Teacher Self-Use Predicts Classroom Adoption of Generative AI Among Japanese High School Informatics Teachers

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Abstract

Generative AI (GenAI) is rapidly entering schools, but teacher adoption is shaped not only by positive expectations (e.g., perceived usefulness) and concerns (e.g., accuracy, copyright, and governance) but also by teachers' everyday experience using these tools in their own work. This study examines a two-stage model of GenAI adoption among Japanese high school Informatics teachers: (1) intention to use GenAI in class and (2) classroom adoption (whether GenAI has already been used in class). A nationwide online survey was administered in May 2025 to Informatics teachers across Japan ($n = 104$). Expectations, concerns, and intention were measured with multi-item scales; self-use frequency was measured on a four-level ordinal scale; and classroom adoption was measured as a binary outcome. Analytic sample sizes varied slightly by model due to item nonresponse. In Stage 1, ordinary least squares regression showed that expectations ($B = 0.67$, $p < .001$) and self-use frequency ($B = 0.25$, $p = .003$) predicted stronger intention, whereas concerns were not a significant predictor. In Stage 2, logistic regression showed that self-use frequency predicted classroom adoption ($OR = 2.33$, $p = .010$), while expectations and concerns were not significant when self-use was included. Predicted adoption probabilities rose from 0.33 (trial only) to 0.86 (almost daily self-use) at median expectations and concerns ($AUC = 0.679$). These findings suggest that expectations are sufficient to generate intention, but sustained self-use may be a practical bridge to classroom adoption. Implications are discussed for professional development that builds short, authentic self-use routines and for school-level guidelines that operationalise key concerns as simple, checkable classroom rules.

Keywords: generative AI, teacher adoption, informatics education, technology acceptance, professional development

Introduction

Generative AI (GenAI), including large language model (LLM)–based tools such as ChatGPT and Copilot, is increasingly available to teachers and students. Because these tools can generate natural language text, code, and other artefacts on demand, they can potentially support teaching and learning in ways that differ from earlier educational technologies: teachers can request examples, explanations, alternative representations, and formative feedback at the point of need. At the same time, GenAI introduces distinctive risks for schooling. Outputs can be plausible but incorrect; the provenance of information can be opaque; and classroom use intersects with copyright, privacy, and academic integrity. As a result, policy and governance discussions increasingly emphasise not only access, but also transparency, verification, and the continued role of human responsibility (Miao & Holmes, 2023; Organisation for Economic Co-operation and Development [OECD], 2023).

Japan has responded to these challenges through national guidance. The Ministry of Education, Culture, Sports, Science and Technology (MEXT) released guidance for primary and secondary education that frames GenAI as a tool to be used under human oversight, with explicit attention to information accuracy, ethical considerations, and school-level governance (MEXT, 2024). In practice, however, schools and local boards of education vary in how quickly they develop policies and how strongly they restrict access (e.g., network blocks). Such heterogeneity creates uncertainty for teachers, who must decide whether and how to integrate GenAI while being accountable to students, parents, and institutional rules.

High school Informatics in Japan is a particularly consequential context for GenAI adoption. Informatics is a compulsory subject for almost all students, and its learning goals include problem solving with digital tools, programming and networks, and data utilisation. These goals naturally connect to GenAI literacy: students need to understand what GenAI can and cannot do, how to prompt and evaluate outputs, and how to use tools responsibly in real tasks. Informatics teachers therefore occupy a dual role. They are both potential users of GenAI for lesson preparation and assessment, and also responsible for guiding students' safe and critical use. Because the subject is compulsory, teacher decisions in Informatics can influence a large proportion of students' opportunities to develop AI-relevant information-utilisation competencies.

Despite strong public attention to GenAI, teacher adoption is rarely a single, static decision. Teachers may endorse GenAI in principle—believing it could improve efficiency or enrich learning—while still delaying classroom use due to concerns, institutional constraints, or limited personal familiarity. Importantly, intention and behaviour can diverge (Ajzen, 1991). Intention reflects willingness, whereas classroom adoption requires concrete enactment: preparing activities, managing student use, handling accountability for mistakes, and aligning with school rules. Consequently, understanding adoption requires attention to both motivational determinants (e.g., expectations of benefit) and practical determinants that enable enactment (e.g., hands-on experience and routines).

