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Teachers' Intention to Adopt AI Assisted Lesson Planning in Bangladesh

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ABSTRACT

AI for lesson planning opens up a new range of possibilities for developing learning objectives, learning activities, differentiated content and assessment questions. Willingness to use the tools depends upon teachers' perceptions of their instructional value; ease of use; the nature of the intervention in relation to their professional expectations; available support; and control over pedagogical decisions. This study analyzes these relationships, using an extension of the Unified Theory of Acceptance and Use of Technology with the inclusion of professional autonomy. Measuring six constructs, the 24 agreement items were completed by 360 eligible respondents and analysed using partial least squares (PLS) structural equation modelling. The result of the measurement assessment showed that each indicator had satisfactory reliability, internal consistency, convergent, and discriminant. All five hypothetised positive relationships were supported by bootstrap inferences based on 5000 resamples. The results showed that the most significant path coefficient (standardized) was performance expectancy ($\beta = 0.294$), social influence ($\beta = 0.097$), effort expectancy ($\beta = 0.119$), facilitating conditions ($\beta = 0.2255$), and professional autonomy ($\beta = 0.268$). The 31.36% of the variance in behavioural intention was accounted for by the combination of the predictors. All four intention indicators achieved their positive predictive relevance in repeated cross validation, and the prediction errors were less than those of the linear model benchmark. The results suggest that the intention to adopt is related to the expected pedagogical advantage, readiness for adoption and preservation of professional autonomy. Institutional strategies should showcase sound planning applications, offer reachable support, and ensure that the AI offers suggestions which are clearly meant for teachers to review, adapt, or dismiss.

INTRODUCTION

Lesson planning links curriculum expectations to the practice of teaching. In this, teachers must be able to identify the learning outcomes that are intended, list the contents of the subject, choose the activities and prepare for the different abilities of learners and how the learning will be evaluated. A number of decisions involve procedural work and professional judgement. A lesson outline must be well structured, but flexible enough to provide instruction directions and be sensitive to the specific class (Adelana *et al.*, 2024). The use of AI to make suggestions could be applicable at various phases of this process, and this makes the decision to allow AI into teachers' work and authority over this practice relevant.

AI-assisted lesson planning includes here the use of AI tools to assist in planning lesson aims, lesson plans, class activities, lesson materials, differentiated tasks, and assessment questions. This can be as simple as suggesting an activity, to offering other ideas to explain a tricky subject. The teacher then decides on the accuracy of the suggestion, its appropriateness and usefulness. This definition puts AI in the context of a teacher-led planning process. It also sets a baseline to compare adoption intention among the respondents with varying degrees of adoption experience (Al-Abdullatif, 2024).

The respondents of the teaching context in Bangladesh in this study are from all levels of education, categories of institutions, subjects and geographic divisions. This diversity implies that the adoption will depends, not only on personal interest but also on professional circumstances, hence the question about the intention to adopt. There are varied access to appropriate devices, connectivity, training & practical support for teachers. Permission may also vary, from explicit to uncertainty about the appropriate use in institutional situations. Considering how the perceived benefits, the enabling conditions, and professional decision making are interrelated, offers a structured framework into which the intentions in the above circumstances can be considered (An *et al.*, 2023).

The issue of professional autonomy is relevant in particular as lesson planning is an expression of pedagogical responsibility. Teachers determine which examples are suitable, which activities can be carried out and which assessment questions are relevant to the learning outcomes. An AI suggestion might be helpful but need a great deal of context. Intention to adopt may thus be greater when teachers believe that they can make decisions about a lesson, rather than simply follow up on ideas and concepts generated by others (Ashoori Tootkaboni & Maghsoudi, 2025). In this present study, autonomy is regarded as a measurable expectation of control over AI assisted planning.

The central organising framework used is the Unified Theory of Acceptance and Use of Technology. Performance expectancy reflects the extent to which an

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improvement in performance is expected for planning. The effort expectancy takes into account the ease with which the tools can be learned and used. Social influence relates to others' approval in the professional arena, including from colleagues, academics and others who are important to the student (Ballenas & Lasco, 2024). Facilitating conditions are resources, knowledge, and assistance. This framework is extended to professional autonomy, which involves the teachers' expectations to maintain control over the content and teaching strategies when using AI suggestions.

The model looks at a person's intention to behave in the next six months. This will include a concrete anticipated outcome instead of a blanket EOI. The questionnaire items include plans to use AI tools for lesson preparation in the past two months, as well as intention, planning, and effort to use them in the next two months. The separate recording of previous experience enables the analysis to differentiate between respondents' backgrounds and the constructs. The model that emerges reviews the conditions that contribute to the expression of future intentions to adopt within a specified professional task (Cabero-Almenara *et al.*, 2024).

This study has three related objectives. The second is to examine the relationships among the four constructs related to Technology Acceptance and teachers' behavioural intentions to adopt AI assisted lesson planning. The second is to look at the further connection between professional autonomy and intention. The third is to analyze the quality of the measurement, the explanatory power and the predictive power of the specified model. These goals together form a link between theoretical and practical considerations for institutional assistance and the design of professional development.

The main research question relates to the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and professional autonomy with adoption intention amongst teachers in Bangladesh. The survey model which analyzes the question has 5 direct paths to a single endogenous construct. It does so by adding professional expertise to assumed technology, and suitability. The results provide a grounded basis for a discussion on how institutions might facilitate the use of AI in lesson preparation without infringing educators' autonomy in making pedagogical choices.

