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Lecturers' pathways to integrating artificial intelligence in business and economics curricula

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A B S T R A C T

Objective: This article aims to identify the factors affecting business and economics lecturers' inclusion of artificial intelligence (AI) in the curricula.

Research Design & Methods: We applied a quantitative approach to test a research model based on the theory of planned behaviour. We used partial least squares structural equation modelling to verify hypotheses using a sample of 133 university lecturers from business and economics.

Findings: The study reveals that key background factors, including prior AI education and prior AI use, indirectly contribute to the inclusion of AI in the curricula. AI education contributed by enhancing lecturers' cognitive attitudes and self-efficacy and AI use only contributed through self-efficacy. Contrary to expectations, previous instances of AI integration in teaching have had an insignificant influence on the inclusion of AI into the curriculum.

Implications & Recommendations: The inclusion of AI in business and economics university teaching is a precondition for equipping graduates with skills expected in the job market. Based on the findings of this study, two paths seem to be particularly helpful in achieving this objective: improving lecturers' attitudes via AI education and improving their self-efficacy through personal AI use.

Contribution & Value Added: The contribution of this study consists of identifying the factors that influence lecturers' intentions to incorporate AI into their curricula. Shedding light on these determinants can guide higher education policies and support the development of strategies to promote the effective incorporation of AI into current teaching programmes.

Article type:	research article
Keywords:	artificial intelligence; higher education; curriculum; theory of planned behaviour; business education
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INTRODUCTION

Artificial intelligence (AI) is a field that combines the science and engineering of creating intelligent systems and machines (Sarker, 2022). These systems are designed to perform intricate human cognitive tasks, including problem-solving, pattern recognition, language understanding, and decision-making (Hassani *et al.*, 2020). The recent rise in interest in AI was fueled by the introduction of large language models like Generative Pre-trained Transformer (ChatGPT), sparking fears of AI replacing human labour. The challenge of substituting human work with information and communication technologies is not new, though, as it has already taken place in less creative industries (Zhang *et al.*, 2023). That said, Usabiaga *et al.* (2022) argue that the risk of automation is lower for non-routine jobs, yet these are most likely to require Information and Communication Technology (ICT) skills. Therefore, we may assume that managers will soon expect employees to possess AI skills (Ratten, 2024), making those who possess such skills more competitive in the labour market and less likely to be substituted by technology. This phenomenon is not limited to the ICT sector but extends to other areas, notably higher education. Hence, it is reasonable to ask if higher education institutions (HEIs) are ready to meet this challenge and adopt AI courses in their offering.

According to Bewersdorff *et al.* (2023), learners display numerous misconceptions about AI, potentially leading to limited use. Therefore, developing AI literacy programmes is indispensable (Kong *et al.*, 2023). Notwithstanding the need for such a general cognitive AI literacy, Hornberger *et al.* (2023) highlight the heterogeneous nature of students' needs in terms of AI education and recommend developing AI education that would respond to these diverse needs. This is further supported by Nyale *et al.* (2024), whose review on the alignment between AI higher education programmes underscores the role of digital skills for graduates' employability. In this study, we considered the issue of introducing AI education at the university level, specifically for the fields of business and economics.

Although some understanding of the technical background of AI is undoubtedly of value irrespective of the student's background, linking AI teaching with specific applications in business requires an understanding of business and economics topics. Artificial intelligence is a transdisciplinary topic (Tsao *et al.*, 2024), although its inclusion in curricula cannot be limited to the common core. Therefore, the implementation of AI education tailored to the needs of business/economics students requires that at least part of this education is undertaken by lecturers with subject expertise. Here, it is important to understand pathways that lead business/economics lecturers to offer AI-oriented courses or implement AI topics in business/economics curricula.

The theory of planned behaviour (TPB) (Ajzen, 1991) provides a theoretical framework for explaining this problem, where its three explanatory variables, attitude towards the behaviour, subjective norms, and perceived control, are extended by prior knowledge and exposure of lecturers to AI. The aim of this study is to explore the factors that lead business/economics lecturers to develop intentions towards implementing AI-oriented courses or topics into business/economics curricula. Despite the increasing interest in AI applications in education (O'Dea, 2024), research is yet to fully uncover the adoption of more advanced deep learning technologies within educational contexts (Roy *et al.*, 2022). Hmoud *et al.* (2023) noted the slow pace of technological innovation adoption in higher education contexts (unlike other sectors) and called for more studies exploring potential triggers. Chatterjee and Bhattacharjee (2020) raised the need for further research on AI adoption at the individual level, where students, educators, and administrators are key stakeholders. Mohd Rahim *et al.* (2022) added that attempts to tackle AI adoption at the individual level should draw on information system theories. While the issue of AI adoption, even if understudied, has been the subject of empirical studies, including quantitative approaches, the question of integrating AI into university teaching curricula has received much less attention. Therefore, the focus on educators as a primary stakeholder and their inclusion of AI topics in the curriculum constitutes an important contribution of this article, as most prior works focused on general AI adoption as a tool. Furthermore, this study contributes by taking a quantitative approach informed by a solid theoretical background, while extant studies on the topic tend to rely on specific cases, such as that of the University of Florida, which embarked on integrating AI into its curricula (Southworth *et al.*, 2023). The contribution of this study consists in uncovering the triggers of lecturers' behavioural intentions to integrate AI into their teaching content. This can inform higher education policies and help develop adequate support measures, fostering the integration of AI into existing teaching programmes.

The article is organised in the following way. First, the theoretical framework provides an overview of the theory of planned behaviour, followed by formulated hypotheses. The next section presents methods. Finally, we present and discuss the survey results conducted among university lecturers of business /economics.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The TPB (Ajzen, 1991) is among the most prominent theories explaining and predicting human behaviour. Its primary purpose is to predict human behaviour by linking behaviour with its intentions and deriving intentions from an individual's beliefs about the behaviour, namely attitude towards the behaviour, subjective norms, and perceived behavioural control. TPB is rooted in a socio-cognitive approach to human behaviour whereby personal cognition and social pressure contribute to human behaviour. The model has been applied in various contexts, including health-related decisions, technology adoption, sexual behaviour, or physical exercise (Ajzen, 2020). Scholars have also applied it in education-related studies (Knauder & Koschmieder, 2019), including ones dealing with the adoption of technology in learning-related situations either by teachers (Watson & Rockinson-Szapkiw, 2021) or, more frequently, by students (Budhathoki *et al.*, 2024; Strzelecki, 2024). Although other theoretical frameworks, such as technology acceptance model (Davis *et al.*, 1989) and unified theory of acceptance and use of technology UTAUT (Venkatesh *et al.*, 2003) have been more popular than TPB in the context of technology adoption, they seem less relevant for our context where the outcome involved inclusion of AI into curricula rather than AI's adoption.

