

Artificial Intelligence, Digital Transformation and the Future of Society

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ABSTRACT

Artificial intelligence (AI) is accelerating digital transformation across work, education, healthcare, public administration, communication and everyday decision-making. Yet the social value of this transformation depends not only on technical capability, but also on digital access, human skills, public trust and accountable governance. This article presents a simulated empirical study designed to examine societal readiness for an AI-enabled future. A synthetic, stratified cross-sectional dataset representing 720 illustrative adults across urban, semi-urban and rural settings was generated using reproducible assumptions and five-point scales. The analysis tested the effects of digital access, AI literacy, trust, perceived usefulness, privacy concern, job-displacement concern and support for governance. Simulated results showed an overall societal-readiness mean of 3.35 (SD = 0.70). Urban respondents recorded higher readiness (M = 3.69) than semi-urban (M = 3.32) and rural groups (M = 3.04), $F(2, 717) = 62.70$, $p < .001$, $\eta^2 = .149$. The regression model explained 51.3% of the variance in readiness. Digital access ($\beta = .268$), trust ($\beta = .238$), AI literacy ($\beta = .195$) and perceived usefulness ($\beta = .188$) were the strongest positive predictors, while privacy concern ($\beta = -.090$) and job-displacement concern ($\beta = -.057$) had smaller negative effects. The findings are illustrative rather than population estimates, but they demonstrate a coherent empirical framework for studying how inclusion, capability and governance can shape the future of society. The article concludes that AI policy should combine infrastructure, universal AI literacy, human oversight, transparency and social protection.

Keywords: Artificial Intelligence, Digital Transformation, Society, AI Literacy, Digital Inclusion, Responsible AI.

I. Introduction

Artificial intelligence has moved from a specialized computational field into a general-purpose layer of digital transformation. Machine learning, generative models, computer vision, natural-language processing and automated decision systems are now embedded in commercial platforms, public services and individual workflows. This diffusion is occurring alongside cloud computing, datafication, mobile connectivity and platform-based organization. The result is not a single technological change, but a reconfiguration of how institutions produce knowledge, allocate resources, communicate with citizens and coordinate work. The OECD has therefore treated AI as a societal and economic transformation rather than merely a software innovation (OECD, 2019; OECD, 2024).

The pace of adoption is significant but uneven. OECD data released in 2026 reported that more than one-third of individuals across participating countries used generative AI tools during 2025, while firm-level adoption also expanded rapidly (OECD, 2026). At the same time, the World Bank (2025) emphasized that AI capability depends on access to computing, data, skills and connectivity, all of which remain concentrated across countries, firms and social groups. These differences create a central tension: AI can widen access to expertise and services, yet it can also reproduce existing inequalities when infrastructure, language coverage, affordability or digital competence are weak.

The social consequences extend beyond productivity. AI can support personalized learning, preventive healthcare, accessible public services, scientific discovery and environmental monitoring. It can also create privacy risks, opaque decisions, misinformation, labour-market disruption and new forms of dependency on technology providers. UNESCO's Recommendation on the Ethics of Artificial Intelligence frames these issues around human dignity, rights, fairness, transparency and environmental sustainability (UNESCO, 2021). The European Union's Artificial Intelligence Act similarly establishes a risk-based regulatory approach for the development and use of AI systems (European Parliament and Council, 2024).

This study asks how societal readiness can be understood as a measurable combination of access, literacy, trust, usefulness, concern and governance. Four research questions guide the analysis: (RQ1) How are digital access, AI literacy, trust and perceived usefulness associated with societal readiness? (RQ2) Do privacy and job-displacement concerns reduce readiness? (RQ3) Does support for accountable governance strengthen readiness? and (RQ4) Are there meaningful differences across urban, semi-urban and rural groups? Because no real survey data were supplied, the article uses a transparent simulated dataset. The purpose is methodological and illustrative: to show how a journal-style empirical study could test these relationships without presenting invented findings as real-world evidence.

