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Factors Influencing Digital Transformation Outcomes in AI-Enabled Business Information Systems: An Empirical Survey of Organizational Users

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Abstract

Background: Artificial intelligence is increasingly embedded in business information systems, where it supports analytics, automation, decision support, and organizational transformation. However, business informatics research has not yet fully integrated the organizational and measurement conditions under which AI-enabled business information systems are associated with digital transformation outcomes.

Objective: This study examined the associations of AI readiness, business information system quality, perceived AI opportunities, perceived AI challenges, AI governance, and digital competence with perceived digital transformation outcomes.

Methods: A cross-sectional online survey was administered through the 1KA platform to organizational users of business information systems in Slovenia. Data were collected between 1 May and 11 June 2026. Recruitment combined eligibility-based purposive sampling with snowball sampling initiated through 120 publicly available corporate email addresses. Of 607 submitted questionnaires, 43 incomplete submissions were excluded, leaving 564 complete cases. Analyses included reliability diagnostics, principal component analysis (PCA) with varimax rotation, convergent and discriminant validity assessment, including HTMT, Pearson correlations, multiple linear regression with HC3 robust standard errors, nonparametric bootstrap confidence intervals, and thematic analysis of open-ended responses.

Results: The measurement diagnostics indicated acceptable internal consistency and a theoretically interpretable seven-component solution. The regression model was statistically significant but explained a modest 8.1% of the variance in perceived digital transformation outcomes. AI readiness, AI governance, and business information system quality had statistically significant positive coefficients, whereas perceived AI opportunities, digital competence, and perceived AI challenges were not independently significant.

Conclusion: Perceived digital transformation outcomes were associated more strongly with organizational readiness, governance, and the quality of existing business information systems than with perceived technological opportunities. Because the model explained only 8.1% of the variance and the sample was non-probability-based, the findings should be interpreted as limited, directional associations rather than as evidence of necessary or sufficient conditions for digital transformation.

Index Terms

AI readiness; Artificial intelligence; Business information systems; Digital transformation; AI governance; Business information system quality.

1 INTRODUCTION

Artificial intelligence (AI) has moved from a specialized computational field to a central element of contemporary business information systems. In organizational contexts, AI refers to computational approaches that support learning from data, pattern recognition, prediction, recommendation, natural language processing, automation, and decision support. Its relevance for business information systems lies not only in processing large volumes of data but also in transforming how organizational information is generated, interpreted, and used in managerial and operational decision-making (Dwivedi et al., 2021).

Business information systems (BIS) are sociotechnical systems that connect people, data, technologies, processes, and managerial decisions. They include enterprise resource planning systems, customer relationship management systems, human resource information systems, business intelligence platforms, decision-support systems, workflow systems, and analytics applications. AI extends these systems through predictive analytics, automated classification, intelligent reporting, anomaly detection, and conversational interfaces (Collins et al., 2021).

The integration of AI into BIS also changes the normative expectations placed on information systems. Traditional BIS are expected to provide reliable data, process integration, and managerial control, whereas AI-enabled BIS additionally require explainability, accountability, human oversight, and risk management. Responsible AI perspectives emphasize that the value of AI cannot be separated from transparency, bias, trust, governance, and social consequences (Dennehy et al., 2023).

Digital transformation extends beyond the digitization of documents or the digitalization of isolated processes. It refers to organizational change in which digital technologies reshape business models, value creation mechanisms, customer relationships, operational processes, and strategic capabilities. AI-enabled BIS can therefore be understood as a foundation of digital transformation because they support the transition from process recording to analytics, prediction, automation, and adaptive decision support (Verhoef et al., 2021; Wessel et al., 2021).

Although research on AI, digital transformation, and information systems has advanced rapidly, several gaps remain in business informatics. First, AI readiness is still an emerging research area, and organizations need clearer guidance for assessing assets, capabilities, and commitment before adoption (Jöhnk et al., 2021). Second, research often examines AI strategy, AI capability, governance, or digital transformation separately, whereas fewer studies integrate these constructs into a coherent empirical model. Third, the governance of organizational data, machine-learning models, and AI systems remains difficult to operationalize in practice (Papagiannidis et al., 2025; Schneider et al., 2023).

This study examines how AI readiness, BIS quality, perceived AI opportunities, perceived AI challenges, AI governance, and digital competence are associated with perceived digital transformation outcomes. It contributes to business informatics by integrating technological, organizational, human, and governance-related predictors into a single model and by showing how such a model can be measured and statistically tested.

2 LITERATURE REVIEW AND HYPOTHESES

2.1 AI Readiness and Digital Transformation Outcomes

AI readiness is conceptualized as the extent to which an organization possesses the infrastructure, leadership support, openness to change, and user preparedness required for AI adoption. Readiness is not limited to technical availability; it also includes the organizational capacity to interpret AI outputs, manage data, redesign processes, and align AI projects with strategic priorities (Holmström, 2022; Jöhnk et al., 2021).

From a sociotechnical perspective, AI readiness should influence whether AI-enabled BIS contribute to efficiency, decision quality, agility, and process optimization. Research on AI capability likewise indicates that organizations benefit when technological, human, and organizational resources are combined (Mikalef & Gupta, 2021). Evidence from technology-adoption research further shows that adoption is shaped not only by perceived benefits but also by compatibility, competitive pressure, and industry context (Homan & Beránek, 2023). AI readiness should therefore be interpreted within a broader technology-organization-environment perspective rather than in terms of tool availability alone. Accordingly, the following hypothesis was formulated:

H1: AI readiness is positively associated with perceived digital transformation outcomes.

2.2 Perceived AI Opportunities and Digital Transformation Outcomes

AI-enabled BIS may create value through decision support, predictive analytics, automation, reporting, innovation, and improved organizational responsiveness. Research on AI-based transformation projects indicates that AI may influence performance through process innovation, decision-making, and operational performance (Wamba-Taguimdje et al., 2020). Related work on innovation management suggests that AI can complement human judgment by detecting patterns and expanding analytical capacity (Haefner et al., 2021).

Nevertheless, perceived opportunities do not by themselves guarantee transformation outcomes. They must be translated into redesigned routines, governance arrangements, and managerial decisions. A recent Acta Informatica Pragensia case study on business intelligence adoption likewise found that management support and the continued availability of alternative data sources influenced whether analytical reports were incorporated into organizational routines (Andar & Kašparová, 2024). This evidence reinforces the argument that perceived AI opportunities require managerial action, process redesign, and sustained system use before they become digital transformation outcomes. Accordingly, the following hypothesis was formulated:

H2: Perceived opportunities associated with AI-enabled business information systems are positively associated with perceived digital transformation outcomes.

2.3 AI Governance and Ethical Oversight

AI systems depend on data quality, model monitoring, accountability, cybersecurity, and user trust. Governance and ethical oversight are therefore essential because AI-enabled BIS influence decisions, automate classifications, and affect organizational responsibility structures (Raisch & Krakowski, 2021). AI governance research argues that organizations must specify what is governed, who governs it, and how governance is implemented across data, models, and systems (Schneider et al., 2023). Responsible governance can strengthen confidence in AI-supported outputs, reduce risks related to bias and opacity, and create conditions for human oversight. Hence, the following hypothesis is proposed:

H3: AI governance and ethical oversight are positively associated with perceived digital transformation outcomes.