The basic premise of TPB concerns the relationship between an individual's beliefs and behaviour, mediated by behavioural intentions. The explanatory variables involve attitude (positive or negative evaluation) towards the behaviour, subjective norms 'perceived social pressure to perform or not to perform a behaviour' and perceived behavioural control (PBC), which 'refers to the perceived ease or difficulty of performing the behaviour' (Ajzen, 1991, p. 188). More importantly, the model assumes the presence of antecedents of these beliefs, known as background variables, which shape behavioural intentions via the three core constructs (Ajzen, 2020). The inclusion of such relevant background factors can deepen our understanding of the behaviour and its drivers (Ajzen & Fishbein, 2005, p. 197). While the extant literature often overlooks these factors (Onjewu *et al.*, 2022), Ajzen (2011) urged scholars to recognise the important role of background factors in forming the intention and leading to subsequent behaviour. In studies linked to technology and AI, background factors include basic knowledge of the technology (Sanusi *et al.*, 2024), access to professional development (training and education), perceived usefulness, and ease of use (Foulger *et al.*, 2021). In this study, we did not include perceived usefulness and ease of use as background variables since self-efficacy and attitudes, treated as core constructs, overlap with these constructs. As for access to professional development, it was captured through AI-related education and self-education, which capture different forms of professional learning. Regarding basic knowledge, this is captured through participants' prior experience using AI, which provides a good proxy for their basic understanding of the technology. We discuss the selection of background factors in the corresponding section.

Furthermore, the integration of implementation intentions into the TPB framework offers a valuable perspective in understanding the transition from intentions to actions, a critical aspect in the context of adopting AI in business curricula. Implementation intentions involve specific plans about when, where, and how to perform a behaviour (Gollwitzer, 1999). By formulating concrete action plans, academicians can bridge the gap between their intention to integrate AI into their teaching and the actual execution of this integration. This approach is especially crucial in educational settings where the successful adoption of new technologies like AI requires not only positive attitudes and perceived social support but also clear, actionable strategies to implement these technologies effectively.

The Core Predictors of AI Inclusion

According to the TPB, behavioural intentions are determined by attitudes towards the behaviour, subjective norms, and perceived behavioural control, in our case, proxied by self-efficacy, which is considered as largely overlapping in meaning with PBC (Newman *et al.*, 2019). Positive links between these antecedents and behavioural intentions have been widely confirmed in various studies, including those from the field of education. For example, Lenski *et al.* (2019) reported positive and significant relationships between intentions and all three antecedents in the context of a competency-based approach to instruction, demonstrating that PBC plays the most significant role. Lee *et al.* (2010) found the TPB antecedents to be significant predictors of the intention to use educational technology, while Knabe (2012) found the TPB to explain the intention to teach public relations online. Dunn *et al.* (2018) noted a significant relationship between the TPB antecedents and teachers' intention to engage in professional learning supporting math teaching standards.

Furthermore, a few studies demonstrate the applicability of TPB in explaining the introduction of both methods and content in teaching practice, although with varied outcomes. Sadaf and Gezer (2020) found that attitude towards the behaviour, but not subjective norms or perceived behavioural control, explains teachers' intention to include digital literacy in their teaching. Foulger *et al.* (2021) reported that the TPB factors predicted teachers' candidates' intentions to integrate technology into classroom instructions. Similar findings were obtained by Habibi *et al.* (2023), who applied a modified TPB model to study technology integration for teaching practice among pre-service teachers. They demonstrated that out of the three core TPB antecedents, all of which were significant, PBC showed the highest effect size. Based on a student sample from Korea, Jo (2023) found a positive impact of attitudes and subjective norms, yet a surprisingly trivial role of PBC in shaping the intention to apply AI-related tools. In turn, Lenart *et al.* (2025), based on a Polish student sample, found a positive role of Attitudes for AI use intentions.

Overall, the empirical evidence suggests that TPB is well-suited both in the context of AI and to explain lecturers' intentions concerning integrating new methods and new content in teaching. Therefore, we expected that such antecedents would explain the intentions of university lecturers to include AI in their teaching curricula. Based on this, we hypothesised:

H1(a): A positive attitude towards AI enhances lecturers' intention to include AI in the curricula.

H1(b): Subjective norms vis-à-vis AI enhance lecturers' intention to include AI in the curricula.

H1(c): Lecturers' self-efficacy for AI enhances lecturers' intention to include AI in the curricula.

The Role of Background Factors in Driving AI Adoption

The theory of planned behaviour assumes the presence of background factors that may affect behavioural intention via the three core TPB antecedents. Background factors may include, among others, demographic variables (including education), individual personality (including emotions), and societal variables (including political and economic situation). The relevance of background factors may depend on particular circumstances and behaviours. In this regard, Bae *et al.* (2020) found that prior knowledge about sports had a positive impact on attitude towards sports participation and intention to participate in sports. In a business context, it has been shown that education about behaviour, such as entrepreneurship behaviour, contributes to developing behavioural intentions via TPB antecedents, such as self-efficacy (Nowiński *et al.*, 2019).

Regarding technology-related behaviours, prior knowledge is a background factor that has a positive influence on attitude and behavioural control. Rejali *et al.* (2023) found that prior knowledge concerning fully automated vehicles increased positive attitudes and behavioural control regarding such vehicles. As for educational settings, Tschannen-Moran and Hoy (2007) argued that teachers' self-efficacy beliefs were linked with mastery experiences (satisfaction with past teaching success) for experienced teachers and other factors like teaching resources and interpersonal support being more prominent among less experienced teachers. Habibi *et al.* (2023) linked behavioural intentions to integrate technology into teaching practice with technological pedagogical content knowledge. Technology perceptions related to familiarity with the technology were regarded as contributing factors to attitudes towards including technology in teaching (Shiau & Chau, 2016; Foulger *et al.*, 2021). In the context of AI and teaching practice, Sanusi *et al.* (2024) investigated factors affecting pre-service teachers' intentions to learn AI. They found that having basic knowledge about AI had a positive effect on their self-efficacy perceptions. Kohnke *et al.* (2023) found that familiarity with AI and AI-related training can be important for integrating AI into teaching practice.