LITERATURE REVIEW

AI Assistance Within the Lesson Planning Process

AI-assisted planning can be thought of as a dialogue between possibilities generated by AI and contextual judgement. The tool might include a list of activities, questions, or other explanations and the teacher would check how well it fits in with the curriculum standards, readiness of students, resources, and lesson time (Adelana *et al.*, 2024). This interaction renders the planning process as the right unit of conceptual consideration. Adoption is not just about forming a positive opinion about a blossoming technology; it's about the level of fit between the assistance and the teacher's working practices and instructional responsibilities (Al-Abdullatif, 2024).

Various planning activities can also generate varying values. An outline created independently may be helpful if the teacher is looking for a starting point, while an adapted activity may be more helpful if the basic activity plan is already in existence (Ballenas & Lasco, 2024). Alternative assessment questions can be used to help with preparation without altering the teacher's style of instruction. In all of these tasks the level of support is dependent on the appropriateness of the product and the effort needed to embed the support. These uses are all covered by the definition in the study, which doesn't specify a particular platform or product (Ashoori Tootkaboni & Maghsoudi, 2025).

Performance Expectancy and Adoption Intention

Performance expectancy is the degree to which teachers expect AI support in preparing lessons to improve. In the questionnaire, it includes efficiency, quality, development of activities adapted to learning needs and effectiveness (Ayanwale *et al.*, 2022). These dimensions are indicative of the practical uses of planning. If a teacher expects that technology will enable them to make a valuable contribution to these activities, they have a justifiable reason to invest time and focus on learning the technology and integrating it into their preparation (Cabero-Almenara *et al.*, 2024).

Expected efficiency is significant in conjunction with expected quality. While there may be a temptation to fast-track preparation, the lesson needs to include coherent objectives, appropriate activities and suitable assessments into the lesson (Chiu, 2021). If a creamy haste of material is generated, but it takes a terrific amount of work to review and adapt the material, then it is not really very useful. Performance expectancy thus expresses an opinion on the usefulness of the planning outcome, also considering the effectiveness of the tool to help the teacher carry out the existing tasks (Elmourad *et al.*, 2026).

The intention in the proposed relationship is also said to be prospective. Even those who have never used AI in lesson planning can still develop their expectations based on what they know about AI. Expert participants can develop such expectations based on their previous experiences (Diep & Dang, 2025). The general theory is that this planning benefit is related to greater intention to adopt. H1 therefore claims that there is a positive correlation between performance expectancy and teacher's behavioural intention toward AI assisted lesson planning in Bangladesh (Collie & Martin, 2024).

Effort Expectancy and Adoption Intention

Effort expectancy relates to ease of learning how to use AI tools for planning. The measurement items refer to learning, clarity of instructions, ease of use and to becoming skilful. These perceptions are significant since the provision of aid brings its own demands for

functioning (Elmourad *et al.*, 2026). Teachers need to clearly formulate a task in a manner that allows the tool to create appropriate suggestions and understand the learner's answer and determine if additional instructions are required. Use a manageable interaction to make it easier to integrate experimentation into existing work (Filiz *et al.*, 2025).

The ease of use is not necessarily related to perceived usefulness. The teacher might think that a tool would make preparation easier but may also anticipate a lot of problems getting good outputs. The accessible interface, on the other hand, can be easy to use, but fail to create especially useful lesson resources (Gokturk-Saglam, 2026). This separation provides the model with an opportunity to estimate the relationship between perceived effort and intention, as it considers expected performance benefits and the other predictors (Hao *et al.*, 2026).

The assumption is that if the teacher thinks the learning and interaction is achievable, he or she will be more inclined to plan future use. This training can be sufficient to establish an understanding of a task for a plan and, thus, reinforce a relevant perception even prior to any significant independent use (Hazzan-Bishara *et al.*, 2025). The hypothesis is not about some objectively measured complexity of the technique, but rather about the teacher's perception. H2 proposes that there is a positive correlation between effort expectancy and teachers' behavioural intention toward AI-assisted lesson planning in Bangladesh.

Social Influence and Adoption Intention

Social influence encompasses what people in teachers' professional contexts think and approve. These members of the questionnaire talk about persons who impact upon teaching practice, valued colleagues, academic leaders as well as individuals who are important to professional development (Jatileni *et al.*, 2024). These references place social influences within the process of conversation and assessment of teaching practices, which occurs in the context of professional relationships. The movement toward the adoption of AI tools could be enhanced when educators perceive that trusted peers see AI as a suitable part of lesson planning (Jiang & Li, 2026).

Experiments can have a perceived legitimate of professional approval. When colleagues discuss the varied use of a new planning approach constructively, and/or leaders explain that reviewed proposed AI suggestions are acceptable, a teacher may be more inclined to explore a new planning approach (Lee & Perret, 2022). Such an approval can also take away the uncertainty whether the activity meets institutional expectations. Nevertheless, the construct is of perceived social endorsement and not of the quality of peer advice, the content of the leadership guidance or the effects of a formal requirement (Lin *et al.*, 2026).

Based on the fact that decisions about teaching take place in a professional context, it is assumed that social influence will be positively related to intention. Approval can give brave teachers the nudge to explore a tool they may not have used before, take time to learn, and see some trying out as a normal part of their job (Ofosu-Ampong, 2024). This relationship can run concurrently with one's own perceived usefulness and availability of support. H3 suggests that social influence is positively related to teachers' behavioural intention to adopt AI assisted lesson planning in Bangladesh (Sanusi *et al.*, 2022).

Facilitating Conditions and Adoption Intention

Facilitating conditions refer to the practical resources and support that teachers feel is available to them for using AI in preparation. The four questionnaire items focus on an appropriate digital device, internet connection, knowledge, and help (Xu *et al.*, 2024). All of these conditions render it more possible to make the defiant intention. Even if the teacher thinks that there will be useful outputs, he or she might not be willing to make plans for future use if access is unclear or help is not available during initial challenges (Zhai, 2024).