2.4 Digital Competence

Digital competence refers to users' capability to work with digital tools, interpret data, understand AI-supported recommendations, and apply information responsibly in organizational decisions. AI competence research suggests that human capability remains a key resource in AI adoption because organizations cannot benefit from AI when users lack the skills to interpret, question, or contextualize algorithmic outputs (Mikalef et al., 2022; Pinski et al., 2024). In AI-enabled BIS, competence is expected to influence whether employees can convert system outputs into usable knowledge. Therefore, the following hypothesis is proposed:

H4: Digital competence is positively associated with perceived digital transformation outcomes.

2.5 Perceived AI Challenges

AI adoption produces challenges related to data quality, cybersecurity, privacy, transparency, implementation costs, user resistance, and overreliance on automated decision-making. These challenges may reduce perceived digital transformation outcomes if they undermine trust, slow implementation, or prevent meaningful use of AI-enabled systems (Nishant et al., 2020). The expansion of generative AI has intensified these concerns as AI increasingly enters knowledge work, communication, and decision support across professional domains (Dwivedi et al., 2023).

The managerial challenge is not simply to automate work, but to decide which tasks should be automated, augmented, or reserved for human judgment. Algorithmic systems may also change organizational control, autonomy, and accountability (Kellogg et al., 2020). Accordingly, the following hypothesis is proposed:

H5: Perceived challenges of AI-enabled business information systems are negatively associated with perceived digital transformation outcomes.

2.6 Business Information System Quality

Business information system quality refers to system reliability, usability, integration, data accessibility, and reporting quality. AI functionalities cannot operate effectively when the underlying BIS infrastructure is fragmented, unreliable, or unable to provide accessible and trustworthy data. The literature on AI business value emphasizes that organizations must align data resources, technical infrastructures, and managerial practices to convert AI investment into value (Enholm et al., 2022). BIS quality is therefore expected to provide an infrastructural basis for AI-enabled digital transformation. The following hypothesis is proposed:

> *H6: The quality of business information systems is positively associated with perceived digital transformation outcomes.*

2.7 Conceptual Framework

The conceptual framework links six predictor constructs to perceived digital transformation outcomes. It proposes that AI-enabled transformation is associated with readiness, perceived opportunities, governance, competence, challenges, and the quality of existing business information systems. Figure 1 presents the proposed model.

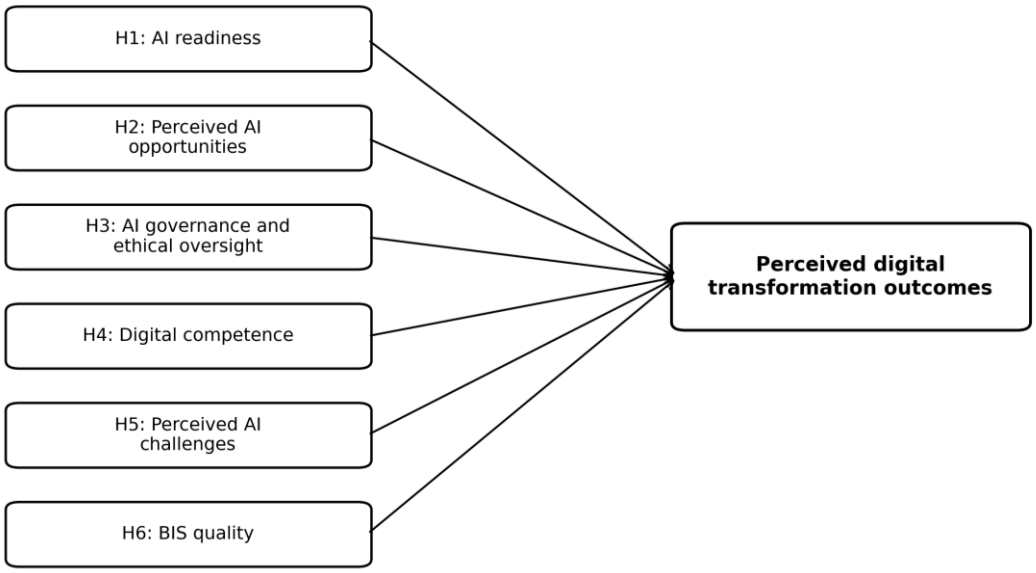


Figure 1. *Proposed research model.*

3 RESEARCH METHODS

3.1 Research Design

A cross-sectional questionnaire design was used because the objective was to quantify associations among AI readiness, BIS quality, perceived AI opportunities, perceived AI challenges, AI governance, digital competence, and perceived digital transformation outcomes. A supplementary qualitative component based on open-ended questions captured respondents' explanations of opportunities, barriers, and support needs.

The study was grounded in the business informatics perspective that information systems are sociotechnical infrastructures. Artificial intelligence was therefore treated not only as a technology but also as a component of organizational information infrastructure, decision-support processes, business analytics, process automation, data governance, and digital transformation.

3.2 Sample and Data Collection

The target population comprised organizational users of business information systems working in Slovenia, including managers, professional staff, administrative staff, IT specialists, and operational employees. Eligibility required current work-related familiarity with at least one type of business information system. The study used a

non-probability design combining purposive and snowball sampling. During the initial recruitment stage, invitations were sent to 120 publicly available corporate email addresses from Slovenian companies selected from the available contact list. Because this contact list was not a complete national sampling frame of organizational BIS users, the initial selection did not constitute probability sampling. Eligible recipients were invited to complete the questionnaire and forward the survey link to eligible colleagues in other organizations, thereby creating a second-stage snowball recruitment chain. Participation was voluntary and anonymous.

To construct the initial contact list, both authors conducted a structured web search for organizations operating in Slovenia. To obtain a more geographically balanced coverage, the search was divided between the northern and southern parts of the country according to the publicly listed location of each organization. One author (BB) searched for organizations in northern Slovenia, while the other (JS) searched in southern Slovenia. Each author identified 60 eligible contacts, resulting in an initial list of 120 email addresses. Organizations were included when their official website provided a publicly accessible general or business email address through which the survey invitation could be distributed. Because no complete sampling frame of all eligible organizations was available and the organizations were not selected using a formal randomization procedure, the initial selection cannot be classified as random sampling. Instead, it represented a geographically balanced purposive approach to constructing the initial contact list. The invitation to participate was sent to the selected email addresses on three occasions: 1 May, 19 May, and 1 June 2026. Recipients were also asked to forward the invitation to colleagues and other relevant professional contacts, after which participant recruitment continued through snowball sampling. The invitation to participate in the study was sent to potential participants on three occasions: 1 May, 19 May, and 1 June 2026. A total of 607 questionnaires were submitted. The sole post-submission exclusion criterion was incomplete submission; 43 questionnaires that had not been completed in full were excluded, leaving 564 complete cases for analysis. This corresponds to a usable-completion rate of 92.9% among submitted questionnaires. Because the number of invitations resulting from subsequent snowball forwarding could not be observed, a conventional response rate could not be calculated. The sample therefore cannot be considered statistically representative of all organizational BIS users in Slovenia, and statistical generalization is limited to the characteristics of this purposively and snowball-recruited sample. No complete national sampling frame or finite population count of organizational BIS users was available.