II. Artificial Intelligence, Digital Transformation and Societal Change

2.1 Work, Productivity and Occupational Change

AI changes work through both automation and augmentation. Task-level evidence suggests that generative AI can improve productivity, especially for less experienced workers, while the distribution of benefits depends on job design, training and managerial practices (Brynjolfsson, Li, & Raymond, 2023). The ILO (2025) reports that clerical and highly digitized professional occupations remain among the most exposed to generative AI. Exposure, however, does not equal job loss: occupations consist of bundles of tasks, and technology can remove, transform or create tasks simultaneously (Acemoglu & Restrepo, 2019). The societal challenge is therefore to align AI deployment with reskilling, worker participation, income security and the creation of meaningful new roles.

2.2 Education and Human Capability

Digital transformation can expand access to tutoring, translation, assessment support and adaptive learning. It can also weaken learning when automated outputs substitute for reflection, or when inaccurate content is accepted without verification. The future of education requires a shift from tool familiarity to AI literacy: understanding model limitations, data provenance, bias, privacy, prompt design, source evaluation and responsible use. Institutions must also preserve teacher judgment and ensure that learners with limited devices, connectivity or language support are not excluded.

2.3 Healthcare, Well-being and Public Services

AI-enabled analytics can support early diagnosis, resource planning, personalized services and administrative efficiency. In public administration, automated systems can improve responsiveness and consistency when data quality and accountability are strong. Yet high-stakes applications require human oversight, contestability and clear responsibility. Errors in welfare eligibility, credit, healthcare or policing can have significant consequences, particularly for individuals who lack the resources to challenge automated decisions.

2.4 Communication, Culture and Democratic Life

Generative systems lower the cost of producing text, images, audio and video. This can enhance creativity, accessibility and local language participation, but it also increases the volume and plausibility of synthetic media. Societies will need stronger provenance systems, media literacy and institutional communication practices to manage misinformation without restricting legitimate expression. The cultural effects are equally important: recommendation systems influence attention, visibility and the economic position of creators, while training-data practices raise questions about consent, attribution and cultural representation.

2.5 Digital Inclusion and Sustainable Transformation

Digital inclusion is not limited to connectivity. It includes affordable devices, reliable infrastructure, accessible interfaces, skills, language coverage, cybersecurity and the ability to obtain redress. Van Dijk (2020) argues that digital inequality evolves through successive differences in motivation, access, skills and usage. AI may amplify each layer because advanced services depend on higher-quality connectivity, computational resources and specialized knowledge. Sustainable transformation also requires attention to energy use, hardware supply chains and the environmental costs of large-scale computing.

Illustrative research model for an inclusive AI-enabled society

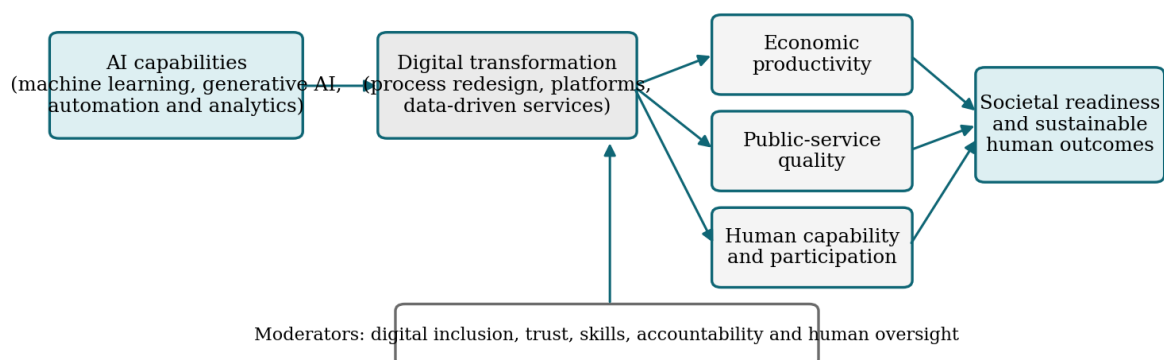


Figure 1. Illustrative conceptual framework linking AI capabilities, digital transformation and societal outcomes.

Note: This framework is an original academic visual created for the simulated study.

III. Literature Review

3.1 Technology Adoption and Readiness

The Technology Acceptance Model proposes that perceived usefulness and ease of use shape technology attitudes and behavioural intentions (Davis, 1989). The Unified Theory of Acceptance and Use of Technology extends this logic through performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). Technology readiness research adds optimism, innovativeness, discomfort and insecurity as individual predispositions (Parasuraman, 2000). Applied to AI, these frameworks imply that adoption depends on both instrumental value and the conditions that allow people to use systems effectively.