Based on the above, it becomes apparent that background factors related to knowledge and learning about the behaviour have relevance for the behaviour, and this can occur via TPB antecedents. Here, we argue that prior AI-related education can positively affect behavioural intentions via two of the three TPB antecedents, namely, attitude towards the behaviour and self-efficacy. This is important because lecturers may feel overwhelmed, not having sufficient knowledge about AI technologies (Walter, 2024). We also argue that prior experience of using AI would serve as a source of experiential education for the lecturers, increasing their AI-related knowledge and positively affecting their attitudes towards the inclusion of AI in the business curricula and their respective self-efficacy perceptions. Furthermore, it is widely accepted that past behaviours affect future behaviours, which is at least partially mediated via TPB antecedents (Ajzen, 2002). Various studies have shown such a link between prior exposure to certain behaviour and intentions to adopt that behaviour. For example, scholars found that prior work in a family business positively affects future entrepreneurial intentions by shaping their TPB antecedents (Carr & Sequeira, 2007; Onjewu *et al.*, 2022). Thus, it is reasonable to expect that prior experience with AI-related teaching would positively affect implementation intentions to include AI in the business curricula. Against this backdrop, it was reasonable for us to hypothesise the following:

H2(a): Prior experience with teaching involving AI enhances lecturers' intention to include AI in the curricula, via enhancing their positive attitudes and self-efficacy.

H2(b): Prior use of AI tools enhances lecturers' intention to include AI in the curricula, via enhancing their positive attitudes and self-efficacy.

H2(c): Education (including self-education) about AI enhances lecturers' intention to include AI in the curricula, via enhancing their positive attitudes and self-efficacy.

Figure 1 summarises the hypotheses.

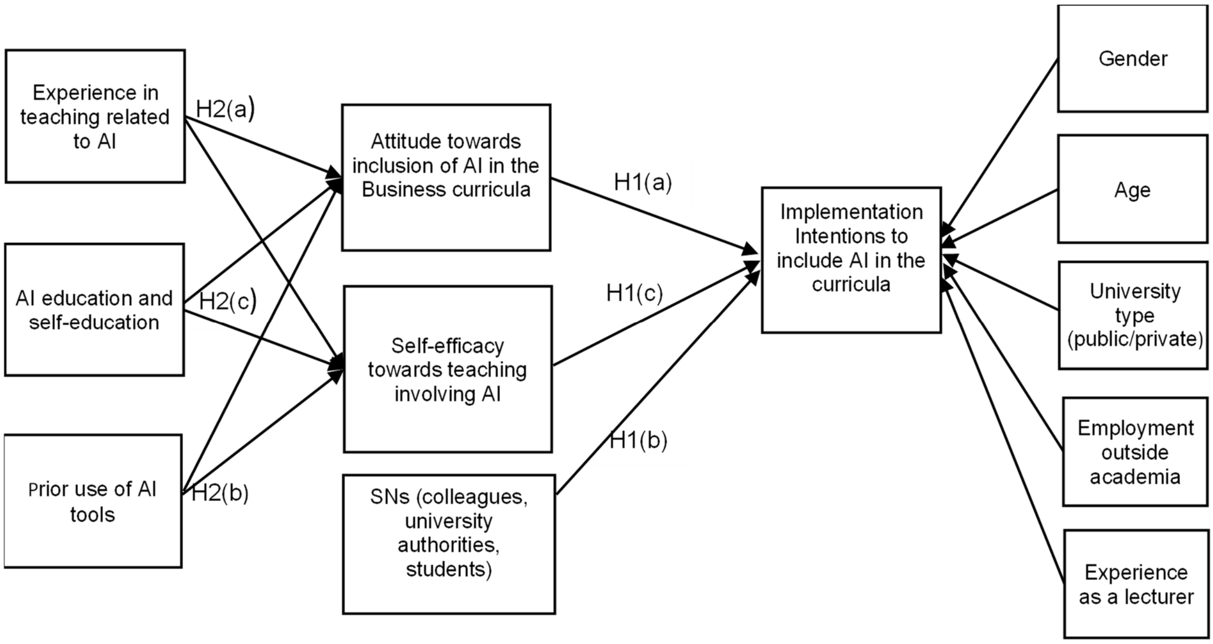

Figure 1. Theoretical framework

Source: own elaboration.

RESEARCH METHODOLOGY

Data Collection

Over the period spanning from June 2023 to September 2023, we collected a cumulative dataset comprising 136 responses from business and economics lecturers, conducted via an online survey using KoBoToolbox (Harvard Humanitarian Initiative, n.d.). We distributed the survey via email to university lecturers. We sent invitations to email addresses available on the Internet. We considered the sample size adequate according to Cohen's (1992) power table, a standard reference in partial least squares structural equation modelling (PLS-SEM) studies for determining the minimum sample size needed based on model complexity, desired statistical power, and significance level. In this case, since the current model comprises three variables affecting a construct, a minimum sample size of 124 is necessary to detect an R^2 of at least 0.10 with a power level of 0.80 and a significance level of 5%. The main focus was on business/economics lecturers from Central and Eastern Europe, including Poland, the Czech Republic, Slovakia, and Hungary, and we undertook efforts to include lecturers from at least two universities per country. Three respondents indicated a different country than the four mentioned Visegrad countries, which we could explain by temporary employment in the region. We excluded these three respondents, leaving 133 respondents in the analysed sample. The predominant part of the sample consisted of participants located in Poland, constituting 87 responses (65.4%), followed by 25 respondents from the Czech Republic (18.8%), which was related both to the size of the business/economics lecturer community and to access to email addresses in these countries. Although we made efforts to target lecturers from different universities and fields in the business/economics realm, we must be cautious regarding their representativeness. In total, 90% of the respondents were employed in public universities or business schools. Only a minority, approximately 28%, had teaching experience in subjects related to AI or in areas incorporating AI elements. Table 1 presents further details about the demographics of the respondents, their expertise in AI, and their relevant experience.

Measures

One can apply TPB across diverse contexts (Ajzen, 2020) where individuals make decisions. Nonetheless, to remain valid, individual constructs need to be adapted to a given behaviour. Therefore, in this study, the attitudes (measured with two items) refer to the positive or negative sentiments held by business and economics lecturers towards AI as a topic for business/economics education. Subjective norms (measured with three items) represent the degree of approval from close peers for a decision to incorporate AI-oriented courses or topics into business/economics curricula. We measured self-efficacy (akin to perceived behavioural control) with three items. It refers to business/economics lecturers' perception of their capacity to incorporate AI-oriented courses or topics into business/economics curricula. We measured implementation intentions with two items reflecting planning and activities towards the inclusion of AI in the curricula. Learning (education) around the topic of AI was measured with three items. We measured all items of the above-mentioned constructs on a 5-point Likert scale. The rest of the variables were single items, either binary (gender, experience in AI-related teaching, university type) or used an ordinal scale (age, teaching experience). As for the exposure to AI tools it was conceptualised as a formative construct and measured with four items. The appendix presents a complete list of items.