No a priori target sample size was imposed. Recruitment remained open for the full 42-day field period, and the final sample was determined by the number of complete eligible responses. A post hoc sensitivity analysis for a six-predictor multiple regression indicated that N = 564 provided approximately 80% power at $\alpha = 0.05$ to detect an effect of $f^2 \approx 0.024$. This demonstrates sensitivity to small regression effects but does not overcome the limitations of the non-probability design or establish population representativeness. All statistical analyses were performed using IBM SPSS Statistics version 26.0 (IBM Corp., Armonk, NY, USA).

3.3 Questionnaire Development and Content Validation

The questionnaire was not adopted from a single standardized instrument. Instead, its thematic domains were derived conceptually from recent literature on organizational AI readiness, AI capability, AI-enabled information systems, responsible AI governance, digital competence, and digital transformation. This approach follows scale-development logic: item generation begins with construct definition and content-domain specification, followed by item refinement and empirical testing (Elciyar & Satılmış, 2025; Hair et al., 2019).

Recent studies in Acta Informatica Pragensia provide relevant methodological precedents for this design. Rebrica et al. (2025) developed and empirically tested an explanatory survey model using structural equation modelling, Elciyar and Satılmış (2025) demonstrated a systematic item-generation and scale-validation procedure, and El anouar et al. (2025) used a five-point Likert questionnaire with confirmatory factor analysis and structural equation modelling to examine perceived information system constructs.

The AI readiness section was informed primarily by Jöhnk et al. (2021) and Mikalef and Gupta (2021). Items related to BIS quality, AI-enabled information systems, and digital transformation outcomes were conceptually informed by Verhoef et al. (2021), Ågerfalk et al. (2022), Collins et al. (2021), and Enholm et al. (2022). The section on perceived opportunities was based on literature linking AI to decision support, automation, analytics, and value creation (Enholm et al., 2022; Wamba-Taguimdje et al., 2020). The section on perceived challenges drew on research addressing data quality, transparency, privacy, cybersecurity, accountability, and implementation barriers (Berente

et al., 2021; Dennehy et al., 2023; Dwivedi et al., 2021). The governance and ethical oversight section was informed by work on responsible AI, human oversight, and AI governance (Papagiannidis et al., 2025; Raisch & Krakowski, 2021). Digital competence items were informed by research on AI competencies and human capability requirements (Mikalef et al., 2022; Mikalef et al., 2023).

The questionnaire administered through 1KA comprised a demographic and organizational section, a section on the use of business information systems, seven multi-item construct sections, and three open-ended questions. The construct sections measured AI readiness, BIS quality, perceived AI opportunities, perceived AI challenges, AI governance and ethical oversight, digital competence, and perceived digital transformation outcomes. All 35 construct items used a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The complete question sequence, item wording, response categories, and introductory consent text are reproduced in Appendix A.

3.4 Measures and Operationalization

The main constructs were operationalized through multi-item Likert-type scales, and composite scores were calculated as arithmetic means of the relevant items. Higher scores indicate stronger agreement with the measured construct. Table 1 summarizes the measurement domains and analytical roles, while Appendix A presents the full list of questionnaire items.

Table 1. *Overview of measurement domains.*

Measurement domain	Definition and examples	No. of items / variables	Analytical role
Demographic and organizational profile	Gender, age, education, position, work experience, sector and organization size	7 variables	Control and descriptive variables
Use of business information systems	ERP, CRM, HRIS, BI, DSS, workflow systems, AI-supported reporting and chatbots	8 binary variables	Contextual variables
AI readiness	Digital infrastructure, leadership support, openness to change and preparedness for AI	5 items	Independent construct
BIS quality	Reliability, usability, integration and reporting quality of business information systems	4 items	Independent construct
Perceived AI opportunities	Decision-making, automation, analytics, reporting, responsiveness and innovation	6 items	Independent construct
Perceived AI challenges	Data quality, cybersecurity, privacy, bias, transparency, costs and resistance	6 items	Independent construct
AI governance and ethical oversight	Rules, accountability, transparency, human oversight and data protection	5 items	Independent construct
Digital competence	User capability, AI literacy, data literacy and confidence in digital work	4 items	Independent construct
Digital transformation outcomes	Efficiency, decision quality, agility, innovation and process optimization	5 items	Dependent construct
Open-ended responses	Opportunities, barriers and support needs	3 text variables	Qualitative illustration

3.5 Analytical Strategy

Data analysis proceeded in several stages. First, descriptive statistics were calculated for demographic and organizational characteristics, BIS use, and construct-level variables. Frequencies and percentages were used for categorical variables, while means, standard deviations, medians, and ranges were used for Likert-scale composites.

Second, data screening and measurement diagnostics were conducted before hypothesis testing. Common method bias was assessed using Harman's single-factor test (Podsakoff et al., 2003), and sampling adequacy was examined using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. Dimensionality was explored using principal component analysis (PCA) with varimax rotation. PCA was used as a data-reduction procedure to

determine whether the observed item groupings were consistent with the prespecified construct domains; it was not treated as exploratory factor analysis (EFA) or as a latent-variable measurement model.

Third, internal consistency and convergent validity were assessed using Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and standardized item loadings. The loadings used to calculate CR and AVE were obtained from separate single-construct measurement models for the prespecified constructs and are reported in Table 5; they are distinct from the rotated PCA loadings reported in Table 4. Let λ_i denote the standardized loading of item i and ε_i its error variance, where $\varepsilon_i = 1 - \lambda_i^2$. CR was calculated as $(\Sigma\lambda_i)^2 / [(\Sigma\lambda_i)^2 + \Sigma\varepsilon_i]$, and AVE as $\Sigma\lambda_i^2 / [\Sigma\lambda_i^2 + \Sigma\varepsilon_i]$. Values of approximately 0.70 or higher were considered acceptable for alpha and CR in exploratory research. AVE values around 0.50 or higher were interpreted as evidence of convergent validity; values slightly below 0.50 were interpreted cautiously when reliability was acceptable and theory supported retaining the items (Bagozzi & Yi, 1988; Fornell & Larcker, 1981; Nunnally & Bernstein, 1994).

Fourth, Pearson correlations were used for preliminary bivariate hypothesis testing. Positive associations with digital transformation outcomes were expected for H1, H2, H3, H4, and H6, whereas a negative association was expected for H5. Fifth, multiple linear regression was used to estimate the independent contribution of each predictor to perceived digital transformation outcomes. Because observed composite scores were entered as predictors, this analysis did not constitute structural equation modeling and is described throughout as multiple linear regression. HC3 robust standard errors were used because the Breusch-Pagan test indicated possible heteroscedasticity. Final hypothesis decisions were based on coefficient direction, statistical significance, and confidence intervals in the multiple regression model.