This study therefore proposes and tests a two-stage model of GenAI adoption among Japanese high school Informatics teachers. Stage 1 models teachers' intention to use GenAI in Informatics lessons as a function of expectations, concerns, and self-use frequency. Stage 2 models whether teachers have already adopted GenAI in class (yes/no), using the same predictors. By separating intention from adoption, the analysis clarifies which factors primarily shape "wanting to use" versus "already using," and it informs professional development (PD) and governance strategies that can better bridge policy guidance and classroom practice. The study also contributes empirical evidence from a subject area—Informatics—where GenAI literacy and information ethics are not peripheral but central to the curriculum.

Another reason the Informatics context is important is that the subject area is undergoing rapid expansion. Teachers are expected to address not only conventional computing topics but also data science–adjacent practices, AI literacy, and ethical issues in digital society. In many schools, Informatics teachers teach across multiple grades and must align instruction with high-stakes assessment expectations and school-wide digital policies. Professional development opportunities on GenAI are still uneven, so many teachers rely on self-directed exploration and peer communities. In this environment, teachers' personal self-use of GenAI becomes a plausible entry point to later classroom adoption: it is often the most immediately accessible way to learn what the tools can do, what can go wrong, and how to build checking routines before exposing students to risks.

Literature Review and Conceptual Framework

Technology Acceptance and Teacher Adoption

Research on educational technology adoption commonly models teachers' behavioural intention as a proximal predictor of later use. This focus aligns with the technology acceptance model (TAM) (Davis, 1989). Prominent frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) highlight perceived performance benefits, effort expectancy, social influence, and facilitating conditions as key determinants of intention and use (Venkatesh et al., 2003). Across many technologies, perceived usefulness or value tends to be a strong predictor of intention, particularly when teachers see clear benefits for instructional effectiveness or workload. However, actual use is also shaped by practical constraints (e.g., access and policy) and by teachers' confidence and routines in integrating tools into authentic classroom practice. In GenAI contexts, emerging research echoes these patterns while emphasising new dimensions. Studies have reported that teachers' perceived value of GenAI and their confidence in using it are associated with stronger intention to integrate GenAI tools at work, including in planning and instructional tasks (Collie et al., 2024; Kong et al., 2024). These findings suggest that standard acceptance constructs remain relevant, but they also highlight the need to account for how teachers learn to use GenAI responsibly, including how they verify outputs and manage risks.

Expectations, Concerns, and Governance

GenAI has features that intensify the coexistence of hope and worry. On the one hand, teachers may expect GenAI to save time, provide alternative explanations, and generate creative ideas. On the other hand, they may worry about inaccurate or biased outputs, unclear authorship, copyright infringement, and privacy problems. Policy reports emphasise that responsible educational use depends on explicit norms and governance structures, including disclosure of use, verification of key claims, and data protection (MEXT, 2024; OECD, 2023). From the perspective of individual teachers, such governance can appear as both enabling and constraining: clear rules may reduce uncertainty and support safe experimentation, whereas unclear or restrictive rules may suppress classroom trials regardless of a teacher's interest. Reports and surveys in Japan indicate that expectations and concerns are simultaneously present among educators and students, reflecting simultaneous interest in potential benefits (e.g., efficiency and idea generation) and awareness of risks (e.g., accuracy and ethics).

Moreover, teacher experience with GenAI may shape how these expectations and concerns are evaluated. Noborimoto et al. (2023) reported differences in perceptions and attitudes between primary and secondary teachers who had used GenAI and those who had not. Such findings suggest that personal experience may not simply reduce concerns; rather, experience may help teachers differentiate manageable concerns (addressed through checking routines) from non-negotiable constraints (e.g., prohibited access).

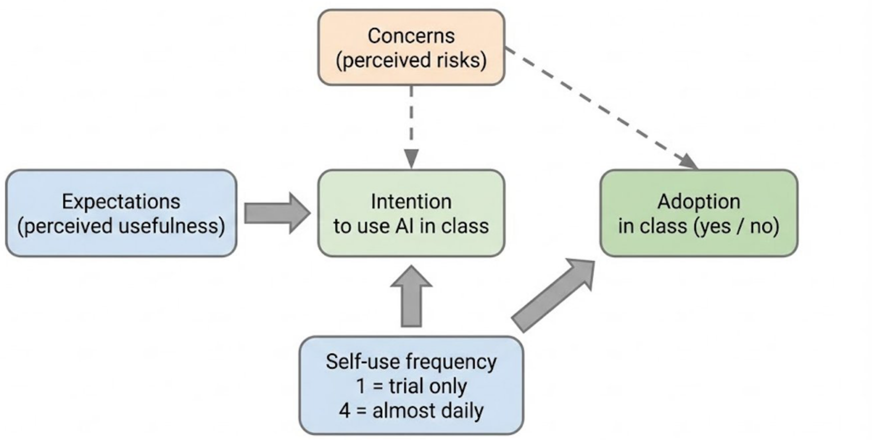
Self-Use as Experience and Routine

A distinctive feature of GenAI adoption is that many teachers can use these tools privately before introducing them to students. This creates a potential developmental pathway: teachers first use GenAI for their own work (self-use), then consider whether and how to involve students. Self-use frequency is therefore more than a background variable; it is a proxy for experience and emerging routines. Frequent self-use may help teachers learn prompting strategies that produce useful outputs, recognise common failure modes, and develop habits of checking and revising. Such procedural knowledge can reduce the subjective cost of classroom implementation and can increase confidence that risks can be managed in front of students.