RESULTS AND DISCUSSION

To test the study hypotheses, we adopted a PLS-SEM approach through the Smart PLS 4 software (Ringle *et al.*, 2022). We deemed this variance-based approach suitable for this study due to the complexity of the tested model and the greater predictive power in comparison to covariance methods (Hair *et al.*, 2017). Our model is inherently complex due to the presence of multiple indirect relationships involving mediating variables across seven constructs. This complexity makes PLS-SEM an appropriate technique as it is suitable for handling intricate models with multiple layers of relationships, particularly when theory is still developing or evolving, as is the case with AI integration in education. Moreover, the PLS-SEM is particularly advantageous for the study purpose, because it focuses on maximising explained variance in the dependent variable. This approach aligns well with our aim to predict the drivers of academics' intention to adopt AI in curricula. Two steps exist in PLS-SEM, namely measurement and structural models. The former refers to the relationships between the latent constructs and their items, whereas the latter captures the relationships between the latent constructs.

Measurement Model

We assessed reliability and validity in the measurement model as per Hair *et al.'s* (2016) guidance. For reflective variables, reliability is checked through two indicators, composite reliability (CR) and Cronbach's alpha (α). Here, the variables should exhibit a score greater than 0.7. Validity comprises two types, convergent and discriminant validity. Convergent validity is assessed through the items' loadings and the average variance extracted (AVE). Both should be 0.5 or higher. As for discriminant validity, it is inspected through the square roots of AVE (Table 3). Following Fornell and Larcker's (1981) criterion, those values should be higher than the ones on the diagonal. Moreover, collinearity should be checked to ensure no major issues in this regard. This is inspected through the variance inflation factor (VIF), which should be less than 5. Table 2 showcases the findings for reliability and validity. Regarding collinearity, all VIF values were less than 5.

Table 1. Research sample characteristics

Control variables	Response	N	%
Country of residence	Poland	87	65.4
	Czech Republic	25	18.8
	Hungary	12	9.0
	Slovakia	9	6.8
Field of Teaching	Finance	15	11.3
	Economics	47	35.3
	Marketing	21	15.8
	HR management	4	3.0
	Logistics and production	9	6.8
	Management	37	27.8
Gender	Male	75	56.4
	Female	56	42.1
Age range	20-30 years	4	3.0
	31-40 years	39	29.3
	41-50 years	53	39.8
	51-60 years	18	13.5
	61 years or older	19	14.3
Work	Public university	120	90.2
	Private university	13	9.8
Job title	A full-time lecturer focused on teaching	9	6.8
	A full-time lecturer – both teaching and doing research	117	88.0
	A part-time lecturer	7	5.3
Years of teaching experience at university	Less than 5 years	9	6.8
	5-10 years	24	18.0
	11-15 years	22	16.5
	More than 15 years	78	58.6
Are you currently employed outside academia?	No	90	67.7
	Yes, I run my own business	18	13.5
	Yes, I am employed in business	4	3.0
	Yes, I am employed in public/local administration	13	9.8
	Yes, other	9	6.8
Previous teaching experience related to AI	Yes	37	27.8
	No	96	72.2
Previous exposure (application) of AI tools (in education or elsewhere)			
Chatbot	Yes	55	41.4
	No	78	58.6
ChatGPT	Yes	90	67.7
	No	43	32.3
Automatic translators	Yes	111	83.5
	No	22	16.5

Source: own study.

Table 2. CR, α, AVE, and VIF

Indica-tor	Previous AI Teaching	AI Education	Prior AI Use	SE	ATT	SNs	AI Implementation Intention
CR	Single Item	0.879	Formative	0.940	0.854	0.896	0.945
α	Single Item	0.795	Formative	0.904	0.660	0.836	0.884
AVE	Single Item	0.711	Formative	0.841	0.747	0.747	0.897

Note: SE – self-efficacy (towards teaching involving AI); ATT – attitude (towards the inclusion of AI in the Business curricula); SNs – subjective norms.
Source: own study in Smart PLS 4.0.

Table 3. Square roots of AVE

Variables	AI_E	Age	Att	Exper.	Gender	IIs	P_AI_T	E_o_A	SE	SNs	Univ.
AI education	0.843										
Age	0.033	1									
Attitude	0.516	-0.079	0.865								
Experience	-0.171	0.533	-0.138	1							
Gender	-0.111	-0.201	0.059	-0.135	1						
IIs	0.696	-0.032	0.545	-0.101	-0.013	0.947					
Previous AI teaching	0.545	0.004	0.239	-0.103	-0.028	0.428	1				
Empl. outside academia	0.278	-0.086	0.219	-0.031	-0.143	0.174	0.134	1			
SE	0.724	-0.073	0.394	-0.116	-0.197	0.631	0.437	0.168	0.917		
SNs	0.254	-0.163	0.384	-0.125	0.021	0.291	0.156	0.014	0.196	0.869	
Univ.	0.111	0.281	-0.008	0.141	-0.183	0.021	0.078	0.145	0.114	0.203	1

Note: IIs – implementation intentions [to include AI in the curricula]; SE – self-efficacy; SNs – subjective norms; Univ. – University; P_AI_T – Previous AI teaching [experience]; E_o_A – Employment outside academia.
Source: own study in Smart PLS 4.0.

Structural Model

Table 4 illustrates the results of the structural model, which captures the hypothesised links. To begin

Table 4. Structural model results and indirect effects

Direct Effects	Sample mean (M)	P values
AI education -> Attitude	0.541	0.000
AI education -> SE	0.519	0.000
AI use -> Attitude	0.058	0.889
AI use -> SE	0.709	0.000
Age -> IIs	0.090	0.255
Attitude -> IIs	0.292	0.001
Experience -> IIs	-0.014	0.831
Gender -> IIs	0.156	0.220
Previous AI teaching -> Attitude	-0.140	0.459
Previous AI teaching -> SE	0.163	0.207
Empl. outside academia -> IIs	0.112	0.475
SE -> IIs	0.514	0.000
SNs -> IIs	0.108	0.206
University type ->IIs	-0.251	0.265
Indirect effects	**Sample mean (M)**	**P values**
AI education -> Attitude -> IIs	0.159	0.007
AI education -> SE -> IIs	0.268	0.000
AI use -> Attitude -> IIs	0.017	0.896
Previous AI teaching -> Attitude -> IIs	-0.040	0.484
AI use -> SE -> IIs	0.365	0.000
Previous AI teaching -> SE -> IIs	0.083	0.204

Source: own study in Smart PLS 4.0.

with, the path analysis reveals that SE is driven by AI Education ($\beta = 0.519$, $P \leq 0.01$) and AI Prior Use ($\beta = 0.709$, $P \leq 0.01$), whereas ATT is influenced by AI Education only ($\beta = 0.541$, $P \leq 0.01$). In turn, both ATT and SE hold a positive and significant influence on AI Implementation Intention (β = 0.292, 0.514, $P \leq 0.01$), but SNs do not. None of the control variables had a significant relationship with Implementation Intention.