Coefficient stability was additionally assessed using 2,000 nonparametric bootstrap samples. Each sample contained 564 cases drawn with replacement from the original analytical dataset. The regression model was re-estimated for each sample, and percentile 95% confidence intervals were defined by the 2.5th and 97.5th percentiles of the bootstrap distribution of each standardized coefficient.

HTMT was calculated from the item-level response matrix for the 35 Likert-scale items (Q9-Q43) in the 564 complete cases. The seven prespecified multi-item constructs comprised ARD (5 items), BISQ (4), OPP (6), CHL (6), GOV (5), DIGC (4), and DTO (5). For each pair of constructs a and b, HTMT was computed as the mean absolute correlation between items measuring different constructs divided by the geometric mean of the average absolute within-construct item correlations. Percentile 95% confidence intervals were obtained from 2,000 nonparametric case-resampling bootstrap samples, each consisting of 564 cases drawn with replacement from the analytical dataset.

Open-ended responses were analyzed separately for opportunities, barriers, and support needs. Responses were read repeatedly, segmented into distinct meaning units, assigned initial codes, and grouped into higher-order themes. A response could contain more than one meaning unit and could therefore contribute to more than one theme. The final code set was reviewed for consistent application before frequencies were calculated. Theme frequencies represent the number of respondents whose answer contained the relevant theme, and percentages were calculated using the full analytical sample of N = 564 as the denominator. Table 11 reports the three most frequent themes in each domain; the percentages are not intended to sum to 100%.

This analytical reporting format is consistent with recent Acta Informatica Pragensia survey studies that combine measurement diagnostics, model testing, and transparent hypothesis decisions (El anouar et al., 2025; Rebrica et al., 2025). The inclusion of reliability and validity checks also follows recent scale-development work in the journal (Elciyar & Satılmış, 2025).

3.6 Ethical Considerations

The survey was administered voluntarily and anonymously through 1KA. Before proceeding to the survey items, respondents were informed that participation was voluntary and anonymous, that they could discontinue before submission, and that submitting the completed questionnaire constituted consent. No names or other direct personal identifiers were collected. Under the internal rules of the University of Novo mesto, this anonymous, non-interventional questionnaire study did not require prior review or approval by the University's internal ethics committee. Accordingly, no ethics committee application was submitted.

4 RESULTS

4.1 Sample Characteristics

The final sample comprised 564 organizational users and was intentionally heterogeneous across sectors, organization sizes, and organizational roles. The largest share of respondents was female (57.3%), aged 40–49 years (34.0%), and held a bachelor's degree (42.7%). Professional or expert roles represented the largest occupational category (40.0%).

Table 2. *Demographic and organizational characteristics of respondents. Percentages are calculated on the basis of N = 564 respondents.*

Variable	Category	n	%
Gender	Female	323	57.3
	Male	226	40.1
	Other/prefer not to say	15	2.7
Age group	Under 30	109	19.3
	30–39	135	23.9
	40–49	192	34.0
	50 or older	128	22.7
Education	Secondary or vocational	64	11.3
	Bachelor	241	42.7
	Master	207	36.7
	Doctorate	52	9.2
Sector	Services	150	26.6
	Manufacturing	98	17.4
	Healthcare	79	14.0
	IT/Telecommunications	72	12.8
	Education	72	12.8
	Finance/Banking	52	9.2
	Public administration	41	7.3
Organization size	Micro (<10)	38	6.7
	Small (10–49)	150	26.6
	Medium (50–249)	184	32.6
	Large (250+)	192	34.0
Role	Professional/expert	226	40.1
	Manager	105	18.6
	IT specialist	105	18.6
	Administrative	87	15.4
	Operational	41	7.3
Work experience	0–5 years	79	14.0
	6–10 years	181	32.1
	11–20 years	169	30.0
	21 years or more	135	23.9

4.2 Use of Business Information Systems and AI-Enabled Functionalities

Binary indicators captured the use of selected business information systems and AI-enabled functionalities. ERP systems were the most frequently represented system type (63.3%), followed by workflow systems (56.0%), CRM

systems (54.6%), HRIS systems (53.4%), and business intelligence tools (50.0%). AI-supported reporting was reported by 42.7% of respondents, while chatbots or virtual assistants were reported by 35.3%.

Table 3. *Use of business information systems and AI-enabled functionalities.*

Business information system / AI functionality	n	%
ERP	357	63.3
CRM	308	54.6
HRIS	301	53.4
Business intelligence (BI)	282	50.0
Decision-support systems (DSS)	226	40.1
Workflow systems	316	56.0
AI-supported reporting	241	42.7
Chatbots / virtual assistants	199	35.3

Note. Multiple system types could be selected; therefore, percentages do not sum to 100%.

4.3 Data Screening, Common Method Bias, and Suitability for Component Analysis

All 564 cases were complete for the main constructs. The first unrotated component in Harman's single-factor test explained 11.56% of the total variance, below the commonly used 50% threshold, indicating that a single general component did not dominate the item covariance structure. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.680, and Bartlett's test of sphericity was statistically significant, $\chi^2(595) = 6153.68$, $p < 0.001$, indicating that the item correlation matrix was suitable for principal component analysis.

4.4 Principal Component Analysis

The PCA yielded a theoretically interpretable seven-component solution corresponding to the proposed construct domains. Together, the seven components explained 52.75% of the total variance. The rotated loadings were strongest on the intended components, with limited cross-loadings. Table 4 reports the dominant loading range for each component.

Table 4. *Principal component analysis summary.*

Component	Construct represented	No. of items	Loading range	Explained variance (%)
1	Perceived AI opportunities	6	0.578–0.759	11.56
2	Perceived AI challenges	6	0.611–0.708	9.12
3	BIS quality	4	0.697–0.776	8.55
4	Digital competence	4	0.700–0.810	6.58
5	AI governance and ethical oversight	5	0.647–0.757	6.21
6	AI readiness	5	0.585–0.728	5.74
7	Digital transformation outcomes	5	0.622–0.721	4.98

Note. Principal components were extracted and rotated using varimax as an exploratory data-reduction diagnostic. The table reports the dominant absolute loading of each item group on its theoretically intended component.

4.5 Measurement Reliability and Validity

Internal consistency and convergent validity were assessed using Cronbach's alpha, composite reliability, and average variance extracted. Composite reliability values ranged from 0.804 to 0.859, indicating acceptable reliability for exploratory research. AVE values were above or close to the 0.50 threshold for most constructs. AI readiness (AVE = 0.451), perceived AI challenges (AVE = 0.459), and digital transformation outcomes (AVE = 0.474) were retained because their composite reliability values exceeded 0.80, their standardized loading ranges were acceptable,

and the items were required to preserve the conceptual breadth of the constructs. These three constructs are therefore treated as having borderline convergent validity, and results involving them are interpreted cautiously.