3.2 Trust, Ethics and Institutional Legitimacy

Trust in AI is multidimensional. People may trust a system's technical competence while distrusting the organization that deploys it, the data used to train it or the rules governing its decisions. Floridi et al. (2018) proposed beneficence, non-maleficence, autonomy, justice and explicability as foundations for a good AI society. UNESCO (2021) translated related principles into a global policy framework emphasizing proportionality, safety, fairness, privacy, human oversight and accountability. These perspectives suggest that public acceptance is unlikely to be sustained by performance alone.

3.3 Labour-Market Transformation and Distributional Effects

Economic research distinguishes displacement from reinstatement. Automation may reduce demand for certain tasks, while new tasks and complementary roles can restore labour demand (Acemoglu & Restrepo, 2019). Experimental and field evidence on generative AI indicates that productivity gains can be substantial but heterogeneous, often benefiting workers with lower initial experience (Brynjolfsson et al., 2023). The ILO's refined exposure index shows that generative AI increasingly affects specialized professional tasks as well as clerical work (ILO, 2025). Consequently, social outcomes depend on training access, bargaining power, organizational design and the speed at which institutions adapt.

3.4 Digital Divides and Unequal Capacity

Digital transformation can produce cumulative advantage. Individuals and organizations with better connectivity, data, capital and skills are able to adopt more capable systems, generate more data and improve faster. The World Bank's 2025 report highlights the concentration of cloud infrastructure, computing and data resources, while the OECD documents persistent divides by age, education, income and geography (OECD, 2024; World Bank, 2025). These patterns support the inclusion of digital access and AI literacy as core predictors of societal readiness.

3.5 Research Gap and Analytical Model

Existing work frequently examines adoption, ethics, labour or inequality separately. Fewer studies integrate these dimensions into a single readiness model that combines access, literacy, usefulness, trust, risk perception and governance. The present simulated study addresses that gap with an illustrative model. It hypothesizes positive effects for digital access, AI literacy, trust, perceived usefulness and governance support, negative effects for privacy and job-displacement concerns, and higher readiness among groups with stronger digital access.

IV. Methodology

4.1 Research Design and Transparency

A simulated cross-sectional survey design was used. No real participants were recruited and no institution, community or field site is represented. All observations, scale scores and statistical results are synthetic. The design is intended to demonstrate a plausible empirical workflow that can later be replaced with ethics-approved primary data.

4.2 Illustrative Sample

The synthetic sample contained 720 records, balanced across urban, semi-urban and rural residence categories (240 each). Age, gender, education and employment categories were generated with plausible but non-representative distributions. Balancing residence groups allowed direct comparison of access and readiness while avoiding unequal group sizes in the demonstration.

4.3 Measures

Eight constructs were represented by four simulated five-point Likert items each: digital access, AI literacy, trust in AI, perceived usefulness, privacy concern, job-displacement concern, governance support and societal readiness. Higher scores indicated more of the named construct. The readiness scale captured confidence that society can obtain broad benefits from AI while maintaining human agency, fairness and institutional control. Simulated internal-consistency estimates ranged from $\alpha = .734$ to $\alpha = .864$.

4.4 Data-Generation Procedure

Latent construct scores were generated from a correlated multivariate structure with fixed random seed 20260721. Group-specific shifts were applied to digital access and AI literacy to create a plausible urban-rural gradient. Societal readiness was generated as a weighted function of access, literacy, trust, usefulness, privacy concern, job concern and governance support, plus random error. Values were bounded to the one-to-five scale. These assumptions were selected for coherence, not to estimate any actual population.

4.5 Statistical Analysis

The analysis included frequencies, means, standard deviations, Cronbach's alpha, Pearson correlations, one-way analysis of variance and ordinary least-squares regression. Standardized coefficients were used to compare predictor strength. Statistical significance is reported because it is part of the empirical demonstration; it should not be interpreted as evidence about real societies. All figures and tables are explicitly labeled as simulated or illustrative.

V. Simulated Results and Analysis

5.1 Illustrative Sample Profile

Table 1. Simulated sample profile (N = 720).