Two-Stage Model of Adoption

Based on these considerations, this study adopts a two-stage model (Figure 1) that distinguishes between intention and adoption. In Stage 1 (intention), expectations are expected to play a major role because teachers are likely to form willingness to try GenAI when they anticipate clear benefits. Concerns may reduce intention to the extent that they are perceived as severe or uncontrollable. Self-use may also strengthen intention because it increases familiarity and perceived feasibility. In Stage 2 (adoption), self-use is expected to be particularly important because classroom adoption requires enactment—designing activities, managing students, and responding to errors—which depends heavily on practical fluency and routines. Expectations may be sufficient to generate intention but may not be sufficient for adoption once self-use is considered. Concerns may remain important for the quality and governance of implementation even if they do not statistically distinguish adopters from non-adopters. Accordingly, the study addresses two research questions. RQ1: How do expectations, concerns, and self-use frequency relate to teachers' intention to use GenAI in Informatics lessons? RQ2: How do the same factors relate to classroom adoption (whether GenAI has already been used in class)?

Figure 1
Two-Stage Model of Teacher GenAI Adoption



Note. Solid lines indicate hypothesised positive paths; dashed lines indicate hypothesised negative paths.

Methodology

Participants and Procedure

A nationwide online survey was administered from May 9 to May 17, 2025. Participants were high school teachers responsible for Informatics courses (including Informatics I and related subjects). Recruitment used professional networks and online channels commonly used by Informatics teachers (e.g., teacher communities and social media). A total of 104 valid responses were collected. Respondents included 85 men and 15 women; 2 respondents did not answer the gender item and 2 selected “prefer not to say.” Most respondents reported teaching Informatics I (n = 91), and many also taught school-specific Informatics-related subjects (n = 40), general “inquiry-based learning” periods (n = 37), or Informatics II (n = 18). Regarding grade level, 73 respondents reported teaching Grade 10, 50 taught Grade 11, and 55 taught Grade 12 (multiple selections were allowed). School type was reported as public (n = 34), private (n = 28), or national (n = 2), but this item had substantial nonresponse (n = 39). Because the survey was voluntary and online, the sample should be interpreted as a national convenience sample rather than a probability sample. Nevertheless, respondents came from a range of school contexts and grade levels, providing a useful snapshot of Informatics teachers’ perceptions and practices during a period of rapid policy and technological change. All responses were anonymised, and participation was optional. Analytic sample sizes varied slightly across models due to item nonresponse. Figure 2 provides a visual overview of the nationwide sample (n = 104).

Figure 2
Nationwide Online Survey Sample

Note. High school informatics teachers in Japan; n = 104.

Measures

Expectations. Expectations of GenAI use were measured with four items addressing perceived reduction of work time, improved understanding through clearer explanations, support for creative ideas, and reduced fatigue or stress. Responses used a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). A composite expectations score was computed as the mean of the four items ($\alpha = .71$). Concerns. Concerns about GenAI use were measured with four items addressing accuracy anxiety, ethics and copyright, lack of school/government guidelines or restrictions, and blocked access in school networks. Responses used the same 5-point Likert scale. A composite concerns score was computed as the mean of the four items ($\alpha = .43$). Given the heterogeneity of concern content, this composite should be interpreted as a broad index of perceived risk and constraint rather than a unidimensional scale. Intention to use in class. Intention was measured with five items addressing willingness to use GenAI actively in future lessons, to recommend use to colleagues, and to increase opportunities for students to use GenAI appropriately in class and at home. Responses used the same 5-point Likert scale, and the composite intention score was the mean of the five items ($\alpha = .90$). Self-use frequency. Teachers' self-use frequency during the previous month was measured on a four-level ordinal scale: trial use only, monthly use, weekly use, and almost daily use. This variable operationalises the extent to which GenAI is already incorporated into teachers' everyday work routines. Higher values indicate more frequent self-use. Classroom adoption. Classroom adoption was measured as a binary variable indicating whether the teacher had already addressed or used GenAI in class (0 = no, 1 = yes). The survey also asked teachers who had adopted GenAI to indicate the types of classroom activities used (e.g., conceptual introductions, demonstrations, student prompting activities, and ethics/copyright instruction), which are reported descriptively.