Table 5. *Reliability and convergent validity of measurement scales.*

Construct	Items	M	SD	Cronbach's α	CR	AVE	Loading range
AI readiness	5	3.32	0.59	0.695	0.804	0.451	0.610–0.711
BIS quality	4	3.25	0.71	0.735	0.835	0.558	0.723–0.793
Perceived AI opportunities	6	3.60	0.65	0.794	0.855	0.498	0.604–0.774
Perceived AI challenges	6	2.88	0.63	0.764	0.836	0.459	0.626–0.712
AI governance	5	3.00	0.72	0.754	0.836	0.504	0.677–0.730
Digital competence	4	3.28	0.76	0.780	0.859	0.603	0.730–0.797
Digital transformation outcomes	5	3.50	0.63	0.721	0.818	0.474	0.618–0.747

Note. CR = composite reliability; AVE = average variance extracted. The values are reported as exploratory measurement diagnostics.

4.6 Discriminant Validity and Correlations

The Fornell-Larcker criterion was used to assess discriminant validity. For each construct, the square root of AVE exceeded the corresponding absolute inter-construct correlations, providing supportive evidence of discriminant validity at the construct level. Pearson correlations were then used for preliminary hypothesis testing. AI readiness, AI governance, and perceived AI challenges were significantly associated with digital transformation outcomes in the expected directions at the bivariate level, whereas perceived AI opportunities, digital competence, and BIS quality were not statistically significant in the bivariate analysis.

HTMT was used as an additional discriminant-validity diagnostic (Henseler et al., 2015) and was calculated from the item-level responses to Q9–Q43 for all 564 complete cases. The matrix of point estimates is reported in Table 7, and percentile bootstrap confidence intervals are reported in Table 8.

Table 6. *Fornell-Larcker matrix and Pearson correlations.*

Construct	ARD	BISQ	OPP	CHL	GOV	DIGC	DTO
ARD	0.672						
BISQ	-0.070	0.747					
OPP	0.219***	-0.034	0.706				
CHL	-0.124**	0.193***	-0.014	0.678			
GOV	0.169***	-0.007	0.086	-0.092*	0.710		
DIGC	0.043	-0.104*	0.191***	0.023	0.013	0.776	
DTO	0.207***	0.082	-0.008	-0.085*	0.176***	0.014	0.688

*Note. Diagonal values are square roots of AVE. ARD = AI readiness; BISQ = BIS quality; OPP = perceived AI opportunities; CHL = perceived AI challenges; GOV = AI governance; DIGC = digital competence; DTO = digital transformation outcomes. * p < 0.05; ** p < 0.01; *** p < 0.001.*

Across the 21 construct pairs, HTMT values ranged from 0.060 to 0.339. The highest value was observed for ARD-DTO (HTMT = 0.339; percentile 95% bootstrap CI [0.249, 0.424]). All point estimates and upper confidence limits were below the conservative threshold of 0.85, supporting discriminant validity.

Table 7. *HTMT matrix.*

Construct	ARD	BISQ	OPP	CHL	GOV	DIGC	DTO
ARD	-						
BISQ	0.251	-					
OPP	0.275	0.148	-				
CHL	0.134	0.199	0.134	-			
GOV	0.209	0.183	0.193	0.237	-		
DIGC	0.164	0.210	0.240	0.117	0.060	-	
DTO	0.339	0.188	0.183	0.151	0.278	0.176	-

Note. ARD = AI readiness; BISQ = BIS quality; OPP = perceived AI opportunities; CHL = perceived AI challenges; GOV = AI governance; DIGC = digital competence; DTO = digital transformation outcomes. The conservative decision rule is HTMT < 0.85.

For the ARD-DTO pair, the mean absolute cross-construct item correlation was 0.19195; the mean absolute within-construct item correlations were 0.57598 for ARD and 0.55769 for DTO. Thus, HTMT = 0.19195 / √(0.57598 × 0.55769) = 0.33867, reported as 0.339.

Table 8. *HTMT estimates and percentile bootstrap confidence intervals.*

Construct pair	HTMT	Percentile 95% bootstrap CI
ARD-BISQ	0.251	[0.165, 0.342]
ARD-OPP	0.275	[0.188, 0.359]
ARD-CHL	0.134	[0.068, 0.231]
ARD-GOV	0.209	[0.125, 0.300]
ARD-DIGC	0.164	[0.085, 0.260]
ARD-DTO	0.339	[0.249, 0.424]
BISQ-OPP	0.148	[0.081, 0.242]
BISQ-CHL	0.199	[0.110, 0.292]
BISQ-GOV	0.183	[0.093, 0.278]
BISQ-DIGC	0.210	[0.118, 0.297]
BISQ-DTO	0.188	[0.095, 0.290]
OPP-CHL	0.134	[0.070, 0.231]
OPP-GOV	0.193	[0.109, 0.281]
OPP-DIGC	0.240	[0.149, 0.329]
OPP-DTO	0.183	[0.105, 0.272]
CHL-GOV	0.237	[0.158, 0.321]
CHL-DIGC	0.117	[0.055, 0.208]
CHL-DTO	0.151	[0.079, 0.244]
GOV-DIGC	0.060	[0.049, 0.139]

Construct pair	HTMT	Percentile 95% bootstrap CI
GOV-DTO	0.278	[0.182, 0.368]
DIGC-DTO	0.176	[0.096, 0.271]

Note. Percentile 95% confidence intervals were derived from 2,000 nonparametric case-resampling bootstrap samples, each comprising 564 cases drawn with replacement from the analytical dataset. No confidence interval approached the 0.85 threshold.

4.7 Multiple Regression Model and Hypothesis Testing

Multiple linear regression was used to examine whether AI readiness, perceived AI opportunities, AI governance, digital competence, perceived AI challenges, and BIS quality independently predicted perceived digital transformation outcomes when entered simultaneously. The Breusch-Pagan test indicated possible heteroscedasticity; therefore, HC3 robust standard errors were used for inference. Variance inflation factors ranged from 1.04 to 1.09, indicating no problematic multicollinearity. The overall regression model was statistically significant, $F(6, 557) = 8.18$, $p < 0.001$, but explained only a modest proportion of the variance in perceived digital transformation outcomes, $R^2 = 0.081$, adjusted $R^2 = 0.071$.

In the multiple regression model, AI readiness had a statistically significant positive coefficient ($B = 0.207$, $\beta = 0.195$, $p < 0.001$). AI governance also had a significant positive coefficient ($B = 0.125$, $\beta = 0.143$, $p < 0.001$), as did BIS quality ($B = 0.098$, $\beta = 0.111$, $p = 0.005$). Perceived AI opportunities, digital competence, and perceived AI challenges were not statistically significant. The coefficient for perceived AI challenges was negative, as hypothesized, but did not reach the prespecified $p < 0.05$ significance threshold ($p = 0.088$); therefore, H5 was not supported.