Characteristic	Category	n (%)
Residence	Urban	240 (33.3)
	Semi-urban	240 (33.3)
	Rural	240 (33.3)
Age	18-24	157 (21.8)
	25-34	212 (29.4)
	35-44	172 (23.9)
	45-54	120 (16.7)
	55-65	59 (8.2)
Gender	Female	352 (48.9)
	Male	353 (49.0)
	Non-binary/Prefer not to say	15 (2.1)
Education	Secondary or below	189 (26.2)
	Diploma	184 (25.6)
	Bachelor	264 (36.7)
	Postgraduate	83 (11.5)
Employment	Student	122 (16.9)
	Employed	405 (56.2)
	Self-employed	108 (15.0)
	Unemployed/Other	85 (11.8)

Note: Counts are generated for illustration and do not describe real participants.

5.2 Reliability and Descriptive Statistics

Table 2. Simulated scale reliability and descriptive statistics.

Construct	Items	Cronbach's α	Mean	SD
Digital access	4	0.864	3.52	0.76
AI literacy	4	0.823	3.22	0.69
Trust in AI	4	0.771	3.20	0.56
Perceived usefulness	4	0.765	3.71	0.58
Privacy concern	4	0.764	3.82	0.56
Job-displacement concern	4	0.766	3.66	0.55
Governance support	4	0.734	3.60	0.49
Societal readiness	4	0.820	3.35	0.70

Note: All variables use a five-point scale. Higher scores indicate more of the named construct.

Perceived usefulness recorded the highest positive orientation ($M = 3.71$, $SD = 0.58$), while societal readiness was moderate ($M = 3.35$, $SD = 0.70$). Privacy concern ($M = 3.82$) and job-displacement concern ($M = 3.66$) were also elevated, indicating that optimism and concern can coexist. Governance support averaged 3.60, suggesting broad preference for oversight, transparency and accountability even among respondents with relatively favourable attitudes toward AI.

5.3 Residence-Based Differences

Societal readiness differed significantly across residence groups, $F(2, 717) = 62.70$, $p < .001$, $\eta^2 = 0.149$. The urban group had the highest mean ($M = 3.69$), followed by semi-urban ($M = 3.32$) and rural respondents ($M = 3.04$). The same ordering appeared for digital access and AI literacy, whereas trust varied less sharply. The pattern supports the interpretation that material access and capability are more uneven than basic public openness to AI.

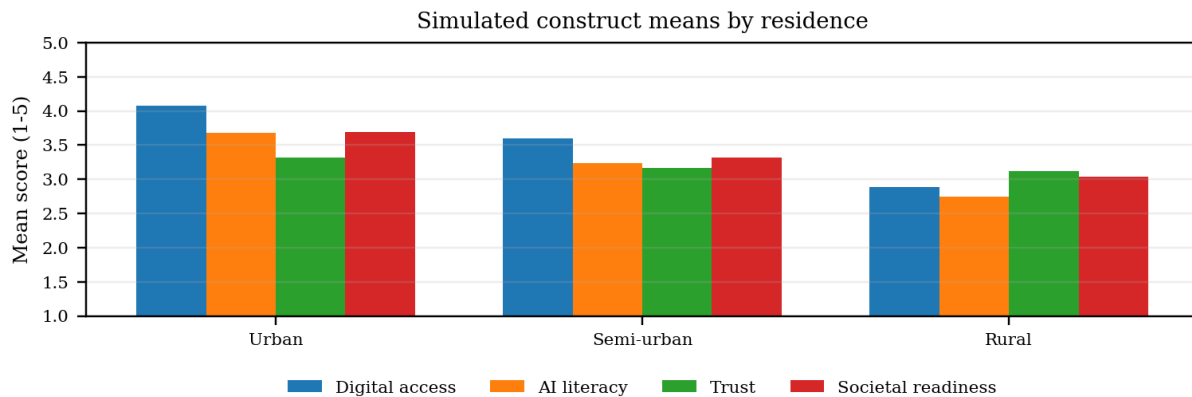


Figure 2. Simulated mean scores for key constructs across residence groups.

Note: Values are synthetic. Error bars are omitted to preserve the compact visual style of the template.

