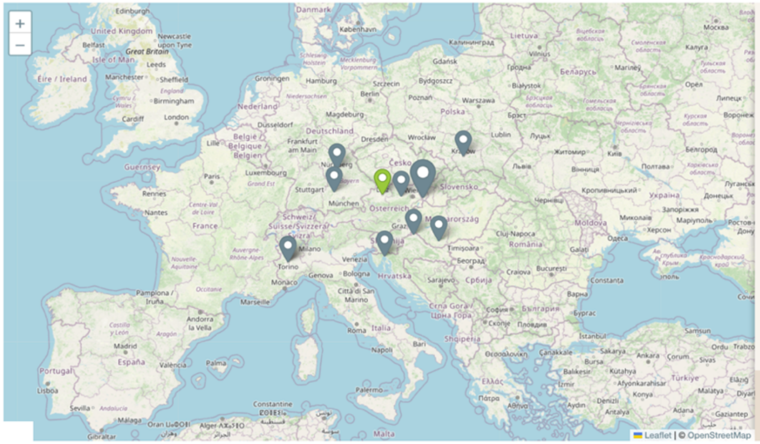


Duration

Start date **06.2024**

End date **11.2026**

Project partnership



Project partner
University of Economics in Bratislava

Faculty of Business management

Address
Dolnozemská cesta 1
85235 Bratislava

Country
Slovakia (SK)

Web
www.euba.sk

Total partner budget
174 020 €

Project partners

Lead partner
Business Upper Austria

Mechatronics Cluster + Circular Economy Team @ Plastics Cluster

Address
Hafenstraße 47-51
4020 Linz

Country
Austria (AT)

Web
https://www.biz-up.at

Project partner

- **ConPlusUltra Ltd**
- **University of Economics in Bratislava**
- **Chamber of Commerce and Industry of Pécs- Baranya**
- **South Poland Cleantech Cluster Ltd.**
- **STEP RI science and technology park of the University of Rijeka Ltd.**
- **Development and Training Centre for the Metal Industry – Metal Centre Čakovec**
- **MESAP Innovation Cluster**
- **Science and Technology Park - Envipark**
- **Bayern Innovativ**
- **Cluster of Environmental Technologies Bavaria**

Project overview

Circular design and development of Sustainable products in 4 key sectors in Central Europe

The ongoing transition to a circular economy is not only a tedious obligation for the manufacturing industry. It also offers an opportunity to develop innovative sustainable products. The CURIOST project helps small- and medium-sized companies in sectors like mechanics, packaging, plastics, and construction to harvest the potential benefits. They help selected companies to co-develop tailor-made, innovative, sustainable and circular product prototypes. The learnings are then aggregated into a universal strategy and action plans to accelerate the green transition in the manufacturing industry.

1,90 m €
Project Budget

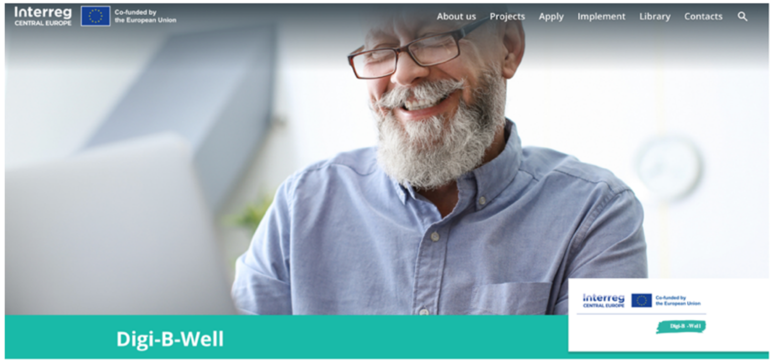
80%
of the Budget is funded by ERDF

7
Countries

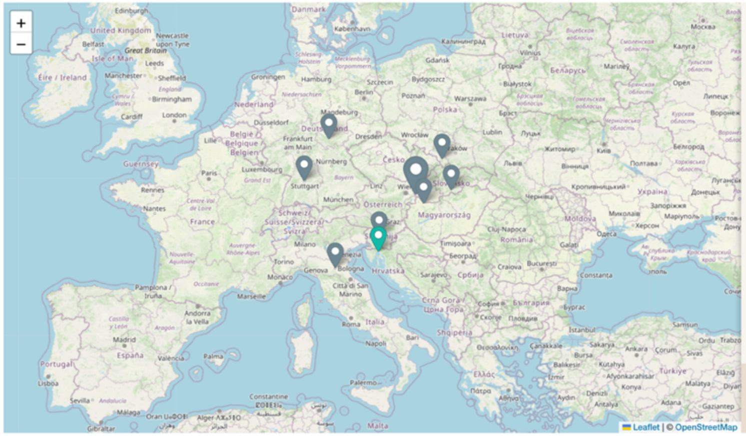
10
Regions

11
Partners

1
Pilots



Project partnership



Project partner
University of Economics in Bratislava

Faculty of Business Management

Address
Dolnozemská cesta 1/B
85235 Bratislava

Country
Slovakia (SK)