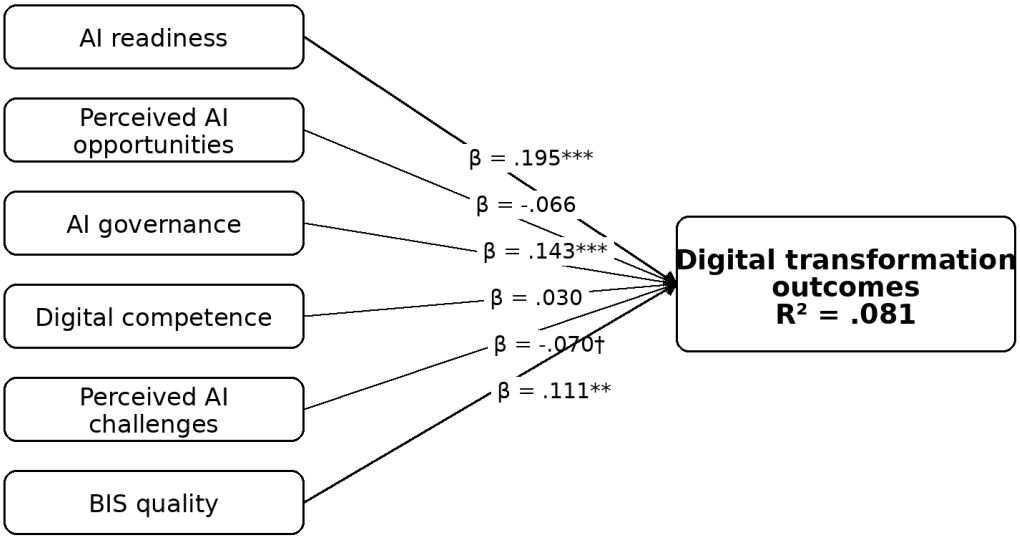


Figure 2. *Multiple regression model results.*

Table 9. *Multiple regression estimates and hypothesis decisions.*

Hypothesis	Path	B	β	Robust SE	p	95% CI	Decision
H1	AI readiness → DTO	0.207	0.195	0.047	< 0.001	0.115; 0.299	Supported
H2	AI opportunities → DTO	-0.064	-0.066	0.044	0.142	-0.149; 0.021	Not supported
H3	AI governance → DTO	0.125	0.143	0.036	< 0.001	0.053; 0.197	Supported
H4	Digital competence → DTO	0.025	0.030	0.037	0.505	-0.048; 0.098	Not supported
H5	AI challenges → DTO	-0.071	-0.070	0.042	0.088	-0.152; 0.010	Not supported
H6	BIS quality → DTO	0.098	0.111	0.034	0.005	0.030; 0.166	Supported

Note. Dependent variable: perceived digital transformation outcomes. HC3 robust standard errors are reported. Final hypothesis decisions are based on the multiple regression model.

Table 10. *Bootstrap confidence intervals for standardized regression coefficients.*

Path	β	Bootstrap 95% CI lower	Bootstrap 95% CI upper	Interpretation
AI readiness → DTO	0.195	0.090	0.293	Positive and statistically supported
AI opportunities → DTO	-0.066	-0.151	0.020	Not supported
AI governance → DTO	0.143	0.057	0.229	Positive and statistically supported
Digital competence → DTO	0.030	-0.055	0.113	Not supported
AI challenges → DTO	-0.070	-0.151	0.011	Expected direction but not statistically supported
BIS quality → DTO	0.111	0.033	0.189	Positive and statistically supported

Note. Percentile 95% confidence intervals are based on 2,000 nonparametric bootstrap samples of 564 cases drawn with replacement from the original analytical dataset.

4.8 Thematic Summary of Open-Ended Responses

Open-ended responses were summarized thematically to complement the quantitative results. The most frequent opportunity concerned the automation of repetitive business processes, while the most frequent barriers involved insufficient data quality, fragmented systems, privacy, and cybersecurity concerns. The most frequently represented support needs were better data integration, cybersecurity procedures, clear AI governance, human oversight, and structured employee training.

Table 11. *Thematic summary of open-ended responses (N = 564).*

Domain	Theme	n	%
Opportunities	Automation of repetitive business processes	154	27.3
Opportunities	Faster customer and employee support	132	23.4
Opportunities	Improved reporting and less manual work	94	16.7
Barriers	Poor data quality and fragmented systems	124	22.0
Barriers	Privacy and cybersecurity concerns	124	22.0
Barriers	Costs, legacy systems and resistance	120	21.3
Support needs	Data integration and cybersecurity procedures	124	22.0
Support needs	Clear AI governance and human oversight	117	20.7
Support needs	Training and practical AI examples	117	20.7

Note. Frequencies represent respondents whose answers contained the listed theme. Because responses could contain multiple meaning units and only the three most frequent themes per domain are shown, percentages do not sum to 100%.

5 DISCUSSION

5.1 AI Readiness as a Significant Predictor of Digital Transformation Outcomes

H1 was supported: AI readiness was positively associated with perceived digital transformation outcomes. The standardized coefficient was modest (β = 0.195), so the finding should not be interpreted as evidence that readiness is a dominant or sufficient determinant of digital transformation. Nevertheless, organizations may be better

positioned to derive value from AI when digital infrastructure, leadership support, openness to change, and user preparedness are present. Prior research similarly conceptualizes organizational AI readiness as a combination of assets, capabilities, and commitment (Jöhnk et al., 2021).

This finding also aligns with the AI readiness framework, which treats AI deployment as an organizational design challenge rather than a purely technical decision (Holmström, 2022). In practical terms, readiness may function as an enabling mechanism that helps organizations translate AI possibilities into redesigned processes, improved reporting routines, and more confident decision-making.

This interpretation is compatible with technology adoption evidence from Homan and Beránek (2023), who found that perceived relative advantage, compatibility, competitive pressure, and industry context were significant factors in SME cloud computing adoption. Although cloud computing and AI-enabled BIS are not identical technologies, both require organizational alignment before technological potential becomes practical adoption or transformation.

5.2 Why Perceived Opportunities Were Not Independently Significant

H2 was not supported, even though perceived AI opportunities had the highest mean score among the constructs. This suggests that recognizing opportunities is not equivalent to achieving transformation outcomes. Organizations may believe that AI can improve automation, prediction, and analytics, but these perceived benefits require readiness, governance, and process redesign before they become organizational outcomes.

This interpretation is consistent with research on AI business value, which argues that AI contributes to performance only when embedded in complementary resources and organizational capabilities (Enholm et al., 2022; Mikalef & Gupta, 2021). The result is also consistent with studies showing that AI-enabled value creation depends on how AI is integrated into decision routines rather than on the technical availability of AI alone (Chen et al., 2022; Wamba-Taguimdje et al., 2020).

The finding also corresponds to BI adoption evidence reported by Andar and Kašparová (2024), where managerial support and access to alternative data sources affected the actual use of new BI reports. In the present model, AI opportunities may remain unrealized unless management actively embeds them in reporting routines, workflow expectations, and decision practices.

5.3 AI Governance as a Significant Independent Predictor of Digital Transformation Outcomes

H3 was supported in the multiple regression model, although the standardized coefficient was modest ($\beta = 0.143$). AI governance and ethical oversight may contribute independently to perceived digital transformation outcomes by clarifying rules, responsibilities, human oversight, and data-protection requirements. This association should be interpreted as one element within a broader set of organizational influences, not as evidence that governance alone enables transformation.