5.4 Correlation Structure

Readiness was positively correlated with digital access, AI literacy, trust, perceived usefulness and governance support. Privacy and job-displacement concerns showed negative associations with readiness and positive associations with one another. The strongest positive relationships occurred among access, literacy and usefulness, consistent with the expectation that facilitating conditions and capability shape perceived value. The correlation matrix also indicates that no pair of predictors was so highly correlated as to make the regression model conceptually redundant.

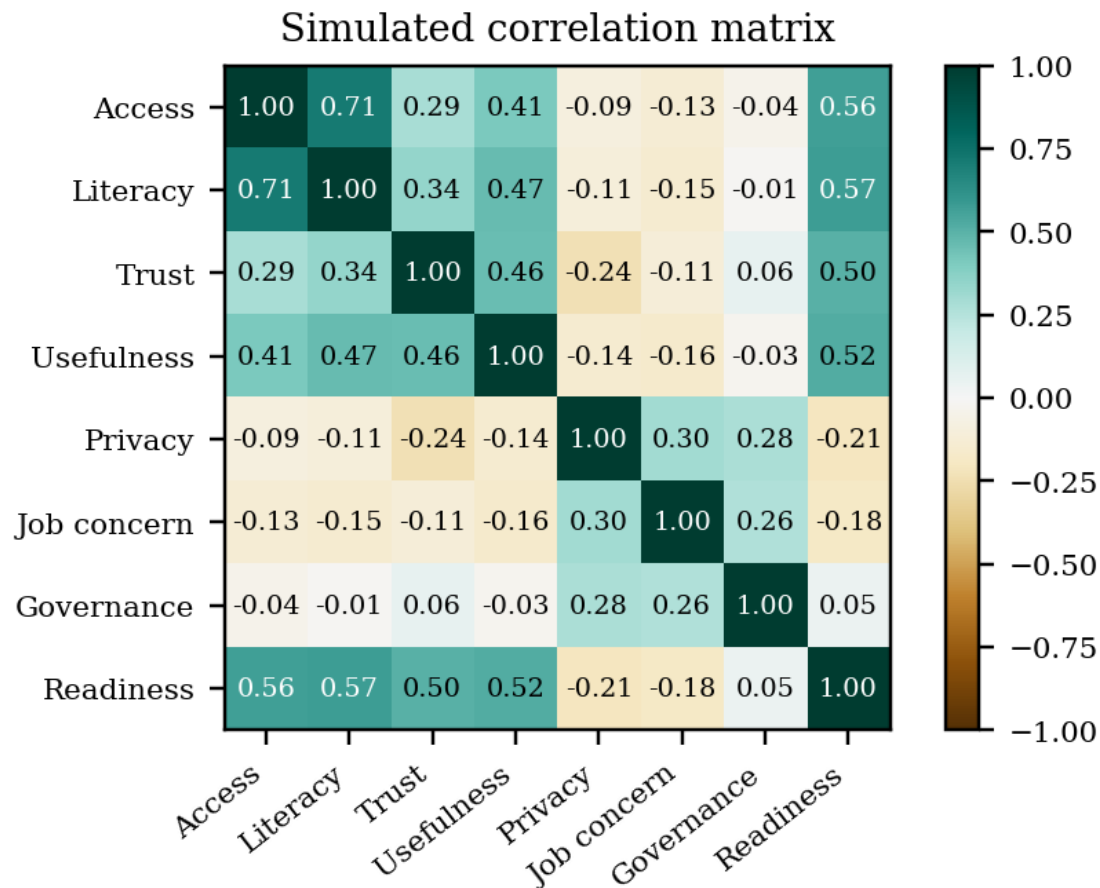


Figure 3. Simulated Pearson correlation matrix for the study constructs.

Note: Correlations are based entirely on the reproducible synthetic dataset.

5.5 Predictors of Societal Readiness

Table 3. Simulated ordinary least-squares regression predicting societal readiness.

Predictor	B	SE	β	t	p
Digital access	0.247	0.035	0.268	7.11	< .001
AI literacy	0.197	0.040	0.195	4.97	< .001
Trust in AI	0.295	0.038	0.238	7.75	< .001
Perceived usefulness	0.227	0.039	0.188	5.85	< .001
Privacy concern	-0.112	0.036	-0.090	-3.13	0.002
Job-displacement concern	-0.072	0.036	-0.057	-2.03	0.043
Governance support	0.133	0.040	0.093	3.31	< .001

Note: $N = 720$. Model $R^2 = 0.513$; adjusted $R^2 = 0.508$; $F(7, 712) = 107.15$, $p < .001$.