Data Processing and Analytic Strategy

Scale scores were computed as mean scores to preserve the original response metric (1–5). Descriptive statistics were computed for all variables. Because the self-use measure is ordinal and adoption is binary, bivariate associations were summarised using Spearman correlations. To test the two-stage model, Stage 1 used ordinary least squares regression predicting intention from expectations, concerns, and self-use frequency. Stage 2 used logistic regression predicting classroom adoption from the same predictors. Missing data were limited for the main predictors, with two missing values for self-use frequency and two missing values for adoption; the multi-item scales had complete responses. Regression models therefore used listwise deletion, resulting in slightly smaller analytic samples. For Stage 2, odds ratios (OR) are reported for interpretability, and model performance is summarised with the area under the ROC curve (AUC) and the Brier score.

Results

Descriptive Patterns of Use

Almost all respondents reported having personally used GenAI at least once (102 of 104). Self-use frequency during the previous month was reported as trial use only ($n = 5$), monthly use ($n = 20$), weekly use ($n = 39$), or almost daily use ($n = 38$); two responses were missing. When asked about contexts of GenAI use (multiple selections), teachers most commonly reported using GenAI for lesson preparation ($n = 80$), information search ($n = 70$), self-learning or skill development ($n = 57$), and administrative document writing ($n = 54$). Many also reported using GenAI for creative production such as images, music, or video ($n = 48$). These patterns suggest that, for many Informatics teachers, GenAI is already embedded in professional tasks beyond classroom instruction. Classroom adoption was reported by 74 teachers, while 28 reported they had not yet used GenAI in class (two missing responses). Among adopters, the most common classroom activities (multiple selections) were introducing basic concepts of GenAI ($n = 58$), demonstrating GenAI tools in class ($n = 52$), providing students with hands-on prompting experiences ($n = 42$), and addressing ethics and copyright issues ($n = 40$). Some teachers also reported incorporating GenAI into report-writing tasks (n = 28). Taken together, these responses indicate that early classroom adoption in Informatics often focuses on foundational understanding, demonstration, and controlled student experimentation rather than unrestricted or high-stakes use.

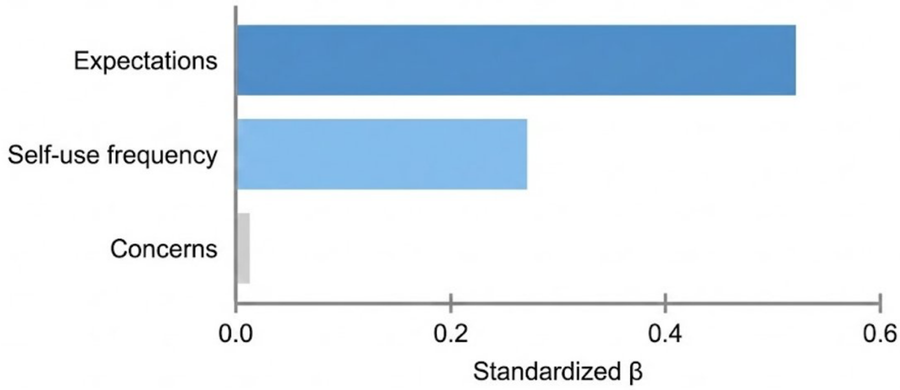
Descriptive Statistics and Correlations

Respondents reported moderately high expectations for GenAI (M = 3.99, SD = 0.64) and moderately high intention to use GenAI in class (M = 4.09, SD = 0.81). Concerns were moderately high (M = 3.39, SD = 0.73), indicating that positive expectations and perceived risks coexisted. Spearman correlations (Table 1) indicated a strong positive association between expectations and intention ($\rho = .70$), consistent with acceptance models emphasising perceived usefulness. Self-use frequency was also strongly associated with intention ($\rho = .59$). By contrast, intention showed only a weak association with classroom adoption ($\rho = .01$), whereas self-use frequency showed a positive association with adoption ($\rho = .26$). Concerns showed small negative associations with expectations and self-use frequency.