For the intention centered model this study postulates a direct link between facilitating conditions and intention. The logic being that perceived readiness can be a factor in a decision prior to routine use (Zhao & Yang, 2026). Availability of resources and support can assist teachers in determining if the implementation of adoption can be integrated into their practice or if it is realistic for them to implement. The construct thus is more than just infrastructure itself. It includes the knowledge and assistance needed to start using the tools for the particular task under consideration (Ashoori Tootkaboni & Maghsoudi, 2025).

This conceptualization is also turning the facilitating conditions into something that is different from effort expectancy. Ease of interaction relates to the apparent ease of using the technology, and facilitating conditions relates to whether the teacher has or can acquire the required resources to use the technology. When a teacher faces challenge in initial learning, the help may be available to become supportive (Ballenas & Lasco, 2024). H4 predicts that there will be a positive correlation between facilitating conditions and teachers' behavioural intention to adopt AI assisted lesson planning in Bangladesh.

Professional Autonomy and Adoption Intention

Professional autonomy refers to the control that teachers desire to have while utilizing AI support. These concern the final control of lesson content, the right to refuse an inappropriate suggestion, to change the material for the pupils and to control the teaching method (Al-Abdullatif, 2024). These expectations account for the fact that the use of content created by AI is part of an ongoing professional decision making journey. The teacher is still responsible for choosing and adapting material with regard to the aims of the curriculum and the situation in the classroom (Ballenas & Lasco, 2024).

Autonomy may render the acceptance of adoption more acceptable as assistance can be integrated selectively. A

teacher can use a valuable activity without discarding an unappropriate instance of it, change some difficulty in an assessment question or reorganize a series of tasks (Chiu, 2021). This discretion, one might expect, would enable the technology to guide and not dictate a planning decision. The construct thus connects with the designated intention of the teacher in relation to the AI tool's compatibility with the role of a teacher (Diep & Dang, 2025).

Integrated Conceptual Framework

The framework identifies five direct links between relationships and behavioural intention that are positive. Performance expectancy is the value one expects to gain from the service; effort expectancy is how manageable one perceives the service might be; social influence is how professionals think the service will be endorsed; and facilitating conditions is how practically ready the service might be and professional autonomy is how much pedagogy may be retained (Filiz *et al.*, 2025). Using the joint model, the strength of each association can be estimated, taking the others into account. This may be helpful because multiple perceptions can lead to a positive adoption decision rather than a single predominant perception (Hao *et al.*, 2026).

Facilitating conditions is directly connected to intention to reflect the said outcome of the study, while professional autonomy is added as an additional predictor. No mediation, moderation or path to observed usage is stipulated. Demographic factors and past AI use add description and do not constitute further structural predictors (Mnguni, 2025). Figure 01 provides the proposed relationships and the five hypotheses to provide a consistent foundation for measuring and assessing structure in the following.

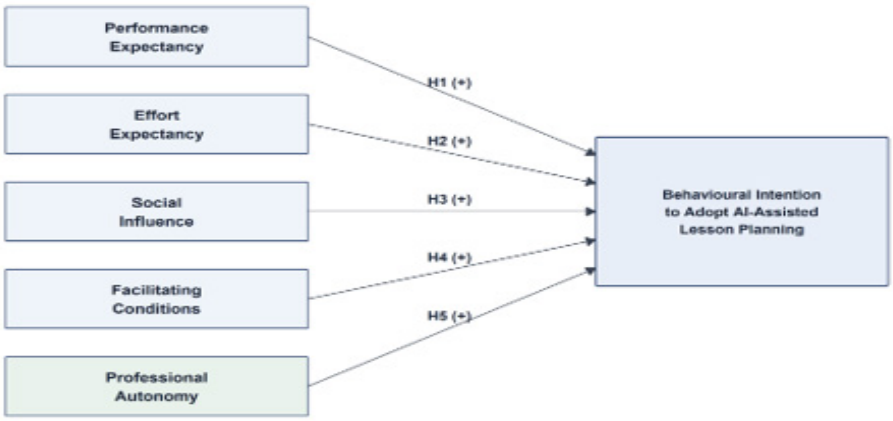

Figure 1: Conceptual framework

MATERIALS AND METHODS

Research Design and Analytical Sample

A quantitative survey design was employed to explore relationships between teachers' perceptions of AI-assisted lesson planning and their behavioral intention to adopt AI-assisted lesson planning. The number of retained response records, or analytical sample, was 360. Eligibility criteria were voluntary participation, age 18 years old or higher, an educational institution where they are currently teaching and a role that involved lesson preparation and contribution to lesson preparation. These criteria were used to place the respondents in the category of the professional activity to which the model related (Holtom *et al.*, 2022).

There were 360 people who took the screening process, and 360 usable cases. Four eligibility checks were performed and there were no records excluded, and the number of incomplete and invalid responses to the measurement items were not recorded. No identical activities were observed in the screening output either. Thus, the study employs the identical 360 cases for measurement and structural evaluations. This retained sample was used as the denominator for calculating categorical profile percentages, and summarising workload numerically.

Respondents included teachers of primary, secondary, higher secondary, undergraduate and post graduate level, in addition to a small group of others. They were enrolled in general schools, general colleges, universities, Madarasas and technical and vocational institutions. All eight divisions were represented in the analytical profile as were rural and urban institutions (Wu *et al.*, 2022). These are the qualities of the analysed sample and are used to understand the aggregate model. The unit of analysis is the respondent.