As for the indirect effects, AI Education held a positive and significant indirect effect on AI Implementation Intention through both SE and ATT (β = 0.268, 0.159, $P \leq 0.01$). As for Prior AI use, it had a positive, significant indirect effect on AI Implementation Intention through SE only ($\beta = 0.365$, $P \leq 0.01$) and not ATT. In contrast, the indirect influence of Previous AI teaching on AI Implementation Intention failed to materialise. Therefore, we found support for H1a and H1c but not for H1b. Moreover, we rejected H2a, found partial support for H2b, and support for H2c. Overall, the model explains 52.3% of AI Implementation Intention.

Discussion

This study has uncovered the mechanism underlying business lecturers' inclusion of AI in university curricula. While extant works have explored the adoption of AI in various contexts as a tool, scholars have overlooked its inclusion into the higher education curricula. Responding to calls for a better understanding of AI applications in education (Roy *et al.*, 2022; Fernández-Batanero *et al.*, 2023; Hmoud *et al.*, 2023), this study offers novel insights on the factors triggering business lecturers' inclusion of AI in their teaching content. Leveraging the TPB framework, this study uncovered the important role of background factors, including prior AI use and prior AI education. Self-efficacy is driven by AI education and AI prior use, whereas Attitude is influenced by AI education only. Surprisingly, we found that previous teaching with AI tools plays a non-significant role, while subjective norms did not lead to AI inclusion.

Findings on the role of TPB factors are consistent with prior research on the adoption and integration of technology in teaching. Shiau and Chau (2016) reported significant effects of attitudes and PBC (akin to self-efficacy) on the intention to use cloud computing classrooms. Similarly, PBC (Habibi *et al.*, 2023) and self-efficacy (Wang *et al.*, 2021) were reported to play a significant role in explaining intentions to integrate technology into teaching practice. However, unlike earlier studies (Habibi *et al.*, 2023; Sadaf & Gezer, 2020; Shiau & Chau, 2016), our findings found subjective norms to play a trivial role. This is interesting, especially since AI has recently received significant attention in the media, and anecdotal evidence suggests that it has become a subject of intense discussion among university faculty and university governing bodies. Nonetheless, it seems that the influence of close peers does not directly affect implementation intentions. Perhaps, this is because the attention of higher education institutions has focused on regulatory issues (Korseberg & Elken, 2024) and not so much on embedding AI in the curricula. The observed trivial effect of subjective norms might also be, to some extent, explained by a very strong effect of self-efficacy. According to La Barbera and Ajzen (2020), the effect of subjective norms often becomes less pronounced and even insignificant at high levels of PBC/SE. The impact of cultural environment might also play a role, as subjective norms may have a more pronounced role in technology adoption in collectivistic societies (Zhao *et al.*, 2020).

Interestingly, the results diverge from what was found in the context of university students' use of AI. In this regard, Jo (2023) showed a surprisingly trivial role of perceived behavioural control. Thus, it seems that while students are prone to experimenting with AI tools even when their self-efficacy concerning AI tools is low, the faculty, especially when teaching is concerned, perceive their AI skills as much more important. It suggests that both the sample and the context in which AI implementation is studied may have important consequences for the obtained results.

Moving forward to the effect of background factors, the extant findings reveal that the prior use of AI tools has a strong positive impact on self-efficacy but not on attitude towards the inclusion of AI in teaching. This is consistent with Horowitz Kahn *et al.'s* (2023) findings concerning the impact of familiarity with AI on the acceptance and willingness to use this technology. However, the observed lack of significant impact on attitude towards including AI in the curricula is not entirely consistent with those studies that combine TPB with the technology acceptance model (TAM), where perceived utility (PU) and perceived ease of use (PEOU) are regarded as antecedents of both positive attitudes towards the behaviour and PBC/self-efficacy (Shiau & Chau, 2016; Teo *et al.*, 2016). Simultaneously, our results provide support for qualitative findings on the preparedness of language instructors for AI (Kohnke *et al.*, 2023), highlighting the relevance of familiarity with AI tools in identifying ways to employ them in teaching.

Surprisingly, prior experience in teaching involving AI does not have a positive impact on self-efficacy or attitude. Here, we may provide two potential explanations. On the one hand, prior coverage of AI applications in business may not affect lecturers' self-efficacy due to the pace at which the field of AI is expanding. On the other hand, self-efficacy is a perceptual measure of personal skills and thus may be subject to over-optimism biases when new technologies are concerned. Such over-optimism is particularly likely among those with limited exposure to the topic.

Lastly, prior AI education has a positive influence on both self-efficacy and attitudes. This finding aligns with some prior studies that show educational efforts aimed at teachers to increase their technology-related self-efficacy. Specifically, Lee and Lee (2014) demonstrated that pre-service teachers' self-efficacy beliefs for technology integration increased after completion of the technology course. Similarly, prior studies based on the TPB framework, although in a different context, indicated that context-specific education significantly affects behavioural intentions via its impact on self-efficacy (Nowiński *et al.*, 2019). We may also compare the current findings to those of Aslan and Zhu (2016), who found a significant effect of both perceived ICT competence and perceived competence in integrating ICT into lessons on the actual integration of ICT into teaching practices. It is also consistent with a recent study of Chai *et al.* (2024), who uncovered the instrumental role of AI knowledge in AI teaching intentions in Chinese primary and secondary schools.

On a general level, our findings concur with research indicating the importance of teacher ICT education for incorporating ICT in the educational process (Tondeur *et al.*, 2018). However, when considering practical implications, we should also note contextual differences. While in the case of general ICT skills, these can be provided by means of fairly standard training, training opportunities in such a dynamic field as AI are less available. Therefore, the inclusion of AI in the curricula may require much more personal involvement on behalf of the lecturers and more contextualised training (Luckin *et al.*, 2022) than with more mature technologies.

CONCLUSIONS

This study provides probably the first assessment of university teachers' intentions to implement AI in their teaching curricula. Based on the theoretical foundations of TPB, it sheds light on the antecedents of the inclusion of AI in teaching, demonstrating that context-specific self-efficacy perceptions and attitudes towards the behaviour are significantly related to the implementation intentions. Surprisingly, despite substantial attention paid to AI, a trivial role of subjective norms is found. At the same time, the study reveals background factors that contribute to self-efficacy and attitudes, with the role of prior teacher education and the use of AI tools being related to self-efficacy, as well as a significant role of education for attitudes. Interestingly, the prior inclusion of AI in teaching did not contribute to self-efficacy or attitudes.