The regression explained 51.3% of the simulated variance in societal readiness. Digital access was the strongest standardized predictor ($\beta = .268$), followed by trust ($\beta = .238$), AI literacy ($\beta = .195$) and perceived usefulness ($\beta = .188$). Governance support also contributed positively ($\beta = .093$). Privacy concern ($\beta = -.090$) and job-displacement concern ($\beta = -.057$) had statistically significant but smaller negative effects. The results imply that reducing concern alone would be insufficient; readiness is more strongly associated with enabling people to access, understand and trust AI-enabled systems.

5.6 Perceived Opportunities and Risks

The illustrative opportunity profile placed education and healthcare at the top, followed by public services and economic productivity. Media and information received the lowest benefit rating, reflecting concern about synthetic content and information quality. Misinformation and privacy loss were the highest-rated risks, with algorithmic bias, job displacement and digital exclusion also receiving substantial concern scores. This dual

pattern reinforces the need to evaluate benefits and safeguards together rather than treating optimism and risk awareness as opposites.

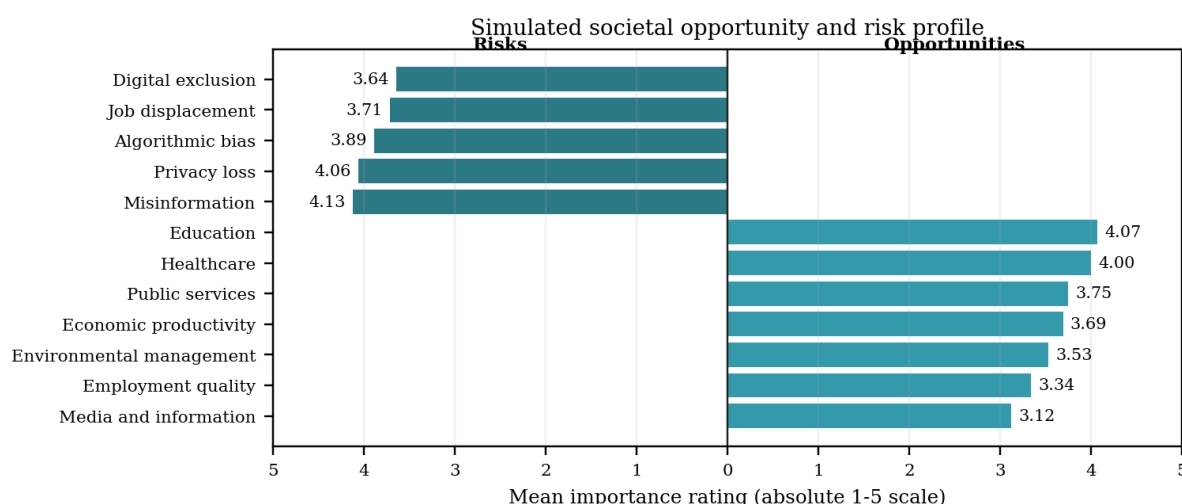


Figure 4. Simulated ratings of societal opportunities and risks associated with AI-enabled transformation.
Note: Opportunity scores appear to the right and risk scores to the left; both use the absolute five-point scale.

VI. Discussion

6.1 Readiness Depends on Capability, Not Exposure Alone

The strongest simulated predictor was digital access, and the largest group differences appeared in access and literacy. This is consistent with the broader literature on digital inequality: the capacity to benefit from technology depends on material access, skills and meaningful use, not merely the availability of a tool (van Dijk, 2020). A society may display high awareness of AI while remaining poorly prepared to use it productively or challenge harmful outcomes. Policy should therefore measure readiness through capability indicators rather than adoption counts alone.