Questionnaire Structure and Participant Information

Participant information started the questionnaire, outlining the scope of the study, the voluntary nature of participation and the collective analysis of the information for academic purposes. Respondents were asked not to reveal their names, institutional names or any other information that might allow direct identification before submitting, and were instructed to not reveal any of these during the interview. The first definition presented above described AI supported lesson planning in the following manner; by providing concrete preparation tasks and one example of how AI could be used by a teacher to review suggested activities but before concluding a lesson. This

framing resulted in a common understanding of the activity under evaluation (Schwalbe & Finzel, 2024).

The instrument consisted of questions assessing eligibility, demographics, professional questions, familiarity and experience with AI and the construct scales. Respondents were instructed to answer institutional questions in regards to the institution from which they came. No prior experience with AI was required, and teachers who were unfamiliar with AI were asked to answer based on their present expectations. The absence of previous lesson plan use was associated with the response of never to recent frequency in a routing instruction. No routing flags found in the experience output.

Questions in the background included institution type, management category, subject, division, location, workload, experience of the teacher, age and gender of students. Other questions included the question of familiarity, general use, past experience using for lesson planning, recent frequency, institutional policy, and voluntariness. These are variables portraying the professional and technological environment within which the respondents operate. These were analysed descriptively but not included with the 5 predictor structural model.

Construct Operationalisation

There were four indicators for each of the six constructs, resulting in 24 measurement items. Responses were scored on a 5-point agreement scale (1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree). No items were reverse coded. Performance expectancy assessed the expected efficiency, quality, suitability of activities for learners and overall effectiveness. The effort expectancy was comprised of perceived ease of learning, perceived clarity of interaction, ease of use, and skill development.

Social influence was measured as perceived approval from professionally relevant people. Facilitating conditions included access to devices, connectivity, knowledge and assistance. Professional autonomy assessed empowerment in decision making on lesson content and teaching methods, freedom to reject suggestions and freedom in the adaptations of materials. Behavioural intention. Intention to use measured future use that was intended, planned, expected and effortful over the next 6 months. The distinction in the operation of these constructs were carried over for measurement and structure specification. Conventional Mode A partial least squares estimation was used for analysis. Each construct was represented by its respective indicator block and the structural model posited the relationships between the five exogenous constructs and behavioural intention. All of the listed items were kept. This ensured that the estimated model remained within the conceptual framework, and prevented other explanatory pathways from being added that were not included in the plan for the study (Schwalbe & Finzel, 2024).

Assessment of the Measurements and Structures.

Outer loadings and their squares were used as evidence of the reliability of indicators in measuring assessment. Cronbach's, rho A and composite reliability were used to test the internal consistency of the items. Convergent validity was determined by average variance extracted. Loadings were mostly equal or above 0.708, while alpha and rho A were equal or above 0.70, composite reliability ranged between 0.70 and 0.95 and average variance extracted was 0.50 or above. They were analyzed in combination as measures of the targeted model.

The heterotrait monotrait ratio and bootstrap confidence intervals were used to test the discriminant validity. The descriptive threshold was 0.85 and interval assessment checked the upper limit of the two sided 95 per cent confidence interval was less than one. Structural assessment comprised inner variance inflation factors, standardised path coefficients, bootstrap standard errors, test statistics, confidence intervals, explained variance and predictor effect sizes. Inner collinearity was assessed by reference to the guideline values given (which is not reported; they prefer to see collinearity below 3).

5,000 resamples were used in bootstrap inference, and two sided 95% percentile confidence intervals. For the positive hypothesis the approach was considered supported if the lower bound of the hypothesis confidence interval was larger than 0. Reported p values represent normal approximation based on the bootstrap standard errors; values <0.001 are shown as such. Predictor effect sizes were calculated using the fixed score calculation, which compares the amount of variance explained by the full model to the variance after removing each predictor. The reporting makes this distinction to these incremental contributions from the statistical support for a path (Holtom *et al.*, 2022).

Predictive Assessment

Repeated direct antecedent PLSpredict with 10 folds, 10 repetitions, was used to examine the predictive performance. Transformation and models have been adapted within training folds. Prediction errors were compared with a training fold mean benchmark for predictive relevance, and root mean squared error was the principle comparison metric with a linear model benchmark. Also mean absolute error was reported (Sharma *et al.*, 2021). This procedure assessed the predictive value of the four indicators of behavioural intention for the items in the recorded cross validation.

The analytical process transitioned from the basic level of screening and contextual description to measurement assessment, structural inference, and prediction. The order guaranteed that when interpreting hypotheses, evidence relating to indicators and construct distinctions was provided. It also separated in sample explanation from cross validated prediction. Results are presented in rounded form for readability and based on the bootstrap confidence intervals for deciding on a hypothesis.

RESULTS AND DISCUSSION

Respondent Characteristics and Professional Context

Of these, 180 identified as male, 174 as female, three as other and three as not stating gender. The largest age group of teachers was 25-34 (36.39%) followed by 35-44 (31.11%). The age group of 45-54 years was 19.72% of the respondents, the youngest age group was 5.83% and the oldest age group was 6.94%. The percentage of holders of masters' degree was 57.22% while the percentage of holders of bachelor's degree was 28.89%. Selected demographic and professional characteristics are summarised in Table 01.

Among the respondents, secondary teachers (28.61%) were the largest group followed by primary teachers (23.89%), higher secondary teachers (23.06%), Undergraduate teachers (20.00%) and Post graduate teachers (3.61%). The profile thus comprises a number of steps of educational provision. This breadth is pertinent to the overall definition of lesson planning in this study as it involves the range of activities required to prepare for lessons and are shared at a cross level basis, with the ability for respondents to evaluate the items in context of their own lesson planning activities (An *et al.*, 2023).