The study's theoretical implications concern TPB's applicability for future research on integrating emerging technologies into business and economics education. In terms of practical implications, the study points to the importance of the lecturer's self-efficacy shaped by technology education and technology use. Given the rapid rise of AI and the urgent need for student education in this respect, implementing train-the-trainer programmes should occur as soon as possible to prepare students entering the workforce for the AI revolution (Walter, 2024). Moreover, the dynamic nature of technological advancement calls for stronger and mutual ties between academia and business (Schaeffer *et al.*, 2021), which could help university lecturers stay current with their field-specific AI developments. This would enable them to offer more relevant, context-specific AI instruction, particularly crucial when the focus is on AI application rather than its technical development. To conclude, in light of growing concerns about AI's impact on employment, we cannot overstate the importance of embedding field-specific AI education in university curricula.

Lastly, this study is not without limitations. First and foremost, the sample was not representative and limited to business and economics university lecturers from Central and Eastern Europe. While non-probability sampling and a limited number of respondents constitute an important limitation, it is worthwhile to note that few studies addressing technology in (higher) education have relied on active lecturers due to challenges related to data collection. To overcome this limitation in the future, we recommend involving important external stakeholders in the data collection process, such as the Ministry responsible for Higher Education, which could encourage broader participation in future surveys. As for the theoretical model and construct measures being applied, future studies could use more elaborate measures of lecturer education and familiarity with AI. Lastly, an extension of this research into other contexts, such as other education levels and fields other than business economics, would certainly be welcome. Finally, it is important to highlight that our model indicates more than 45% unexplained variance. We may attribute this to possible omitted variables, including institutional policies and external technological pressures. Thus, we call for future research to incorporate additional variables at both organisational and environmental levels to enhance explained variance.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-t

Ajzen, I. (2002). Residual effects of past on later behavior: Habituation and reasoned action perspectives. *Personality and Social Psychology Review*, *6*(2), 107-122. https://doi.org/10.1207/S15327957PSPR0602_02

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology & Health*, *26*(9), 1113-1127. https://doi.org/10.1080/08870446.2011.613995

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(4), 314-324. https://doi.org/10.1002/hbe2.195

Ajzen, I., & Fishbein, M. (2005). The influence of attitudes on behavior. In D. Albarracín, B. Johnson, & M. Zanna (Eds.), *The handbook of attitudes* (pp. 173-222). Lawrence Erlbaum Associates.

Aslan, A., & Zhu, C. (2016). Influencing factors and integration of ICT into teaching practices of pre-service and starting teachers. *International Journal of Research in Education and Science*, *2*(2), 359-370.

Bae, J., Won, D., Lee, C., & Pack, S.M. (2020). Adolescent participation in new sports: Extended theory of planned behavior. *Journal of Physical Education and Sport*, *20*, 2246-2252. https://doi.org/10.7752/jpes.2020.s3301

Bewersdorff, A., Zhai, X., Roberts, J., & Nerdel, C. (2023). Myths, mis-and preconceptions of artificial intelligence: A review of the literature. *Computers and Education: Artificial Intelligence*, *4*, Article 100143. https://doi.org/10.1016/j.caeai.2023.100143

Budhathoki, T., Zirar, A., Njoya E.T., & Timsina, A. (2024). ChatGPT adoption and anxiety: A cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT). *Studies in Higher Education*, *49*(5), 831-846. https://doi.org/10.1080/03075079.2024.2333937

Carr, J.C., & Sequeira, J.M. (2007). Prior family business exposure as intergenerational influence and entrepreneurial intent: A theory of planned behavior approach. *Journal of Business Research*, *60*(10), 1090-1098. https://doi.org/10.1016/j.jbusres.2006.12.016

Chatterjee, S., & Bhattacharjee, K.K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*, 3443-3463. https://doi.org/10.1007/s10639-020-10159-7

Chai, C.S., Liang, S., & Wang, X. (2024). A survey study of Chinese teachers' continuous intentions to teach artificial intelligence. *Education and Information Technologies*, *29*(11), 14015-14034. https://doi.org/10.1007/s10639-023-12430-z

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*(1), 155-159.

Davis, F.D., Bagozzi, R.P., & Warshaw, P.R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982-1003.https://doi.org/10.1287/mnsc.35.8.982

Dunn, R., Hattie, J., & Bowles, T. (2018). Using the theory of planned behavior to explore teachers' intentions to engage in ongoing teacher professional learning. *Studies in Educational Evaluation*, *59*, 288-294. https://doi.org/10.1016/j.stueduc.2018.10.001

Fernández-Batanero, J.M., Montenegro-Rueda, M., Fernández-Cerero, J., & López Menéses, E. (2023). Adoption of the Internet of things in higher education: opportunities and challenges. *Interactive Technology and Smart Education*, *21*(2), 292-307. https://doi.org/10.1108/ITSE-01-2023-0025

Fornell, C., & Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.2307/3151312

Foulger, T.S., Buss, R.R., & Su, M. (2021). The IT2 survey: contextual knowledge (XK) influences on teacher candidates' intention to integrate technology. *Educational Technology Research and Development*, *69*(5), 2729-2760. https://doi.org/10.1007/s11423-021-10033-4

Gollwitzer, P.M. (1999). Implementation intentions: Strong effects of simple plans. *American Psychologist*, *54*(7), 493-503. https://doi.org/10.1037/0003-066X.54.7.493

Habibi, A., Riady, Y., Samed Al-Adwan, A., & Awni Albelbisi, N. (2023). Beliefs and knowledge for pre-service teachers' technology integration during teaching practice: An extended theory of planned behavior. *Computers in the Schools*, *40*(2), 107-132. https://doi.org/10.1080/07380569.2022.2124752

Hair Jr, J.F., Hult, G.T.M., Ringle C.M., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage.

Hair Jr, J.F., Matthews, L.M., Matthews, R.L., & Sarstedt, M. (2017). PLS-SEM or CB-SEM: updated guidelines on which method to use. *International Journal of Multivariate Data Analysis*, *1*(2), 107-123. https://doi.org/10.1504/IJMDA.2017.087624

Harvard Humanitarian Initiative (n.d.) KoBoToolbox [Computer software]. Retrieved from https://www.kobotoolbox.org/ on May 15, 2023.