Stage 1: Predicting Intention

Stage 1 regression results are shown in Table 2. The model explained 58.2% of variance in intention ($R^2 = .500$). Expectations were a strong positive predictor of intention (B = 0.67, SE = 0.07, $\beta = .52$, $p < .001$). Self-use frequency was also a positive predictor (B = 0.25, SE = 0.05, $\beta = .27$, $p = .003$). Concerns were not a statistically significant predictor of intention when expectations and self-use were included (B = 0.03, SE = 0.08, $\beta = .03$, $p = .674$). Figure 3 visualises the standardized β coefficients.

Figure 3
Standardized β for Predictors of Intention (Stage 1 OLS Regression)



Stage 2: Predicting Classroom Adoption

Stage 2 logistic regression results are shown in Table 3. Self-use frequency predicted classroom adoption (B = 0.85, SE = 0.33, OR = 2.33, $p = .010$), indicating that each one-level increase in self-use frequency approximately doubled the odds of having already used GenAI in class. Expectations (B = 0.26, SE = 0.43, OR = 1.30, $p = .552$) and concerns (B = −0.44, SE = 0.35, OR = 0.64, $p = .207$) were not statistically significant predictors when self-use was included. Model performance was moderate (AUC = 0.679; Brier score = 0.18). Figure 4 visualises predicted probabilities of adoption by self-use frequency at median expectations and concerns, rising from 0.33 (trial only) to 0.86 (almost daily use). Table 4 lists these predicted probabilities by self-use level.

Table 1
Descriptive Statistics, Reliability, and Spearman Correlations Among Key Variables

#	Variable	N	M	SD	α	1	2	3	4	5
1	Expectations	104	3.99	0.64	0.71					
2	Concerns	104	3.39	0.73	0.43	−0.181				
3	Intention	104	4.09	0.81	0.90	0.703***	−0.134			
4	Self-use frequency	102	3.08	0.87		0.606***	−0.218*	0.593***		
5	Classroom adoption	102	0.73	0.45		0.085	−0.111	0.014	0.255**	

Note. Spearman correlations are shown below the diagonal. * $p < .05$. ** $p < .01$. *** $p < .001$. Self-use frequency: 1 = trial only, 2 = monthly, 3 = weekly, 4 = almost daily. Classroom adoption: 0 = no, 1 = yes.

Table 2
Stage 1 OLS Regression Predicting Intention to Use GenAI in Class

Predictor	B	SE	β	t	p
Intercept	0.542	0.509		1.062	.291
Expectations	0.669	0.114	0.524	5.887	< .001
Concerns	0.034	0.082	0.031	0.422	.674
Self-use frequency	0.249	0.083	0.267	3.005	.003

Note. n = 102. $R^2 = .500$. B = unstandardized coefficient. β = standardized coefficient.

Table 3
Stage 2 Logistic Regression Predicting Classroom Adoption of GenAI (Yes/No)

Predictor	B	SE	OR	p
Intercept	1.951	2.045	7.040	.340
Expectations	−0.559	0.460	0.572	.224
Concerns	−0.369	0.338	0.692	.275
Self-use frequency	0.845	0.330	2.329	.010

Note. n = 102. OR = odds ratio. Model performance: AUC = 0.679; Brier score = 0.182.

Figure 4
Predicted Probability of Classroom Adoption by Self-Use Frequency (at Median Expectations and Concerns)

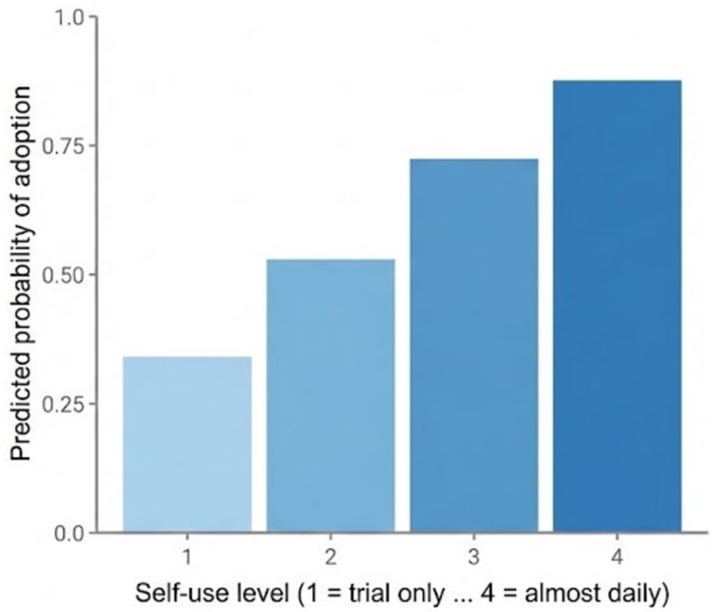


Table 4
Predicted Adoption Probabilities by Self-Use Frequency (Median Expectations = 4.00; Median Concerns = 3.50)

Self-use frequency	Coding	Predicted probability
Trial use only	1	0.325
Monthly use	2	0.528
Weekly use	3	0.723
Almost daily use	4	0.859

Discussion

This study tested a two-stage model of GenAI adoption among Japanese high school Informatics teachers, distinguishing intention from classroom adoption. The findings clarify that determinants of "wanting to use" and "already using" are not identical. Expectations of benefit were strongly associated with intention, while teachers' everyday self-use frequency was the key predictor of classroom adoption.

