Digital Learning as a Predictor of AI Adaptation Readiness: A Logistic Model with Implications for Safe AI Use

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***Abstract*—The rapid diffusion of artificial intelligence (AI) technologies raises fundamental questions about user adaptation and digital competence. This study examines the structural determinants of AI adaptation readiness using a binary logistic regression model applied to a sample of 1,146 respondents. The analysis focuses on informal digital learning, educational content consumption, age, social media use, and daily AI tool usage. The results show that informal digital learning practices and daily AI use are positively associated with high adaptation readiness, while age shows a negative association. In contrast, the intensity of social media use does not independently predict adaptation. The results suggest that AI readiness is primarily competence-based rather than access-based, underscoring the role of learning-oriented digital engagement in supporting more conscious and potentially safer AI use.**

Keywords—Artificial Intelligence; Information Systems

I. Introduction

The rapid spread of artificial intelligence (AI) technologies is transforming the digital environment, labour market expectations and the requirements for individual competences. AI applications are no longer exclusively specialised professional tools, rather, they have become part of everyday digital practice, from content generation to decision support and automated problem solving. In this context, a central question is the extent to which individuals can adapt to AI-based systems, and which social and digital factors structure their adaptability.

AI adaptation should not be interpreted purely as a problem of technological access. The structure of digital competences, informal learning patterns and conscious content consumption can all influence the depth and effectiveness with which individuals integrate AI tools into everyday practices. Skill learning in the social media environment, engagement with educational content, and regular use of AI tools may reflect behavioural patterns that are related to the level of technological adaptation. In addition, age and educational attainment may differentiate adaptation opportunities in terms of generational and human capital dimensions.

The aim of the study is to examine empirically the extent to which these factors contribute to the predictive explanation of AI adaptation readiness. The research is not only aimed at exploring statistical correlations but also develops a classification model that can reliably distinguish between groups with high and low levels of adaptation. This approach is also relevant from a perspective of security science and information security, as differences in adaptation may be potentially related to differences in technological vulnerability and resilience. The study therefore interprets AI use not as an isolated technological phenomenon, but as a structurally embedded digital learning process. Since the present study does not measure direct information security outcomes, the safety-related interpretation is treated as an indirect and exploratory implication of adaptation readiness rather than as an empirically tested security effect. The novelty of the study lies in combining competence-related digital learning variables with a classification-oriented logistic modelling approach to distinguish between low and high AI adaptation readiness groups. The practical benefit of this approach is that it can support educational and organisational decision-makers in identifying user groups that may need additional support before the introduction of AI-based tools.

II. Literature

The rapid expansion of artificial intelligence (AI) technologies in recent years has shed new light on the issues of digital competence, technological adaptation, and societal preparedness. AI-based systems are not only tools, but also complex decision-support and knowledge-generating infrastructures, the use of which requires novel learning patterns and adaptation mechanisms. Accordingly, AI adaptation should not be reduced to a question of technological access but conceptualised as a structurally embedded digital learning and behavioural process.

The literature on AI-driven adaptive learning systems emphasises that the successful technological integration is closely associated with users' learning orientation and digital self-efficacy [1]. Empirical research examining technological readiness points out that AI acceptance is shaped not only by attitudes towards technology, but also by competence-based and structural factors [2]. In an educational context, it has been shown that the use of AI tools correlates positively with learning performance, especially when combined with active and reflective use [3]. Similar results have been obtained by sustainability-focused models examining AI adoption in the context of technological readiness and individual competence levels [4].

Studies conducted in higher education environments based on structural equation modelling indicate that informal digital learning and technological self-efficacy are direct precursors to AI acceptance [5]. Beyond user attitudes and perceived usefulness, regular, practice-oriented AI use is also a determining factor in deepening adaptation [6]. Empirical analysis of student AI adoption has shown that generational and age factors are significant predictors of AI usage intensity [7]. Research on adaptive platforms suggests that the effectiveness of personalised AI environments depends largely on users' digital learning backgrounds [8].

However, the issue of AI adaptation is not limited to the education sector. User readiness emerges as a critical factor in AI adoption [2, 4]. In higher education, the safe and responsible integration of AI is associated with user preparedness and ethical awareness [5, 7].

Taken together, the findings in the literature suggest that AI adaptation is a multidimensional phenomenon: a competence-based, behaviour-oriented and generationally differentiated process. Digital learning activity, technological self-efficacy and habitual AI use together contribute to the development of user readiness. At the same time, most empirical studies are based primarily on attitude – or acceptance – oriented frameworks and less frequently use a predictive classification approach to distinguish between high and low levels of adaptation. The present study contributes to this discourse by modelling AI adoption readiness along digital learning and behavioural variables and evaluating its predictive performance.