This interpretation aligns with responsible AI research. Organizational AI governance involves structural, relational, and procedural mechanisms that translate abstract ethical principles into operational practices (Papagiannidis et al., 2025; Schneider et al., 2023). The significant regression coefficient suggests that governance should be integrated into readiness and implementation routines because responsible AI adoption depends not only on technical capability but also on accountability, monitoring, and trustworthy use of organizational data.

5.4 Digital Competence, Perceived AI Challenges, and BIS Quality

H4 and H5 were not supported in the multiple regression model, whereas H6 was supported. The lack of support for H4 is noteworthy because digital competence is generally considered important for AI adoption. One possible interpretation is that individual-level competence does not automatically translate into organizational transformation unless it is supported by coherent strategy, system integration, governance, and managerial support. AI literacy may therefore be necessary but insufficient for digital transformation outcomes (Mikalef et al., 2022; Pinski et al., 2024).

The lack of support for H5 suggests that perceived challenges can coexist with transformation efforts. More digitally mature organizations may also be more aware of data-quality, privacy, cybersecurity, and transparency risks. In

such cases, perceived challenges may indicate not only barriers but also more advanced implementation experience. This interpretation is consistent with research on the paradoxical and sociotechnical nature of AI adoption (Raisch & Krakowski, 2021; Strich et al., 2021).

Support for H6 indicates a modest positive association between the quality of existing business information systems and perceived digital transformation outcomes ($\beta = 0.111$). Reliable, integrated, and usable BIS may support the data accessibility, reporting quality, and process integration required for AI-supported analytics and decision-making. Given the small standardized coefficient, BIS quality should be interpreted as a relevant correlate within the present model, not as a sufficient infrastructural prerequisite for strategic digital transformation (Verhoef et al., 2021; Wessel et al., 2021).

6 IMPLICATIONS

6.1 Theoretical Implications

This study contributes to business informatics by integrating AI readiness, BIS quality, perceived AI opportunities, perceived AI challenges, AI governance, and digital competence into a single model. This integrated perspective responds to the need for research that treats AI-enabled BIS as sociotechnical systems rather than as isolated technologies.

Within the present model, readiness, governance, and BIS quality showed statistically significant independent associations with perceived transformation outcomes, whereas perceived AI opportunities did not. However, the overall explanatory power was modest ($R^2 = 0.081$); the model therefore provides a limited rather than comprehensive explanation of AI-enabled transformation.

6.2 Managerial, Professional, and Governance Implications

For managers, the findings suggest that readiness, governance, and BIS quality deserve attention when AI functionalities are introduced or expanded. Organizations may benefit from assessing data reliability, system integration, leadership support, user competencies, governance mechanisms, and the alignment between AI use and business goals. Because the model explained only 8.1% of the variance in perceived outcomes, these implications should be treated as directional rather than prescriptive. A practical starting point is a readiness audit covering digital infrastructure, data quality, leadership support, process maturity, user preparedness, and governance before AI-enabled functions are expanded.

For BIS professionals and IT units, the results emphasize data integration, interoperability, cybersecurity, and explainable reporting. AI-supported decision-making should be designed as human-in-the-loop decision support, especially when outputs affect employees, customers, resource allocation, or strategic priorities. Before scaling AI-enabled functionalities, BIS and IT teams should prioritize interoperability, cybersecurity, auditability, and transparent reporting so that users can understand the source, logic, and limitations of AI-supported outputs.

For governance bodies, governance should be incorporated into the design and implementation of AI-enabled BIS rather than introduced only after problems emerge. Appropriate arrangements include clear accountability, monitoring of AI outputs, human oversight, documentation, risk management, escalation procedures, and human review of consequential AI-supported decisions.

7 LIMITATIONS AND FUTURE RESEARCH

Several limitations should be acknowledged. First, the study used a non-probability design combining purposive and snowball sampling. Initial recruitment began with 120 Slovenian companies selected from the available contact list and reached through publicly available corporate email addresses, but subsequent forwarding of the survey link could not be controlled or enumerated. The available contact list was not a complete national sampling frame. The final sample of 564 respondents is therefore not a representative probability sample, and the findings should not be generalized statistically to all organizational BIS users in Slovenia or to other national contexts. Future studies should use probability-based or stratified sampling frames where such frames can be established.

Second, the multiple regression model explained 8.1% of the variance in perceived digital transformation outcomes, leaving most of the variance unexplained by the included predictors. The statistically significant coefficients for AI readiness, AI governance, and BIS quality were modest and should therefore be interpreted as limited independent associations rather than as key prerequisites or comprehensive determinants of digital transformation.

Third, the study relied on self-reported perceptions. Perceived digital transformation outcomes may differ from objective indicators such as productivity, cycle time, cost reduction, service quality, or innovation performance. Future research should therefore combine survey data with organizational performance indicators.

Fourth, the cross-sectional design does not support causal inference. Longitudinal research is needed to examine how AI readiness, governance, and system quality develop over time and how they are related to subsequent transformation outcomes.

Fifth, AI-enabled BIS are evolving rapidly. Future studies should distinguish among traditional AI, generative AI, business-intelligence augmentation, process automation, and decision-support applications because these technologies may have different organizational effects.

Future studies should validate the measurement scales in independent samples, use probability-based or stratified sampling where feasible, and compare organizational sectors and national settings. Longitudinal designs are needed to examine temporal ordering, while structural equation modeling or partial least squares modeling could test the latent measurement structure and more complex relationships among readiness, governance, BIS quality, and transformation outcomes. Further research should also combine perceptual measures with objective organizational indicators and examine potential moderation or mediation mechanisms, including whether governance conditions the relationship between AI readiness and digital transformation outcomes.

8 CONCLUSION

This study examined the relationships among AI readiness, BIS quality, perceived AI opportunities, perceived AI challenges, AI governance, digital competence, and perceived digital transformation outcomes. In the multiple regression model, AI readiness, AI governance, and BIS quality had statistically significant positive coefficients, whereas perceived AI opportunities, digital competence, and perceived AI challenges were not independently significant.

Taken together, the results identify AI readiness, AI governance, and BIS quality as relevant but modest independent correlates of perceived digital transformation outcomes. The regression model explained 8.1% of the variance, and the non-probability sampling design limits population-level generalization. The findings therefore do not establish these factors as necessary or sufficient conditions for digital transformation. Instead, they identify three organizational dimensions that merit further examination in probability-based, longitudinal, and latent-variable studies. For business informatics, the study supports examining AI-enabled BIS as sociotechnical infrastructures in which people, data, systems, and governance interact with a wider set of organizational and contextual influences.

ADDITIONAL INFORMATION AND DECLARATIONS

Conflict of Interests: The authors declare no conflict of interest.

Author Contributions: B.B.: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft preparation. J.S.: Conceptualization, Supervision, Project administration, Writing – review and editing.