Expectations as a Driver of Intention

Expectations were the strongest predictor of intention, supporting the view that perceived usefulness remains central even in GenAI contexts. Teachers appear to form willingness to use GenAI when they expect tangible professional and pedagogical benefits, such as reduced preparation time and richer explanations. This aligns with technology acceptance research in which performance expectancy or usefulness is consistently linked to behavioural intention (Venkatesh et al., 2003). Informatics teachers may have particularly salient expectations because GenAI can support tasks central to Informatics teaching, including generating alternative examples, debugging code, or preparing data-related exercises. The descriptive results also show that most respondents already use GenAI for lesson preparation and information search, suggesting that usefulness is not hypothetical for many teachers but grounded in lived experience.

Self-Use as a Bridge to Adoption

Self-use frequency predicted both intention and, more importantly, classroom adoption. Even when expectations were controlled, self-use remained the only significant predictor of whether teachers had already used GenAI in class. This pattern is consistent with the idea that classroom adoption requires more than positive beliefs; it requires practical fluency, routines, and confidence in managing risks in front of students. In practical terms, teachers who regularly use GenAI for lesson planning, material preparation, or administrative tasks may develop (a) prompting strategies that produce useful outputs, (b) habits of checking and revising outputs, and (c) a sense of feasibility that lowers the threshold for trying GenAI with students. Self-use may also expose teachers to both strengths and limitations of GenAI, allowing them to design classroom tasks that leverage benefits while constraining risks. This interpretation is consistent with recent research emphasising teachers' GenAI self-efficacy, valuing, and integration at work (Collie et al., 2024) and with evidence that teachers' intention to use GenAI is related to their AI literacy and confidence (Kong et al., 2024). Importantly, the present findings suggest that self-use is not merely correlated with favourable attitudes; it may be a practical mechanism that helps teachers cross the threshold from interest to implementation.

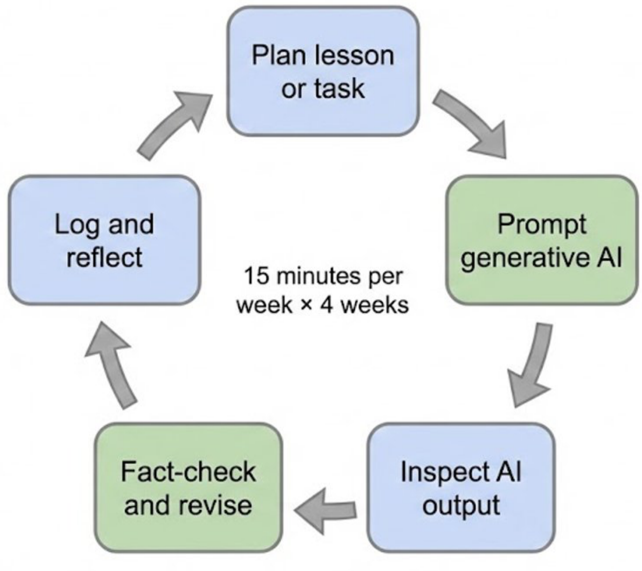
Why Concerns May Not Statistically Distinguish Adopters

Concerns did not predict intention or adoption once expectations and self-use were included. This should not be interpreted as indicating that concerns are irrelevant. Rather, several interpretations are plausible. First, concerns may be pervasive across the sample, reflecting the broader policy environment in which many educators are aware of risks related to accuracy, ethics, and governance. If both adopters and non-adopters share similar concerns, the statistical model will not treat concerns as a differentiating factor. Second, the concerns scale in this study combined qualitatively different elements: epistemic concerns about output accuracy, normative concerns about ethics and copyright, and institutional concerns such as blocked access. The low internal consistency ($\alpha = .43$) supports this heterogeneity. Some concerns may inhibit adoption (e.g., strong access restrictions), while other concerns may coexist with adoption because they are managed through mitigation strategies (e.g., verification routines). This aligns with the observation that many adopters reported teaching ethics and copyright as part of their classroom implementation, suggesting that concern can be transformed into curricular content rather than a barrier. Third, concerns may function less as predictors of "whether to adopt" and more as determinants of "how to adopt." MEXT guidance emphasises responsible use under human oversight, including explicit checking of outputs and attention to ethical issues (MEXT, 2024). Informatics teachers may be especially prepared to operationalise concerns into classroom rules and learning activities because information ethics and critical evaluation are already curriculum-relevant.