III. Research Questions and Methodology

The study aims to empirically examine how adaptation readiness related to artificial intelligence is structured along social and digital behavioural dimensions, and to what extent these factors enable the predictive identification of high adaptation levels. The analysis was based on the theoretical premise that AI adaptation is not merely a question of technological access, but a competence-based process embedded in digital learning patterns. In this study, AI adaptation readiness refers to the individual-level preparedness to integrate AI-based tools into everyday digital practices. It is understood as a behavioural and competence-related construct, reflected in the respondent's AI use, digital learning activity, and ability to engage with AI-related technological change. The concept is therefore examined primarily at the individual and educational level, rather than as an organisational or infrastructural readiness construct. Accordingly, the research examined the relationship between informal digital learning and AI adaptation on the one hand, and the role of age and daily AI tool use on the other and also sought to determine whether these variables together are suitable for statistically sound prediction of the high adaptation group.

The sample consisted of 1,146 respondents recruited through an online questionnaire. The sample included respondents from different age groups, gender categories, and educational backgrounds; however, detailed demographic subgroup analysis was not the primary focus of the present conference paper. The survey included demographic variables such as age, gender, and educational attainment, which were used to describe the background of the respondents and to assess the generalisability of the findings. Since the sample was based on voluntary participation rather than probability sampling, the results should be interpreted as exploratory and not as fully representative of the general population. The dependent variable was a binary indicator of AI adaptation readiness (AI2_bin), where 0 indicated a low level of adaptation and 1 indicated a high level of adaptation. The purpose of binary operationalisation was to enable the creation of a classification model that would allow the separation of high and low adaptation groups in a predictive framework. This binary operationalisation does not imply that adaptation readiness is theoretically a purely dichotomous phenomenon. Rather, the original readiness measure was dichotomised for the specific purpose of classification modelling, where the analytical aim was to identify respondents with clearly higher adaptation readiness. Intermediate levels of readiness are therefore acknowledged conceptually, but they were not modelled separately in the present logistic regression framework. The explanatory variables covered the dimensions of digital learning and demographics. The variables used in the model were coded as follows. AI2_bin denotes the binary indicator of AI adaptation readiness. CMH2 indicates whether the respondent had learned a skill from social media. CMH7 indicates whether the respondent followed educational content. D1 refers to age. T3_cap denotes daily social media use in hours after upper-bound correction. DA4 measures the intensity of daily AI tool use on an ordinal scale. Informal digital learning was measured by a dichotomous variable indicating whether the respondent had learned a skill from social media. Following educational content was also included as a binary variable. Age was included as a continuous variable. Daily social media use was included as a self-reported value expressed in hours, while the intensity of daily AI device use was measured on an ordinal scale. Daily social media use was included not as a direct proxy for AI tool engagement, but as a broader indicator of everyday digital embeddedness. The assumption was that individuals who spend more time in digital communication environments may have more frequent exposure to AI-mediated content, recommendation systems, automated moderation, and digitally circulated learning resources. However, the model also tests whether this general digital exposure remains relevant after controlling for more specific learning-oriented and AI-use variables.

Daily social media use was measured as a self-reported estimate of average hours per day. Extreme self-reported values appeared in this variable, including values exceeding the realistic daily range. To address this, values above 24 hours were winsorised to the theoretical daily maximum of 24 hours. This correction was applied to prevent implausible extreme observations from disproportionately influencing the regression estimates, while preserving the ordinal structure of respondents' reported intensity of use.

Prior to model building, we performed a structural preliminary analysis. We used a chi-square test to examine the relationship between informal learning and following educational content, while the role of age was analysed using non-parametric methods. This step served to verify that AI adaptation is related to digital learning patterns and does not appear as an isolated phenomenon.

The main analysis was based on binary logistic regression, in which we modelled the probability of high adaptation readiness using the above predictors. Model fit was evaluated based on chi-square improvement relative to the null model, Nagelkerke's pseudo-R^2 index, and the Hosmer–Lemeshow test. To examine predictive performance, we used a confusion matrix, accuracy indicators, and ROC analysis, thus evaluating the model not only from an explanatory but also from a classification perspective.

To further examine generational effects, we also estimated an interaction model in which we tested the interaction between the standardised version of age and informal learning. Multicollinearity was checked using variance inflation factors to ensure the stability of the estimates.

The methodological approach thus combined structural pre-analysis and predictive modelling, enabling the joint examination of the social embeddedness and statistical predictability of AI adaptation. The analytical workflow followed six steps: survey data collection, variable coding and cleaning, structural preliminary analysis, binary logistic regression, classification performance evaluation, and interpretation of the results in relation to AI adaptation readiness and potentially safer AI use.