Hassani, H., Silva, E.S., Unger, S., TajMazinani, M., & Mac Feely, S. (2020). Artificial intelligence (AI) or intelligence augmentation (IA). *What is the future? AI*, *1*(2), 143-155. https://doi.org/10.3390/ai1020008

Hmoud, H., Al-Adwan, A.S., Horani, O., Yaseen, H., & Al Zoubi, J.Z. (2023). Factors influencing business intelligence adoption by higher education institutions. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(3), Article 100111. https://doi.org/10.1016/j.joitmc.2023.100111

Hornberger, M., Bewersdorff, A., & Nerdel, C. (2023). What do university students know about artificial intelligence? Development and validation of an AI literacy test. *Computers and Education: Artificial Intelligence*, *5*, Article 100165. https://doi.org/10.1016/j.caeai.2023.100165

Horowitz, M.C., Kahn, L., Macdonald, J., & Schneider, J. (2023). Adopting AI: How familiarity breeds both trust and contempt. *AI & Society*, *39*(4), 1721-1735. https://doi.org/10.1007/s00146-023-01666-5

Jo, H. (2023). Decoding the ChatGPT mystery: A comprehensive exploration of factors driving AI language model adoption. *Information Development*, Advance online publication. https://doi.org/10.1177/02666669231202764

Knabe, A.P. (2012). Applying Ajzen's theory of planned behavior to a study of online course adoption in public relations education. (Publication No. 186) [Doctoral dissertation, Marquette University]. E-Publications@Marquette, https://epublications.marquette.edu/dissertations_mu/186

Knauder, H., & Koschmieder, C. (2019). Individualized student support in primary school teaching: A review of influencing factors using the theory of planned behavior (TPB). *Teaching and Teacher Education*, *77*, 66-76. https://doi.org/10.1016/j.tate.2018.09.012

Kohnke, L., Moorhouse B.L., & Zou, D. (2023). Exploring generative artificial intelligence preparedness among university language instructors: A Case Study. *Computers and Education: Artificial Intelligence*, *5*, Article 100156. https://doi.org/10.1016/j.caeai.2023.100156

Kong, S.C., Cheung, W.M.Y., & Zhang, G. (2023). Evaluating an artificial intelligence literacy programme for developing university students' conceptual understanding, literacy, empowerment and ethical awareness. *Educational Technology & Society*, *26*(1), 16-30. https://doi.org/10.30191/ETS.202301_26(1).0002

Korseberg, L., & Elken, M. (2024). Waiting for the revolution: how higher education institutions initially responded to ChatGPT. *Higher Education*. https://doi.org/10.1007/s10734-024-01256-4

La Barbera, F., & Ajzen, I. (2020). Control interactions in the theory of planned behavior: Rethinking the role of subjective norm. *Europe's Journal of Psychology*, *16*(3), 401. https://doi.org/10.5964/ejop.v16i3.2056

Lee, J., Cerreto, F.A., & Lee, J. (2010). Theory of planned behavior and teachers' decisions regarding use of educational technology. *Educational Technology & Society*, *13*(1), 152-164. Retrieved from https://www.j-ets.net/collection/published-issues/13_1 on December 23, 2023.

Lee, Y., & Lee, J. (2014). Enhancing pre-service teachers' self-efficacy beliefs for technology integration through lesson planning practice. *Computers & Education*, *73*, 121-128. https://doi.org/10.1016/j.compedu.2014.01.001

Lenart, R., Sypniewska, B.A., Chen, J., & Janowski, K. (2025). Antecedents of students’ behavioural intention to use generative artificial intelligence: Quantitative research. *Entrepreneurial Business and Economics Review*, *13*(1), 7-21. https://doi.org/10.15678/EBER.2025.130101

Lenski, A.E., Richter, D., & Lüdtke, O. (2019). Using the theory of planned behavior to predict teachers’ likelihood of taking a competency-based approach to instruction. *European Journal of Psychology of Education*, *34*, 169-186. https://doi.org/10.1007/s10212-017-0356-7

Luckin, R., Cukurova, M., Kent, C., & du Boulay, B. (2022). Empowering educators to be AI-ready. *Computers and Education: Artificial Intelligence*, *3*, Article 100076. https://doi.org/10.1016/j.caeai.2022.100076

Mohd Rahim, N.I., Iahad, N.A., Yusof, A.F., & Al-Sharafi, M.A. (2022). AI-based chatbots adoption model for higher-education institutions: A hybrid PLS-SEM-neural network modelling approach. *Sustainability*, *14*(19), Article 12726. https://doi.org/10.3390/su141912726

Newman, A., Obschonka, M., Schwarz, S., Cohen, M., & Nielsen, I. (2019). Entrepreneurial self-efficacy: A systematic review of the literature on its theoretical foundations, measurement, antecedents, and outcomes, and an agenda for future research. *Journal of Vocational Behavior*, *110*, 403-419. https://doi.org/10.1016/j.jvb.2018.05.012

Nowiński, W., Haddoud, M.Y., Lančarič, D., Egerová, D., & Czeglédi, C. (2019). The impact of entrepreneurship education, entrepreneurial self-efficacy and gender on entrepreneurial intentions of university students in the Visegrad countries. *Studies in Higher Education*, *44*(2), 361-379. https://doi.org/10.1080/03075079.2017.1365359

Nyale, D., Karume, S., & Kipkebut, A. (2024). A comprehensive analysis of the role of artificial intelligence in aligning tertiary institutions academic programs to the emerging digital enterprise. *Education and Information Technologies*, 1-20. https://doi.org/10.1007/s10639-024-12743-7

O’Dea, X. (2024). Generative AI: Is it a paradigm shift for higher education?. *Studies in Higher Education, 49*(5), 811-816. https://doi.org/10.1080/03075079.2024.2332944

Onjewu, A.K.E., Haddoud, M.Y., Tony-Okeke, U., Cao, D., & Nowiński, W. (2022). Dissecting the effect of family business exposure on entrepreneurial implementation intention. *International Journal of Entrepreneurial Behavior & Research*, *28*(6), 1438-1462. https://doi.org/10.1108/IJEBR-05-2021-0350

Ratten, V. (2024). Artificial intelligence: Building a research agenda. *Entrepreneurial Business and Economics Review*, *12*(1), 7-16. https://doi.org/10.15678/EBER.2024.120101

Rejali, S., Aghabayk, K., Esmaeli, S., & Shiwakoti, N. (2023). Comparison of technology acceptance model, theory of planned behavior, and unified theory of acceptance and use of technology to assess a priori acceptance of fully automated vehicles. *Transportation Research Part A: Policy and Practice*, *168*, Article 103565. https://doi.org/10.1016/j.tra.2022.103565

Ringle, C.M., Wende, S., & Becker, J.-M. (2022). *SmartPLS 4 [Computer software]. SmartPLS*. Retrieved from https://www.smartpls.com on May 3, 2023.