Implications for Professional Development

The two-stage findings imply a practical sequence for supporting adoption. If expectations generate willingness but self-use enables enactment, then PD should prioritise building safe, repeatable self-use routines before expecting broad classroom integration. From a design perspective, this calls for PD that is short, authentic, and routine-forming. One feasible model is a short practice loop that respects teachers' time constraints: for example, 15 minutes per week for four weeks. In each cycle, teachers use GenAI for an authentic task (e.g., drafting an explanation, generating quiz items, or creating alternative examples), then check outputs for accuracy and appropriateness, revise key parts, and briefly document prompts and changes. Over repeated cycles, teachers can accumulate a small repertoire of high-quality prompts, examples of output failure modes, and concrete strategies for verification. Because this routine focuses on teachers' own work, it avoids immediate student-risk exposure while still building the competence needed for later classroom trials. Figure 5 illustrates this short practice loop.

Figure 5
Short Practice Loop for Building Teacher Self-Use Routines (15 Minutes per Week × 4 Weeks)



Implications for School-Level Guidelines and Classroom Rules

At the school level, concerns can be translated into simple, checkable rules that support responsible classroom practice. Based on common concerns reflected in policy debates and teacher reports, three rules are especially actionable: (1) disclosure—students should be told when GenAI has been used in lesson materials or tasks; (2) source awareness—key factual claims should be accompanied by sources, references, or explicit verification steps; and (3) a short checking log—teachers and students should keep brief notes on how outputs were checked and revised. These rules align with governance recommendations that emphasise transparency, accountability, and information literacy (OECD, 2023; MEXT, 2024). For Informatics education, these rules can be embedded as learning objectives rather than imposed solely as compliance requirements. Teaching students to disclose AI use, verify claims, and document checking steps directly supports information-utilisation competency and AI literacy. Moreover, because many teachers already use GenAI for lesson preparation and information search, such rules help ensure that GenAI-related risks are addressed consistently in both teacher work and student learning. These rules are summarised in Figure 6.

Figure 6
Three Simple, Checkable Classroom Rules Derived From Common Concerns

☐ **Disclosure**
Tell students when AI has been used.

☐ **Show sources**
Show sources or references for AI-assisted content

☐ **Keep a short checking log**
Record how AI output was checked and fitted

Theoretical Contribution

Conceptually, the two-stage model clarifies that determinants of intention are not identical to determinants of adoption. Expectations predicted "wanting to use," while self-use predicted "already using." For research on teacher GenAI adoption, this distinction suggests that models focused solely on intention may overestimate readiness for implementation, especially in contexts where classroom use requires careful governance and verification routines. Future studies could extend the present approach by incorporating facilitating conditions (e.g., school access and device policies), teacher GenAI self-efficacy, and student-related factors such as assessment integrity concerns. Methodologically, separating adoption from implementation quality (e.g., depth of student engagement, openness of tasks, and integration with ethics instruction) would also allow more fine-grained understanding of how teachers move from initial trials to sustainable practice.

Interpreting the Intention-Adoption Gap and Model Performance

A notable descriptive pattern is that intention was only weakly correlated with classroom adoption, while self-use frequency was more strongly related to adoption. Although the logistic model's predictive performance was moderate (AUC = 0.679), it leaves substantial variance unexplained. This is expected in school settings where adoption depends on factors beyond individual perceptions. Facilitating conditions such as whether GenAI sites are blocked on school networks, whether student device use is permitted, and whether a school has clarified rules for privacy and academic integrity may critically shape whether a teacher can implement GenAI even when motivation is high. Similarly, adoption may depend on teacher role expectations (e.g., being responsible for digital governance in the school), local community attitudes, and the perceived consequences of mistakes. The modest AUC therefore reinforces the value of treating adoption as a multi-level phenomenon: individual self-use may provide a personal bridge, but institutional conditions still matter.