Institutional Review Board Statement: Under the internal rules of the University of Novo mesto, this anonymous, non-interventional questionnaire study did not require prior review or approval by the University's internal ethics committee. Accordingly, no ethics committee application was submitted. No direct personal identifiers were collected.

Informed Consent Statement: Participation was voluntary and anonymous. Respondents were informed that they could discontinue before submitting the questionnaire. No separate signed consent form was required; voluntary completion and submission of the questionnaire constituted informed consent.

Statement on the Use of Artificial Intelligence Tools: Grammarly was used for grammar checking, punctuation correction and language refinement. ChatGPT Pro was used to assist in creating Figures 1 and 2, including the visual

layout of the conceptual and structural models. The authors reviewed, edited and approved all AI-assisted language and visual outputs. No artificial intelligence tool was used to generate research data, statistical results, interpretations or references. The authors take full responsibility for the accuracy, integrity and final form of the manuscript.

Data Availability: Appendix A reproduces the complete question sequence, item wording, response categories, and introductory consent text exactly as administered through 1KA (1ka.si).

APPENDIX A. QUESTIONNAIRE ADMINISTERED THROUGH 1KA PLATFORM

Factors Influencing Digital Transformation Outcomes in AI-Enabled Business Information Systems

The following questionnaire was administered through 1KA (1ka.si). The introductory text shown to respondents stated: "This questionnaire examines organizational users' perceptions of artificial intelligence in business information systems and perceived digital transformation outcomes. Participation is voluntary and anonymous. No names or direct personal identifiers are requested. You may discontinue before submitting the questionnaire. By voluntarily completing and submitting the questionnaire, you indicate consent to participate."

Eligibility statement shown to respondents: "This questionnaire is intended for organizational users who are currently familiar with at least one type of business information system used in organizational work."

Subject: Invitation to Participate in a Study on Artificial Intelligence in Business Information Systems

Dear Participant,

We invite you to participate in a research study examining the use of artificial intelligence in business information systems and the factors associated with digital transformation in organizations.

The survey is intended for employees working in organizations in Slovenia who use business information systems in their work or are familiar with at least one type of business information system used in their organizational environment.

Participation in the study is **voluntary and anonymous**. The questionnaire does not request your name or any other directly identifying personal information. You may discontinue participation at any time before submitting the questionnaire. **By voluntarily completing and submitting the questionnaire, you confirm your consent to participate in the study and to the use of the anonymously collected data for scientific research purposes.**

To reach a broader and more diverse group of organizational users of business information systems, we would also kindly ask you to **forward the survey link to colleagues, professional contacts, or other individuals working in other organizations in Slovenia** who, to your knowledge, use or are familiar with business information systems in their work. Forwarding the invitation will help us achieve broader participation and include a more diverse range of organizational contexts.

Please answer the questions on the basis of your actual experience, perceptions, and knowledge of information systems in your organizational environment. There are no right or wrong answers.

Thank you for your time, participation, and assistance in sharing the survey invitation with other eligible respondents.

Data collection will take place from 1 May 2026 through 11 June 2026. The questionnaire will remain accessible through the 1KA online survey platform throughout this period.

Kind regards,

Boštjan Blažič
Jasmina Starc
University of Novo mesto

Section 1. Demographic and organizational characteristics

Q1. Gender

A. Female

B. Male

C. Other/prefer not to say

Q2. Age group

A. Under 30

B. 30–39

C. 40–49

D. **50 or older**

Q3. Highest level of education

A. Secondary or vocational

B. Bachelor

C. Master

D. Doctorate

Q4. Organizational sector

A. Services

B. Manufacturing

C. Healthcare

D. IT/Telecommunications

E. Education

F. Finance/Banking

G. Public administration

Q5. Organization size

A. Micro (fewer than 10 employees)

B. Small (10–49 employees)

C. Medium (50–249 employees)

D. Large (250 or more employees)

Q6. Current organizational role

A. Professional / expert

B. Manager

C. IT specialist

D. Administrative

E. Operational

Q7. Work experience

A. 0–5 years

B. 6–10 years

C. 11–20 years

D. **21 years or more**

Section 2. Use of business information systems and AI-enabled functionalities

Q8. Which of the following business information systems or AI-enabled functionalities are used in your organization? Select all that apply.

A. Enterprise resource planning (ERP)

B. Customer relationship management (CRM)

C. Human resource information system (HRIS)

D. Business intelligence (BI)

E. Decision-support systems (DSS)

F. Workflow systems

G. AI-supported reporting

H. Chatbots / virtual assistants

Sections 3–9. Study constructs

Response scale for Q9-Q43: 1 = strongly disagree; 2 = disagree; 3 = neither agree nor disagree; 4 = agree; 5 = strongly agree.

Statement	1	2	3	4	5
Section 3. AI readiness					
Our organization has the digital infrastructure required for AI-enabled business information systems.					
Top management supports the implementation of AI-enabled business information systems.					
Employees in our organization are open to AI-supported changes in work processes.					
Our organization is prepared to integrate AI into existing business information systems.					
AI adoption is aligned with our organizational priorities.					
Section 4. Business information system quality					
Our business information systems are reliable in daily work.					
Our business information systems are easy to use.					
Data from different systems are sufficiently integrated.					
Our reporting tools provide information in a useful format.					
Section 5. Perceived AI opportunities					
AI can improve decision-making in our organization.					
AI can automate repetitive business processes.					
AI can improve data analysis and interpretation.					
AI can accelerate reporting and monitoring.					
AI can increase organizational responsiveness.					
AI can support innovation in business processes.					
Section 6. Perceived AI challenges					
Poor data quality is a barrier to AI adoption.					
Cybersecurity risks make AI adoption more difficult.					
Privacy concerns create barriers to AI-enabled business information systems.					

Statement	1	2	3	4	5
Algorithmic bias is a serious challenge in AI-supported decision-making.					
Lack of transparency reduces trust in AI outputs.					
Implementation costs and resistance slow down AI adoption.					
Section 7. AI governance and ethical oversight					
Our organization has clear rules for using AI in business information systems.					
Responsibilities for AI-supported decisions are clearly defined.					
AI-supported outputs are monitored by responsible employees.					
Human oversight is required for important AI-supported decisions.					
Data protection is considered when AI tools are introduced.					
Section 8. Digital competence					
I feel confident using digital tools in my work.					
I can interpret data-based reports in business information systems.					
I understand basic opportunities and risks of AI-supported tools.					
I can critically evaluate AI-supported recommendations.					
Section 9. Perceived digital transformation outcomes					
AI-enabled business information systems can improve organizational efficiency.					
AI-enabled business information systems can improve decision quality.					
AI-enabled business information systems can increase organizational agility.					
AI-enabled business information systems can support innovation.					
AI-enabled business information systems can optimize business processes.					

Section 10. Open-ended questions

Q44 / OE1. What is the most important opportunity of AI in business information systems?

_____

_____

Q45 / OE2. What is the main barrier to responsible AI adoption in business information systems?

_____

_____

Q46 / OE3. What type of support would be most useful for AI-enabled digital transformation?

_____

_____

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