IV. Empirical Results and Model Evaluation

The aim of the empirical study was to explore the extent to which adaptation readiness related to artificial intelligence is statistically associated with informal digital learning, following educational content, age, educational attainment, intensity of social media use, and daily use of AI tools. The analysis was conducted on a sample of 1,146 people.

A. *Structural preliminary analysis*

Before constructing the predictive model, we examined the relationship between informal learning (CMH2) and following educational content (CMH7). The chi-square test showed a significant correlation ($\chi^2 = 44.657$; $df = 1$; $p < 0.001$), suggesting that enrolment and skill learning are not statistically independent phenomena. This result confirms that different forms of digital learning activity are structurally linked. Age showed a significant difference in relation to both variables. According to the Kruskal–Wallis test, there is a strong correlation between informal learning and age ($\chi^2 = 52.595$; $p < 0.001$), while in the case of following educational content, the correlation is weaker but still significant ($\chi^2 = 5.566$; $p = 0.018$). Based on the results, younger age groups participate in informal digital learning at a higher rate and are more likely to follow educational content. The structural preliminary analysis thus supports the interpretation that behavioural variables related to AI adaptation can be understood in the context of digital learning patterns, which provides a basis for further predictive modelling.

B. *Binary logistic regression model*

The dependent variable was AI2_bin (0 = low, 1 = high adaptation readiness). In the logistic model, we modelled the logit of high adaptation probability with the following predictors: CMH2, CMH7, D1 (age), T3_cap (daily social media use adjusted for upper limit correction), and DA4 (daily AI use intensity). The main model showed a significant improvement over the null model ($\chi^2 = 472.905$; $df = 9$, $p < 0.001$). The Nagelkerke R^2 value was 0.463, which is moderately strong explanatory power in social science models. The Hosmer–Lemeshow test showed no fit problems ($\chi^2 = 10.559$; $df = 8$, $p = 0.228$), so the model calibration is adequate. The main characteristics of the statistical model are presented in Table I as follows:

TABLE I. Results of Binary Logistic Regression (AI2 BIN) Source: Own ed.

Vari-able	*B*	*SE*	*p*	*Exp(B)*	*95% CI lower*	*95% CI upper*
CMH2	0.504	0.171	0.003	1.655	1.185	2.313
CMH7	0.227	0.203	0.264	1.255	0.843	1.870
Age (D1)	-0.030	0.007	<0.001	0.970	0.957	0.984
T3_cap	-0.063	0.034	0.064	0.939	0.878	1.004
DA4	1.438	0.093	<0.001	4.210	3.510	5.050

Informal learning significantly increases the likelihood of high adaptation (Exp(B) = 1.655). The strongest predictor is daily AI use, which is associated with a more than fourfold increase in odds (Exp(B) = 4.210). Age shows a negative association with AI adaptation readiness: each additional year is associated with approximately 3% lower odds of high adaptation. Following educational content and the intensity of social media use did not prove to be significant predictors in the overall model, although in the case of social media use, the effect was close to the significance level ($p = 0.064$), which warrants cautious interpretation.

C. *Classification performance and discrimination indicators*

The classification performance of the model was evaluated based on the confusion matrix. Using a decision threshold of 0.5, the model achieved 78.5% overall classification accuracy, which is a significant improvement over the 63.8% rate of the null model. The classification metrics indicate that the model can identify individuals in both the low and high adaptation categories in a balanced manner. The high sensitivity value shows that the model effectively recognises cases of high adaptation, while the adequate specificity level suggests that the classification of the low adaptation group is not systematically distorted. Precision and the F1 score indicate balanced classification performance, which is particularly important in cases of unbalanced class distribution. Based on the ROC analysis, the area under the curve (AUC) fell within the range above 0.80, indicating good discriminatory power. This shows that the model is highly likely to correctly rank individuals based on their readiness to adapt. Cohen's kappa statistic showed moderate strength of agreement, confirming that the classification performance is not merely a consequence of class distribution.

D. Generational moderation

The model extended with a standardised version of age and its interaction with CMH2 did not show a significant interaction ($p = 0.780$). However, the main age-related pattern remained a negative and significant predictor, as it is summarized in the Table II:

TABLE II. INTERACTON MODEL
SOURCE: OWN ED.

Variable	B	SE	p	Exp(B)
CMH2	0.548	0.171	0.001	1.730
StdAge	-0.517	0.169	0.002	0.597
StdAge × CMH2	0.055	0.195	0.780	1.056

Based on the results, the positive association between informal learning and adaptability does not depend significantly on age; learning activity is associated with higher levels of adaptability regardless of generation.

E. Multicollinearity

The VIF values remained below 1.5 for all predictors, which rules out the problem of collinearity and confirms the stability of the estimates. The detailed results of the multicollinearity assessment for the proposed logistic regression model are summarized in Table III.