Web
fpm.euba.sk

Total partner budget
286 428,83 €

Duration

Start date **06.2024**

End date **05.2027**

Project partners

Lead partner
Primorje-Gorski Kotar County

Administrative Department for Regional Development, Infrastructure and Project Management

Address
Adamićeva 10
51000 Rijeka

Country
Croatia (HR)

Web
www.pgz.hr

Project partner

- **Alma Mater Studiorum - University of Bologna**
- **Technical University Ilmenau**
- **bwcon**
- **Chamber of Commerce and Industry of Slovenia**
- **Pannon Business Network Association**
- **University of Economics in Bratislava**
- **Regional Development Agency in Bielsko-Biała**
- **City Lucenec**

Project overview

Enhancement of capacities of SMEs, public authorities and academia for digitalisation, digital era-fit management and achievement of digital well-being.

The digital transformation offers new opportunities for companies but also increases complexity. Especially employees over 55 can suffer from digital stress or burnout at the workplace. The Digi-B-Well project helps companies to transform and make employees fit for the digital age. The partners upskill competences of managers, public authorities, and academia to better prevent digital stress and burnout. They develop and test new tools to self-assess digital maturity and digital transformation models in companies. In addition, a digitalisation strategy and action plans ensure the uptake of their innovative solutions into broader policy and business practices.

2,19 m €
Project Budget

80%
of the Budget is funded by ERDF

7
Countries

9
Regions

9
Partners

1
Pilots

Interreg Danube Region

Co-funded by the European Union

PATHS

Our Solution

PATHS introduces the **Life Path Support Service (LPSS)** model – a new approach to career guidance that is local, inclusive, and tailored to the individual.

Instead of one-size-fits-all programs, LPSS offers:

- Free, accessible services in small municipalities
- Career workshops, camps, and internships rooted in **self-awareness**
- Trained local **mentors** who provide personal guidance and support
- A long-term strategy for sustainable regional development

This model is being piloted in communities across Hungary, Slovakia, Czech Republic, Romania, Croatia, and Bosnia & Herzegovina – with expert support from Austria and Slovenia.

Project overview

Start date: 01 April 2025

Status: ongoing

End date: 31 March 2028

€2,516,726 budget

80.00 % funded by Interreg Funds

9 countries

13 partners

Interreg Europe | Co-funded by the European Union

PERSIST

What did this project achieve?

This project will:

- **Strengthen regions' ability** to deliver smart specialisation in a sustainable way.
- **Develop and test new methods** to move from the Entrepreneurial Discovery Process to the Ongoing Discovery Process.
- **Improve cooperation** between authorities, businesses and researchers.
- **Enable inclusive decisions** and make better use of regional resources.
- **Boost innovation capacity** and strengthen regional competitiveness.
- **Create stronger ecosystems** and new opportunities that benefit both the economy and society.

A few numbers

1,793,584 € budget

01 May 2025- 31 Jul 2029

12 partners

Project summary

Across Europe, regions face similar challenges. How can we build **innovation systems that endure** – systems that meet today's needs while paving the way for a **sustainable future**, **economically**, **socially**, and **environmentally**?

This project helps **regional authorities and agencies** strengthen **long-term cooperation** around smart specialisation.

Through **practical frameworks and tools**, it supports regions in creating **strong, inclusive networks** with **lasting commitment** from key actors.

The project builds on engagement through the **Entrepreneurial Discovery Process** and other **participatory methods**. This ensures that collaboration is rooted in **real regional needs and ambitions**.

Who we are

Persist brings together nine partners from across Europe – regions, universities, and development agencies working together for smarter, more sustainable regional growth.

- **Region Jönköping County** (Sweden)
- **Podkarpackie Region** (Poland)
- **Regional Development Agency of Khmelnytskyi oblast** (Ukraine)
- **University of Economics in Bratislava** (Slovakia)
- **Ústí Region** (Czech Republic)
- **Regional Management Northern Hessen** (Germany)
- **University of Groningen** (Netherlands)
- **Business Innovation Center of Cartagena** (Spain)
- **Udhëtim i Lirë** (Albania)

Together, we share knowledge, test new ideas, and build long-term cooperation to strengthen smart specialisation across Europe.

Interreg Europe
Co-funded by the European Union
ForYouth

A few numbers

1,617,350 €
budget

01 May 2025-
31 Jul 2029

9 partners

Project summary

Youth involvement is essential in all policy areas that affect their lives, as highlighted in the **EU Youth Strategy 2019–2027**. The project aims to develop **mechanisms and instruments** tailored to young people's needs, supporting the strengthening of their **voice in decision-making**, promoting effective use of resources, and fostering **cross-sector collaboration**.

The project's **innovative character** stems both from its **topic** and the **partnership structure**. The topic is highly relevant, as the gap between **urban strategies** and **youth interests** remains visible in the targeted regions. The partnership unites territories with contrasting demographic realities: some face **low birth rates** and an **ageing population**, while others stand out for having a **large youth population**, which is uncommon in many European areas.

The **overall objective** is to improve policies that enable **active youth participation** in community life and decision-making processes. The project seeks to create an environment where young people feel **valued, empowered, and motivated** to contribute to **societal progress and development**.