Table 1: Selected demographic and professional characteristics

Characteristic	Category	n	%
Age	18-24	21	5.83
Age	25-34	131	36.39
Age	35-44	112	31.11
Age	45-54	71	19.72
Age	55 or above	25	6.94
Gender	Woman	174	48.33
Gender	Man	180	50.00
Gender	Another identity	3	0.83
Gender	Prefer not to disclose	3	0.83
Education	Higher secondary or equivalent	2	0.56
Education	Diploma	9	2.50
Education	Bachelor's degree	104	28.89
Education	Master's degree	206	57.22
Education	MPhil	12	3.33
Education	PhD	25	6.94
Education	Other	2	0.56
Teaching level	Primary	86	23.89
Teaching level	Secondary	103	28.61
Teaching level	Higher secondary	83	23.06
Teaching level	Undergraduate	72	20.00
Teaching level	Postgraduate	13	3.61
Teaching level	Other	3	0.83
Management	Government/public	153	42.50
Management	Non-government/private	203	56.39
Management	Other	4	1.11
Location	Rural	187	51.94
Location	Urban	173	48.06
AI training	No	277	76.94
AI training	Yes	83	23.06

N = 360. Percentages are rounded independently.

56.39% said they were non-government/publicly funded institutions while 42.50% were government/publicly funded institutions. About 51.94% were rural institutions while 48.06% were urban institutions. Eight divisions were represented and Dhaka was the largest contributor with 25.28%. The mean workload was 22.28 teaching periods/class sessions per week with standard deviation 7.25 and range 8 to 35. These figures place AI assisted preparation in the context of teaching positions that have regular teaching responsibilities.

AI Familiarity and Institutional Setting

259 respondents (71.94%) indicated that they had used general AI and 163 (45.28%) had used AI for lesson planning. This difference points to the fact that exposure to AI for any purpose and experience with a specific preparation task are two distinct aspects of the sample. Most often familiarity was described as moderate (32.50%), very familiar (23.89%) and slightly familiar (23.06%). Principal experience and institutional categories are reported in Table 02.

59.17% reported using recent lesson planning "never. This is higher than the number who said they never used AI for that purpose, which aligns with some past users saying they didn't use AI over the last three months. Three quarters of all users used the product on a monthly basis, a third used it on a weekly basis, and 3.06% used it four or more times weekly. The distribution facilitates the reporting of future intention as a separate outcome of the previous users and also for teachers who may be thinking of initiating use (Gokturk-Saglam, 2026).

Table 2: AI familiarity and experience

Characteristic	Category	n	%
Familiarity	Not at all familiar	37	10.28
Familiarity	Slightly familiar	83	23.06
Familiarity	Moderately familiar	117	32.50
Familiarity	Very familiar	86	23.89
Familiarity	Extremely familiar	37	10.28
Any AI use	No	101	28.06
Any AI use	Yes	259	71.94
Lesson planning use	No	197	54.72
Lesson planning use	Yes	163	45.28
Past three months	Never	213	59.17
Past three months	Less than once a month	28	7.78
Past three months	1-3 times a month	54	15.00
Past three months	1-3 times a week	54	15.00
Past three months	4 or more times a week	11	3.06
Institutional policy	Permitted without specific conditions	70	19.44
Institutional policy	Permitted subject to conditions	127	35.28
Institutional policy	Prohibited	16	4.44
Institutional policy	No formal policy	97	26.94
Institutional policy	Do not know	50	13.89

N = 360. Previous use and recent frequency refer to different time frames.

23.06% of the respondents had finished their AI training. Permission was reported to be granted on institutional conditions (35.28%), granted without conditions (19.44%) and no formal policy (26.94%). An additional 13.89% were not aware of the position of the institution. These responses offer a real-world context for the understanding of facilitating conditions and professional autonomy. Teachers were evaluating potential use in contexts of differing levels of access to formal preparation and of understanding of the institution's expectations.

Measurement Item Patterns and Indicator Reliability

Item' refers to a range of 3.108 to 3.389 in the five point scale. BI3 (expected future use) had the highest mean, closely followed by FC3 (knowledge required to get started with AI tools. The lowest item mean was PA2, which had to do with freedom to refuse suggestions that disagreed with professional judgement. Means were mostly above the neutral response value and standard deviations ranged from 1.123 to 1.235, reflecting some fluctuation in the respondents' ratings. Table 03 is a combination of the item descriptives and outer loadings.

Outer loadings ranged from 0.780 to 0.885. All 24 of the indicators were maintained and all items surpassed the reported loading guideline. Approval from individuals important to professional development was most prevalent in relation to the largest loading (SI4). PA3 (discretion to adapt generated materials to learners' needs) had the lowest score. Each item had a high percentage of variance with its corresponding construct in the estimated measurement model, with squared loadings ranging from around .609 to .783.

Table 3: Measurement item descriptives and outer loadings

Construct	Item	Mean	SD	Loading
PE	PE1	3.347	1.134	0.828
PE	PE2	3.231	1.175	0.851
PE	PE3	3.328	1.179	0.819
PE	PE4	3.225	1.152	0.822
EE	EE1	3.308	1.232	0.801
EE	EE2	3.264	1.194	0.844
EE	EE3	3.358	1.145	0.783
EE	EE4	3.219	1.231	0.839
SI	SI1	3.253	1.199	0.836
SI	SI2	3.217	1.177	0.845
SI	SI3	3.358	1.123	0.811
SI	SI4	3.247	1.202	0.885
FC	FC1	3.258	1.123	0.832
FC	FC2	3.219	1.192	0.860
FC	FC3	3.386	1.184	0.799
FC	FC4	3.175	1.161	0.818
PA	PA1	3.206	1.157	0.841
PA	PA2	3.108	1.204	0.866
PA	PA3	3.283	1.196	0.780
PA	PA4	3.147	1.167	0.837
BI	BI1	3.311	1.179	0.844
BI	BI2	3.200	1.153	0.861
BI	BI3	3.389	1.203	0.810
BI	BI4	3.250	1.235	0.815

N = 360 for every item. All items use scores from 1 to 5 and span the full response range.