From Intention to Safe Enactment: A Staged Implementation Pathway

The descriptive activity patterns reported by adopters suggest that early classroom adoption often takes a staged form: teachers begin by explaining what GenAI is, demonstrating its outputs, and discussing ethics and copyright before moving to open-ended student use. This staged pathway can be formalised into an implementation sequence that reduces risk while building student competencies. Stage A (teacher-facing preparation) focuses on teacher self-use. Teachers use GenAI for planning and material development while applying verification routines (e.g., cross-checking key facts, rewriting sensitive content in their own words, and removing personal data). Stage B (teacher-led classroom demonstration) introduces GenAI to students through controlled demonstrations, where the teacher models prompting, detects errors, and shows how to correct or reject outputs. Stage C (structured student use) allows students to use GenAI within clearly defined constraints: tasks specify what is allowed (e.g., idea generation, code debugging) and what is not allowed (e.g., submitting unedited GenAI output as final work), and students are required to document prompts and verification steps. Stage D (open-ended integration) is reserved for contexts where students have demonstrated sufficient AI literacy and information ethics, and where assessment design can minimise integrity problems. For Informatics education, this staged pathway can be aligned with existing curricular emphases on information ethics, data utilisation, and computational problem solving. For example, students can compare GenAI-generated explanations with textbook and teacher explanations, identify potential hallucinations, and evaluate the credibility of sources. In programming units, students can use GenAI for debugging but must explain the logic of solutions and cite the interaction. In data utilisation units, GenAI can be used to propose hypotheses or summarise patterns, but students must validate claims with actual data and make reasoning explicit.

Linking GenAI Governance to Information-Utilisation Competency

The governance recommendations in OECD (2023) and the guidance issued by MEXT (2025) share an underlying educational principle: GenAI should not replace human judgement but can be used to strengthen learning when combined with transparency and critical evaluation. This principle aligns closely with the aims of information-utilisation competency in Japan, which emphasises the ability to collect, interpret, and evaluate information and to act responsibly in digital environments. From this perspective, Informatics classrooms can treat GenAI not only as a tool but also as an object of inquiry. Rather than framing GenAI purely as a shortcut or a threat, teachers can position it as a technology whose outputs must be interrogated, contextualised, and ethically managed. Importantly, the present findings suggest that teacher self-use may be one practical lever for improving this kind of instruction. Teachers who frequently use GenAI may accumulate concrete examples of both productive uses and failures (e.g., confident but wrong answers), which can be turned into teaching materials that cultivate students' critical evaluation skills. PD that supports teachers in collecting and curating such examples—along with prompts and verification steps—may therefore contribute to both adoption and instructional quality.

Measurement Implications

Finally, the results highlight a measurement challenge. Concerns about GenAI are not a single construct; they include epistemic risks (accuracy and bias), normative risks (copyright and plagiarism), and institutional constraints (blocked access and unclear rules). Future research should separate these dimensions and examine which types of concern predict intention, which predict adoption, and which predict implementation quality. Such refinement would allow PD and policy to target the concerns that are most actionable in practice, rather than treating "concerns" as a uniform barrier.

Limitations and Future Work

This study has several limitations. First, the sample was a voluntary national sample and may overrepresent teachers who are already interested in GenAI or who have access to professional communities where GenAI is discussed. Second, the design was cross-sectional, so causal ordering cannot be established. It is plausible that early classroom adoption also increases later self-use frequency, and longitudinal data are needed to test directionality. Third, measures were self-reported and did not include classroom observations or artefact analysis. Fourth, classroom adoption was measured as a single binary indicator and did not capture quality, depth, or student outcomes. Finally, the concerns scale combined multiple concern types and showed low internal consistency, suggesting that future work should differentiate ethical, epistemic, and institutional concerns.

Future research should therefore use longitudinal and intervention designs. One promising direction is to evaluate the short PD practice loop proposed above, measuring changes in self-use, verification habits, and classroom adoption over time. Such studies could also test whether PD that targets verification routines reduces risk-related incidents (e.g., use of inaccurate outputs) and increases teachers' confidence in managing student use. Cross-country comparative studies would clarify which aspects of the two-stage model generalise across curricula and governance environments. Within Japan, further work should examine differences across subjects beyond Informatics and should refine measurement of concerns by separating ethical, technical, and institutional dimensions.

Conclusion

In Japanese high school Informatics education, teachers' decisions about GenAI matter because the subject is compulsory and directly connected to information literacy and data utilisation. Using a two-stage model, this study found that expectations of benefit strongly predict teachers' intention to use GenAI, while everyday self-use frequency is the key predictor of whether teachers have already adopted GenAI in class. These findings suggest a practical sequence for bridging policy and classroom practice: build self-use routines first through short, authentic PD cycles, and support implementation through simple, checkable classroom rules that address transparency and verification.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

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