Overall, the results indicate that AI adaptation readiness is significantly correlated with digital learning activity and regular use of AI tools. The mere intensity of media use alone did not prove to be a determining factor. Based on the model's fit and discrimination indices, adaptation readiness can be meaningfully modelled along social and digital behavioural variables, which provides a relevant analytical framework for security science and information security interpretation.

TABLE III. COLLINEARITY INDICATORS
SOURCE: OWN ED.

Variable	Tolerance	VIF
CMH2	0.905	1.105
CMH7	0.941	1.062
D1	0.673	1.487
T3_cap	0.898	1.113
DA4	0.856	1.168

Having presented a comprehensive overview of the empirical findings, we now proceed to a discussion of their broader implications.

V. DISCUSSION

The findings reinforce the argument that AI adaptation readiness cannot be interpreted merely as a question of technological access but is related to structurally embedded digital learning and behavioural patterns. The model identifies informal digital learning and daily AI tool use as the strongest predictors in the analysis, indicating that adaptation is primarily linked to active participation and practical application, rather than simply presence in the digital environment.

Notably, the intensity of social media use alone did not prove to be a significant factor, whereas learning-related activity did. This pattern implies that AI adaptation is organised along qualitative rather than quantitative dimensions. Mere online presence was not significantly correlated with high levels of adaptation; in contrast, competence-oriented digital engagement showed a statistically significant correlation with adaptation readiness.

The negative association between age and AI adaptation readiness indicates a generational slope in AI adaptation. At the same time, according to the results of the interaction model, the positive association between informal learning and AI adaptation readiness does not depend significantly on age. This suggests that although younger age groups show higher levels of adaptation on average, learning activity is associated with higher AI readiness in all generations. This finding may be relevant from a practical point of view when designing educational and organisational development programmes, as it suggests that competence development can potentially strengthen adaptation capacity regardless of generation.

The explanatory power of the model (Nagelkerke $R^2 = 0.463$), its appropriate calibration and balanced classification performance (78.5% accuracy, AUC above 0.80) indicate that AI adaptation can be meaningfully modelled along social and digital behavioural variables. The moderate kappa statistic supports the notion that the prediction is not merely a consequence of class distribution but reflects a structured pattern.

From a security science and information security perspective, the results provide a framework for interpretation. With the spread of AI applications, differences in adaptation may be potentially related to differences in technological vulnerability. Users who actively learn and regularly use AI tools are likely to have higher digital competence, which may contribute to safer and more conscious use. In contrast, low adaptation groups may be at greater risk of misunderstandings, misuse, or manipulation. However, it is important to emphasise that the present study did not measure direct safety outcomes, so these conclusions are interpretative in nature.

Among the limitations of the study, it should be noted that the analysis is based on cross-sectional data, so causal conclusions cannot be drawn with certainty. Furthermore, the self-report measurement method may distort the assessment of AI use intensity and learning activity. Future research may warrant the use of longitudinal studies and the inclusion of objective usage data to more accurately explore the dynamics of adaptation.

The study contributes to the empirical understanding of the social determinants of AI adaptation and suggests that digital learning behaviour plays a significant role in patterns of technological adaptation. Based on the results, adaptation to AI cannot be interpreted solely as a question of access, but rather as a competence- and participation-based process that is differentiated along structural factors.

VI. Conclusions

The results of the study suggest that AI adaptation readiness cannot be interpreted solely as a question of technological access but shows a significant correlation with structured digital learning and behavioural patterns. Based on the binary logistic model, informal digital learning and daily AI tool use proved to be the strongest predictors, while age showed a negative association with AI adaptation readiness. At the same time, according to the interaction analysis, the positive association between learning activity and AI readiness does not depend significantly on age, which supports the general relevance of the competence-based approach.

The explanatory power and classification performance of the model indicate that AI adaptation can be meaningfully modelled along social and digital behavioural variables. This approach may also be relevant to the discourse on security science and information security, as differences in adaptation may be potentially related to differences in technological vulnerability. Although the present research did not examine direct security outcomes, the results suggest that learning-oriented digital participation may contribute to more conscious and secure use of AI tools.

The study contributes to the empirical understanding of the social embeddedness of AI adaptation by examining the role of digital learning and behavioural factors in a predictive framework. Based on the results, adaptation to AI can be understood not only as a process of tool use, but also as a competence- and participation-based process that is differentiated along structural factors. Future research may warrant the use of longitudinal and behaviour-based measurement methods to explore the dynamics of adaptation in greater depth and to examine security dimensions directly and empirically. The practical value of the proposed approach is that it offers a simple classification-oriented framework for identifying user groups that may require additional educational support before the introduction of AI-based tools.

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