Internal Consistency and Convergent Validity

Cronbach's alpha values were found between 0.834 for effort expectancy and 0.867 for social influence. Rho A ranged from 0.835 to 0.888, and composite reliability ranged from 0.889 to 0.908. The six constructs were satisfactory with respect to reported internal consistency criteria. The average variance extracted was above the 0.5 guideline throughout, beginning at 0.668 for effort expectancy and ending at 0.713 for social influence. The construct level measurement assessment is given in Table 04.

The professional autonomy alpha value was 0.851, while the alpha value of rho A was 0.855, composite reliability was 0.900 and the average variance extracted was 0.692. Corresponding values for the behavioural intention were 0.853, 0.855, 0.901 and 0.694. These results are relevant since the additional explanatory construct is autonomy and the outcome is intention. Their measurement

Table 4: Internal consistency and convergent validity

Construct	Alpha	rho A	CR	AVE
PE	0.850	0.853	0.899	0.689
EE	0.834	0.835	0.889	0.668
SI	0.867	0.888	0.908	0.713
FC	0.847	0.853	0.897	0.685
PA	0.851	0.855	0.900	0.692
BI	0.853	0.855	0.901	0.694

CR = composite reliability; AVE = average variance extracted. PE = performance expectancy; EE = effort expectancy; SI = social influence; FC = facilitating conditions; PA = professional autonomy; BI = behavioural intention.

performance allows for an investigation of the intended relationship, while maintaining the separation of the expected professional control and the future planned use.

Discriminant Validity and Structural Collinearity

The value of all of the heterotrait monotrait ratios was below 0.85 (0.085 for performance expectancy and professional autonomy, and 0.422 for performance expectancy and behavioural intention). The 95% upper confidence limits were also less than one for all pairs. The largest upper bound was 0.517. This pattern is compatible with the separation of the six constructs, such as between perceived benefit and professional control and between perceived benefit and adoption intention, which was supported by the empirical results. Table 05 presents the complete pairwise assessment in long format.

An important distinction to note in particular is the difference between performance expectancy and professional autonomy. They have low ratio values suggesting that the indicators are not merely the same evaluation expressed in different ways. Usefulness and decision authority may thus be considered as distinct dimensions in the model as expected usefulness and retained decision authority. There was also a clear distinction between facilitating conditions and effort expectancy to support the conceptual distinction between

Table 5: Discriminant validity

Construct pair	HTMT	95% lower	95% upper
PE / EE	0.209	0.107	0.327
PE / SI	0.120	0.055	0.238
PE / FC	0.087	0.054	0.204
PE / PA	0.085	0.060	0.201
PE / BI	0.422	0.315	0.517
EE / SI	0.161	0.080	0.277
EE / FC	0.230	0.121	0.347
EE / PA	0.154	0.067	0.274
EE / BI	0.310	0.195	0.425
SI / FC	0.116	0.065	0.217
SI / PA	0.095	0.064	0.206
SI / BI	0.216	0.102	0.332
FC / PA	0.107	0.060	0.220
FC / BI	0.354	0.246	0.459
PA / BI	0.390	0.276	0.502

HTMT = heterotrait monotrait ratio. Intervals are two sided bootstrap percentile intervals based on 5,000 resamples.

available resources and the perceived ease of interaction (Sanusi *et al.*, 2022).

Inner variance inflation factors were between 1.028 and 1.093 for the five predictors. All values were less than 3, which suggests that there was not excessive collinearity for the predictor scores associated with the reported diagnostic. This helps to understand the estimated paths as conditional associations of the given model. It also constitutes a basis for comparing their magnitudes, with no indication that there is much predictor overlap, which could lead to instability in the reported estimates.

Hypothesis Testing and Explained Variance

The five direct paths were all positive and the lower bounds of the 95% bootstrap intervals were greater than zero. With the highest coefficient was performance expectancy (0.294), followed by professional autonomy (0.268) and facilitating conditions (0.2255). The smaller positive coefficients were for effort expectancy (0.119) and social influence (0.097). Coefficients, uncertainty estimates, hypothesis decisions, effect sizes and collinearity diagnostics are all shown in Table 06 for easy comparison.

The model accounted for 31.36% of variance in the behavioural intention with an adjusted value of 30.39%. These are values that explain how much of the estimated intention score each of the five predictors explains. Fixed score effect sizes were 0.121 for performance expectancy, 0.102 for professional autonomy and 0.071 for facilitating conditions. These three values were less than or equal to the small effect guideline reported. The values for effort expectancy was 0.019, while the value for social influence was 0.013, both of which was lower than that guideline.

Thus the information that is provided by statistical support and incremental contribution is complementary. All hypotheses were supported by the bootstrap

Table 6: Structural relationships and hypothesis testing

Path	β	SE	t	p	95% CI	f²	VIF
H1 PE → BI	0.2937	0.043	6.846	<0.001	0.208–0.377	0.121	1.042
H2 EE → BI	0.1188	0.046	2.600	0.009	0.033–0.211	0.019	1.093
H3 SI → BI	0.0974	0.048	2.018	0.044	0.008–0.195	0.013	1.034
H4 FC → BI	0.2255	0.043	5.240	<0.001	0.142–0.311	0.071	1.050
H5 PA → BI	0.2677	0.045	6.010	<0.001	0.183–0.357	0.102	1.028

All five hypotheses were supported. Bootstrap resamples = 5,000. P values are normal approximations using bootstrap standard errors. $R^2 = 0.3136$; adjusted $R^2 = 0.3039$. Effect sizes use the fixed score procedure.

interval decision rule but predictors do not contribute equal amounts. As for this model, the ordering of the coefficients and the effect sizes were always expected performance, autonomy and enabling conditions before perceived ease and professional endorsement (Diep & Dang, 2025). The numerical ordering refers to the apparent sizes of the predictors' coefficients in the model under consideration but does not indicate statistically significant differences between the predictors. The estimated structural relationships and explained variance are shown in figure 02.