Roy, R., Babakerkhell, M.D., Mukherjee, S., Pal, D., & Funilkul, S. (2022). Evaluating the intention for the adoption of artificial intelligence-based robots in the university to educate the students. *IEEE Access*, *10*, 125666-125678. https://doi.org/10.1109/ACCESS.2022.3225555

Sadaf, A., & Gezer, T. (2020). Exploring factors that influence teachers’ intentions to integrate digital literacy using the decomposed theory of planned behavior. *Journal of Digital Learning in Teacher Education*, *36*(2), 124-145. https://doi.org/10.1080/21532974.2020.1719244

Sanusi, I.T., Ayanwale, M.A., & Tolorunleke, A.E. (2024). Investigating pre-service teachers’ artificial intelligence perception from the perspective of planned behavior theory. *Computers and Education: Artificial Intelligence*, *6,* Article 100202. https://doi.org/10.1016/j.caeai.2024.100202

Sarker, I.H. (2022). AI-Based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems. *SN Computer Science*, *3*(2), Article 158. https://doi.org/10.1007/s42979-022-01043-x

Schaeffer, P.R., Guerrero, M., & Fischer, B.B. (2021). Mutualism in ecosystems of innovation and entrepreneurship: A bidirectional perspective on universities' linkages. *Journal of Business Research*, *134*, 184-197. https://doi.org/10.1016/j.jbusres.2021.05.039

Shiau, W.L., & Chau, P.Y. (2016). Understanding behavioral intention to use a cloud computing classroom: A multiple model comparison approach. *Information & Management*, *53*(3), 355-365. https://doi.org/10.1016/j.im.2015.10.004

Southworth, J., Migliaccio, K., Glover, J., Golver, J. Reed, D., McCarty, C., … & Thomas, A. (2023). Developing a model for AI across the curriculum: Transforming the higher education landscape via innovation in AI literacy. *Computers and Education: Artificial Intelligence*, *4*, Article 100127. https://doi.org/10.1016/j.caeai.2023.100127

Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *49*(2), 223-245. https://doi.org/10.1007/s10755-023-09686-1

Teo, T., Zhou, M., & Noyes, J. (2016). Teachers and technology: Development of an extended theory of planned behavior. *Educational Technology Research and Development*, *64*, 1033-1052. https://doi.org/10.1007/s11423-016-9446-5

Tondeur, J., Aesaert, K., Prestridge, S., & Consuegra, E. (2018). A multilevel analysis of what matters in the training of pre-service teacher's ICT competencies. *Computers & Education*, *122*, 32-42. https://doi.org/10.1016/j.compedu.2018.03.002

Tsao, J., Kochhar-Lindgren, G., & Lam, A.M.H. (2024). Institutionalising a transdisciplinary curriculum: assemblages, territories, and refrains. *Higher Education*. https://doi.org/10.1007/s10734-024-01250-w

Tschannen-Moran, M., & Hoy, A.W. (2007). The differential antecedents of self-efficacy beliefs of novice and experienced teachers. *Teaching and Teacher Education 23*(6), 944-956. https://doi.org/10.1016/j.tate.2006.05.003

Usabiaga, C., Núñez, F., Arendt, L., Gałecka-Burdziak, E., & Pater, R. (2022). Skill requirements and labour polarisation: An association analysis based on Polish online job offers. *Economic Modelling*, *115*, Article 105963. https://doi.org/10.1016/j.econmod.2022.105963

Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425-478. https://doi.org/10.2307/30036540

Walter, Y. (2024). Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, *21*(1), 15. https://doi.org/10.1186/s41239-024-00448-3

Wang, Y., Liu, C., & Tu, Y.F. (2021). Factors affecting the adoption of AI-based applications in higher education. *Educational Technology & Society*, *24*(3), 116-129. https://www.jstor.org/stable/27032860

Watson, J.H., & Rockinson-Szapkiw, A. (2021). Predicting preservice teachers' intention to use technology-enabled learning. *Computers & Education*, *168*, Article 104207. https://doi.org/10.1016/j.compedu.2021.104207

Zhang, D., Peng, G., Yao, Y., & Browning, T.R. (2023). Is a college education still enough? The IT-labor relationship with education level, task routineness, and artificial intelligence. *Information Systems Research, 35*(3), 992-1010. https://doi.org/10.1287/isre.2021.0391

Zhao, Y., Wang, N., Li, Y., Zhou, R., & Li, S. (2020). Do cultural differences affect users' e-learning adoption?. *British Journal of Educational Technology, 52*(1), 20-41. https://doi.org/10.1111/bjet.13002

Appendix:

Table A. Construct operationalisation

TPB Construct	Item/ Survey Question
Attitude towards the inclusion of AI in the business curricula	Artificial intelligence is an important topic for business education.
	It is not possible to teach students who major in business studies without referring to artificial intelligence.
Self-efficacy towards teaching involving artificial intelligence	I have sufficient knowledge about artificial intelligence to include artificial intelligence in my courses.
	I could handle adding artificial intelligence-related content to my courses without much effort.
	I am knowledgeable enough about artificial intelligence applications to discuss these issues with my students.
Subjective Norms	A decision to include artificial intelligence in my teaching would have been approved by my university colleagues.
	A decision to include artificial intelligence in my teaching would have been approved by my university authorities/managers.
	A decision to include artificial intelligence in my teaching would have been approved by my university students.
AI-related education and self-education	I have been regularly following publications on artificial intelligence applications in business.
	I have attended workshops or seminars to increase my knowledge about artificial intelligence and its applications in business.
	I have devoted significant time to learning about artificial intelligence and its business applications.
Implementation Intentions to include AI in the curricula	I have started planning the inclusion of artificial intelligence content in my courses.
	I have started collecting teaching materials concerning artificial intelligence applications.
Prior AI experience	Have you ever taught any courses related to artificial intelligence, or that included a component related to artificial intelligence?
Prior AI use	Have you ever applied the following artificial intelligence tools (in education or elsewhere)? Chatbot, Chat GPT, Automatic translators, other AI

Source: own study.

Authors

The contribution share of the authors was as follows:
Witold Nowiński (40%) – conceptualization, methodology, investigation, formal analysis, writing – the original draft, review and editing, Mohamed Yacine Haddoud (35%) – conceptualization, methodology, formal analysis, writing – the original draft, review, and editing, Julien Issa (25%) – conceptualization, data curation, formal analysis, writing – the original draft

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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