This objective will be achieved by:

- **Removing barriers and administrative blockages** that prevent young people from feeling appreciated;
- Encouraging them to **remain in or return to their birthplaces** and engage actively in their communities;
- **Engaging key stakeholders** (public institutions, NGOs, education, and private sector);
- **Transferring knowledge and good practices** from advanced regions to those with fewer youth-oriented solutions;
- Developing **tools and mechanisms** based on the gathered experiences;
- Promoting **social inclusion**, with a focus on **young emigrants** and the **youth diaspora**.

The project will be implemented within the framework of **territorial cooperation** among partner regions, through the **exchange of good practices and experiences** on youth participation.

Pokyny pre autorov

Príspevky prijíma redakcia vedeckého časopisu Ekonomika a manažment a uverejňuje ich v slovenskom, českom alebo anglickom jazyku, výnimočne po dohode s redakciou aj v inom jazyku. Základnou požiadavkou je originalita príspevku.

Redakčná rada odporúča autorom, aby rozsah vedeckých príspevkov nepresiahol 15 normalizovaných strán, príspevky do diskusie, prehľady a konzultácie 10 strán, recenzie a informácie 3 strany.

Zaslaním príspevku do redakcie nevzniká autorovi právny nárok na jeho uverejnenie.

Podmienkou publikovania príspevku sú:

- kladné stanovisko redakčnej rady a nezávislého recenzenta, ktorého určí redakčná rada
- úhrada poplatku vo výške 50,- € na účet vydavateľa (Nadácia Manažér)
- podpísanie Licenčnej zmluvy na dielo.

Autor zodpovedá za právnu a vecnú korektnosť príspevku a súhlasí s formálnymi úpravami redakcie.

Všetky príspevky doručené redakcii časopisu sú anonymne recenzované. Autorské práva vykonáva vydavateľ v súlade s platným autorským zákonom. Použitie celých publikovaných textov alebo ich časti, rozmnožovanie a šírenie akýmkoľvek spôsobom (mechanickým či elektronickým) bez výslovného súhlasu vydavateľa je zakázané.

Za textovú, jazykovú a grafickú úpravu jednotlivých príspevkov zodpovedajú autori.

Príspevky nie sú honorované.

Príspevok až po úprave bude recenzovaný.

Príspevky je potrebné zaslať mailom na adresu výkonného redaktora
katarina.grancicova@euba.sk , miroslav.toth@euba.sk

https://fpm.euba.sk/veda-a-vyskum/vedecky-casopis/ekonomika-a-manazment

Šablóna príspevkov a pokyny k formálnej úprave príspevku sú zverejnené na tejto stránke:

Pokyny štruktúra príspevku a formálna úprava príspevku pre časopis FPM Ekonomika a manažment (EaM)

Príspevok časopis EaM FPM v SJ 2021 editovateľný vzor

Contribution editable template for the EaM FPM journal in English language

Redakcia

Instructions for authors

Contributions are accepted by the editors of the scientific journal Ekonomika a manažment and published in Slovak, Czech or English, exceptionally in another language by agreement with the editors. The basic requirement is the originality of the paper.

The Editorial Board recommends to the authors that the length of scientific contributions should not exceed 15 standard pages, contributions to the discussion, reviews and consultations 10 pages, reviews and information 3 pages.

Submission of a Contribution to the Editorial Board does not give the author a legal right to its publication.

The following are the conditions for publication:

- a positive opinion of the editorial board and an independent reviewer appointed by the editorial board
- payment of a fee of 50 € to the account of the publisher (Foundation Nadácia Manažér)
- signing of the Licence Agreement for the Contribution.

The author is responsible for the legal and factual correctness of the Contribution and agrees to formal editing by the editorial board.

All Contributions received by the journal editors are anonymously peer-reviewed. Copyright is exercised by the publisher in accordance with applicable copyright law. The use of all or part of the published texts, reproduction and dissemination by any means (mechanical or electronic) without the express permission of the publisher is prohibited.

The authors are responsible for the textual, linguistic and graphic editing of the individual contributions.

We do not pay royalties to authors of contributions.

Only after editing will the paper be peer-reviewed.

Contributions should be sent by email to the Executive Editor at
katarina.grancicova@euba.sk , miroslav.toth@euba.sk

https://fpm.euba.sk/en/science-and-research/scientific-journal/economics-and-management

A template for submissions and instructions on how to format the paper are posted on this page.

Pokyny štruktúra príspevku a formálna úprava príspevku pre časopis FPM Ekonomika a manažment (EaM)

Príspevok časopis EaM FPM v SJ 2021 editovateľný vzor

Contribution editable template for the EaM FPM journal in English language

Editorial Board

EKONOMIKA A MANAŽMENT
Vedecký časopis Fakulty podnikového manažmentu
Ekonomickej univerzity v Bratislave

ECONOMICS AND MANAGEMENT
Scientific Journal of the Faculty of Business Management
Bratislava University of Economics and Business

Ročník XXIII.
Číslo 2
Rok 2026

ISSN 2454-1028