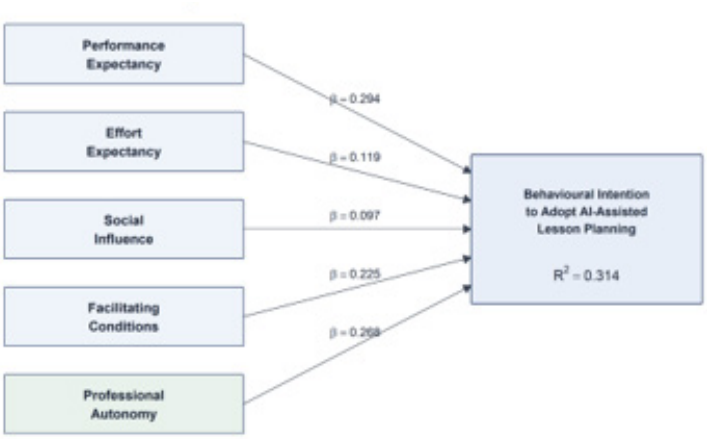

Figure 2: Estimated PLS SEM structural model

Performance Expectancy as a Central Adoption Consideration

The path of performance expectancy was positive and significant, with β = 0.294, t = 6.846, and p < 0.001. The 95% confidence interval ranged from 0.208 to 0.377. After accounting for the other predictors, this finding suggests that those teachers who had higher planning expectations had higher adoption intention. This association is in line with the conception of the study in that, the decision to adopt is closely related to the action use which teachers use for lesson preparations.

To better understand the substantive meaning of this finding, a content analysis of the scale was conducted. It incorporates efficiency and quality as well as activities that are appropriate for the pupils. The relationship is thus one of expected improvement in planning in multiple areas and not just time. This implies, for institutional use, that demonstrations involve linking AI functions to teaching activities (Filiz *et al.*, 2025). The following examples can help in the evaluation of the expected contribution as they include coherent objectives, appropriate activities, and usable assessment questions.

The level of effect size 0.121 also shows that performance expectancy has a significant incremental effect to other predictors being studied in the estimated model. One way to do that as a practical approach is to test tools using full prep workflows. Teachers can be asked if they can design an action plan that is usable and has the right level of review and revision. This approach is applied based on the content of the construct and linking it with the value as perceived and the professional task it is motivated by in order to induce adoption intention.

Professional Autonomy and Retained Pedagogical Authority

The interaction between professional autonomy & intention was positively supported with the value of β of 0.268, t of 6.010 and p < 0.001. The confidence interval of its value was (0.183, 0.357). The effect size was 0.1. These findings suggest that expected control is

a large part of the adoption decision in terms of content and teaching methods. The teachers who expected more flexibility to assess and customize AI recommendations had more intention of utilizing the tools.

The outcome favours the notion of use of adoption as an elective professional activity. There is some teacher freedom with generated material, with the teacher using their judgement on accuracy, sequence, relevance and learner needs. This means the freedom to refuse a suggestion and it also means the freedom to edit valuable information. Explicit permissions in institutional arrangements can support AI support and the ongoing role of the teacher within the lesson. The result has rendered autonomy in the mentioned technology acceptances framework a tangible finding (Hazzan-Bishara *et al.*, 2025).

This relationship can be manifested in practical implementation by using outputs which can be made work, flexible planning forms, and clarity of expression that teachers still have pedagogical autonomy. Examples of revising or discarding a generated activity for a reason based on the lesson objective can be included in professional development. These show that informed selection is an euphemism for use (Xu *et al.*, 2024). They also institute the autonomy construct in the realistic preparation process instead of viewing it as some abstract institutional concept.

Facilitating Conditions and Feasible Adoption

Facilitating conditions were positively correlated with intention ($\beta = 0.2255$; $t = 5.240$; $p < 0.001$). The confidence interval was between 0.142 and 0.311; the effect size is 0.071. These results give support to the intention focused adaptation according to the conceptual framework. The prospective teacher's commitment to lesson planning with AI was correlated with the teacher's perception of access to devices, connectivity, knowledge, and assistance.

The construct consists of technical and human resources that are important for interpretation. Access is through device and internet connection, knowledge and assistance support purposeful use. Adopting institutions can therefore take into account the complete support environment. Practical workshops, examples of how to use them in relation to teachers' subjects and reliable assistance may make the intended use possible in combination with ongoing subject teaching. These actions link directly to the resources being measured by the measurement items (Zhai, 2024).

This implication is supported by the descriptive findings of this study, where less than 1/4 of the respondents had completed AI training. It is not a separate training effect, since training was not provided as a structural predictor. It does, however, point to an area of institutional planning which is relevant. Support arrangements can provide opportunities for teachers at varying levels of support and ensure supports are targeted to the activities of creating and reviewing lesson materials.