6.2 Trust Is Institutional as Well as Technical

Trust was a stronger predictor than perceived usefulness in the simulated model. This suggests that people may recognize the value of AI but remain uncertain about data practices, accountability and error correction. Trustworthy transformation requires more than explainable models; it requires trustworthy institutions, clear responsibility, accessible appeal mechanisms and evidence that systems improve outcomes without discriminatory effects. The positive effect of governance support indicates that oversight need not be viewed as an obstacle to adoption. It can function as an enabling condition.

6.3 Work Transitions Require Social Infrastructure

Job concern reduced readiness, although its simulated effect was smaller than the positive effects of access, literacy and trust. This pattern is compatible with a task-transformation perspective. People may accept AI when they believe they can adapt and retain agency, even while expecting disruption. Training must therefore be connected to real occupational pathways, worker voice and social protection. Generic digital-skills programmes are unlikely to be sufficient if job redesign and employment security are ignored.

6.4 The Future of Society Is a Governance Choice

AI does not determine a single social future. Its effects emerge from institutional choices about procurement, competition, data rights, education, labour, public infrastructure and democratic accountability. The simulated findings show how a balanced model can capture this interaction: usefulness encourages readiness, concerns restrain it, and access, literacy, trust and governance shape whether people can participate on fair terms. This interpretation aligns with human-centred approaches advanced by UNESCO (2021), the OECD (2019) and risk-based regulation in the European Union (European Parliament and Council, 2024).

VII. Challenges and Future Research Directions

7.1 Bias, Transparency and Contestability

AI systems can reproduce historical patterns embedded in data and organizational practice. Future research should test not only average model accuracy, but also subgroup performance, allocation effects and the accessibility of appeal processes. Transparency should be tailored to users: technical documentation for auditors, operational guidance for professionals and understandable notices for affected individuals.

7.2 Privacy, Security and Data Governance

The expansion of AI increases the value and sensitivity of behavioural, biometric, educational, health and workplace data. Data minimization, purpose limitation, secure infrastructure and meaningful consent should be integrated into system design. Research is also needed on privacy-preserving techniques, federated learning and governance models that give communities a voice in how data are collected and reused.

7.3 Misinformation and Knowledge Integrity

The simulated risk profile identified misinformation as the leading concern. Future studies should examine provenance standards, watermarking, verification tools, platform incentives and the effectiveness of public media-literacy programmes. Institutions should also develop disclosure and citation rules for AI-generated content so that productivity gains do not undermine the traceability of knowledge.

7.4 Concentration, Inclusion and Local Capacity

AI capability is concentrated in firms and countries with access to compute, capital, data and specialized talent. This concentration may create dependency, weaken local innovation and limit representation of smaller languages and communities. Public investment in connectivity, open research infrastructure, local datasets and independent evaluation can help distribute capability more broadly.

7.5 Empirical Validation

The present results are simulated and cannot support claims about any real population. A future empirical study should use validated multi-item scales, probability or carefully stratified sampling, multilingual instruments and confirmatory factor analysis. Longitudinal designs would help distinguish short-term novelty effects from durable changes in trust and readiness. Mixed-method research could also explain why similar levels of access produce different social outcomes.

VIII. Conclusion and Future Work

Artificial intelligence is reshaping digital transformation, but the future of society will depend on how technical capability is combined with human capability and institutional responsibility. This simulated empirical article found that access, trust, AI literacy and perceived usefulness were the strongest positive predictors of societal readiness. Privacy and job-displacement concerns reduced readiness, while support for governance strengthened it. Residence-based differences were driven primarily by unequal access and literacy rather than by extreme differences in trust.

The practical implication is that responsible AI policy should be built around five connected priorities: universal digital infrastructure, lifelong AI literacy, transparent and contestable systems, worker-centred transition policies and accountable public governance. These priorities should be evaluated through real data before conclusions are generalized. The synthetic framework, measures, tables and figures in this article provide a reproducible starting point for such validation while maintaining clear separation between illustrative results and actual empirical evidence.

Declarations

Funding: No funding is claimed for this simulated manuscript.

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

Ethics Statement: No human participants, personal records or real institutions were involved. All data are synthetic; therefore, no ethics approval or informed consent is claimed.

Data Availability: The results were generated from a reproducible synthetic procedure using fixed seed 20260721. No real participant dataset exists.

Author Contributions: [Author Name]: conceptualization, methodology, analysis and writing. [Co-author Name]: supervision, review and editing.

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