Effort Expectancy and Social Influence

Effort expectancy showed a positive supported relationship, with $\beta = 0.119$, $t = 2.600$, $p = 0.009$, and a confidence interval of 0.033–0.211. This suggests, perceiving ease-to-learn and ease-to-use was related to greater intention in the joint model. It had an effect size of 0.019, which is lower than the small effect threshold reported. This finding suggests that attention should be given to usability, and that ease of use had a lower incremental contribution in this analysis than the other constructs: expected benefit and autonomy and facilitating conditions.

Social influence also had a positive supported association, with $\beta = 0.097$, $t = 2.018$, $p = 0.044$, and a confidence interval of 0.008–0.195. It had an effect size of 0.013. Professional endorsement was thus relevant, but it made a lesser addition than the three top predictors. Supervisors or peers might facilitate a climate where educators are comfortable trying exploratory use of AI and you can talk about proper uses.

The mixed picture indicates a potential for the professional encouragement to be part of a larger support plan. Acceptable uses and leadership guidance can be bio-graphical, peer examples can assist in introducing useable/useful outputs, and authority retention and practical support can provide solid reasons for teacher to plan for adoption. Opportunities for teachers to share their plans and describe their changes at institutions can be created (Zhao & Yang, 2026). Combines the social endorsement with professional learning and maintains discretion around an individual recommendation's suitability for a particular lesson.

Cross Validated Predictive Performance

The Q^2 predict of all four behavioural intention indicators was positive, with a range of 0.159 to 0.222. The PLS model also resulted in a lower RMSE than the linear

Table 7: Cross validated predictive performance

Item	Q^2 predict	PLS RMSE	LM RMSE	Difference	PLS MAE	LM MAE
BI1	0.222	1.041	1.086	-0.045	0.857	0.878
BI2	0.201	1.032	1.067	-0.035	0.831	0.867
BI3	0.211	1.070	1.109	-0.039	0.874	0.900
BI4	0.159	1.134	1.176	-0.042	0.942	0.977

10 folds and 10 repetitions. LM = linear model benchmark; RMSE = root mean squared error; MAE = mean absolute error. Difference = PLS RMSE minus LM RMSE.

model benchmark for each indicator. The differences varied from −0.035 to −0.045 (negative difference favouring the PLS predictions). Mean absolute error was in the same direction for all four indicators. The predictive assessment from repeated 10 fold, is reported in Table 07. The explained variance and the path estimates are supplemented by the predictive results. Positive Q^2 predict values means improvement over the reported training fold mean reference model. Comparative advantage is consistent at all 4 intention indicators, with lower prediction errors for the nonlinear method compared to the linear method, albeit small. Results suggest that this model has a predictive role in this type of cross validation design without such a correlation being made with actual future teaching practice (Ashoori Tootkaboni & Maghsoudi, 2025).

Integrated Implications for Educational Institutions

The results relate adoption intention to three specific institutional concerns thought to be particularly relevant: the generation of useful preparation outcomes, practical support and maintenance of professional authority. These considerations can be used to guide the design of a coherent implementation process. Institutions can start with specific planning tasks; make resources available for carrying out these tasks; make sure teachers can modify these resources. This mix is representative of the most reported associations and adds usability and professional buy-in to encourage initial engagement (Ayanwale *et al.*, 2022).

One way to begin an implementation sequence is for a teacher to choose a real curriculum objective and determine the kind of support they need. The limited output can then be generated by the tool, either as an activity or a set of questions. The teacher checks this output for accuracy, level, timing, and suitability, revises it and uses the material selected to develop the final plan (Collie & Martin, 2024). It can be discussed with colleagues why those revisions are made. This process converts the Model to a usable preparation process.

Teachers' decision rights can be made clear through institutional policy. The descriptive responses indicate several perspectives on policy and a group of respondents in no certain position. By providing clear instructions on how AI can support the planning process, what content to review and verify, and who retains the final say, clear guidelines can be established (Cabero-Almenara *et al.*, 2024). This type of guidance can also indicate where teachers might look for assistance. These recommendations are based on the constructs and institutional context, and do not necessarily suggest that policy itself was directly tested as an added predictor.

Evaluation can concentrate on the quality and usability of completed plans. Institutions can reflect on the congruence of the objectives, activities and assessments, the appropriateness of materials for students' learning, as well as teachers' opinion of the review process as being feasible. Teacher feedback can help to determine the effectiveness of which tasks offer support and which teacher support to tasks need to be modified. This provides a foundation for further adjustment in implementation in relation to lesson purposes in line with their professional responsibilities, while simultaneously maintaining the teacher's authority in giving lessons (Diep & Dang, 2025).

CONCLUSION

This study explored the intention of teachers to use AI-assisted lesson planning in Bangladesh using an intention-focused technology acceptance model (TAM) which included professional autonomy. The 360 returns analysed found all five postulated positive relationships. Performance expectancy was estimated to be the highest coefficient with professional autonomy and facilitating conditions following in magnitude. The positive relationships for effort expectancy and social influence were also found. The joint model had a variance accounted for in behavioural intention of 31.36% and had positive cross validated predictive relevance for all four outcome indicators.

The results of the measurements showed that the six constructs had coherence and distinctness. All indicators were kept with the internal consistency and convergent validity reported as meeting the criteria; and discriminant validity assessment supported separation of the constructs. These results validate the structural results in terms of relationships between differentiated perceptions. Specifically, expected planning and expected professional control were found to be two unique factors each positively related to intention.

Demonstrations of how AI support can help with real preparation activities should be emphasized in educational institutions. Examples should consider the efficiency, as well as coherence, relevance and adaptability of lessons materials. There should be opportunities for teachers to assess the achievement of the output related to the learning objectives and the learner's needs. This makes the anticipated benefit the focus of adoption support and constitutes a solid foundation for deciding if there is a tool that will be of value for existing preparation practice.

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