Student Perceptions of AI-Augmented HyFlex Learning

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AI-Powered HyFlex Learning for Student Engagement

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Chapter 15
Student Perceptions of AI-Augmented HyFlex Learning:
A Mixed-Methods Study at a Malaysian University

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ABSTRACT

This chapter examines student perceptions of an AI-augmented HyFlex learning model at a private university in Malaysia, using mixed-methods data from 1,168 undergraduates across 28 countries. Guided by the Technology Acceptance Model, Self-Determination Theory, and cultural dimensions theory, the findings show generally positive sentiment (60.7%), with technology effectiveness as the dominant theme. However, acceptance is polarized: while features such as recorded sessions and interactive tools are well received, AI avatar lectures face strong resistance (67.5% negative) due to their perceived lack of human presence. Although overall sentiment does not differ significantly by nationality or academic level, qualitative

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insights reveal different emphases across groups. The study concludes that effective AI integration in HyFlex learning requires human–AI complementarity, supported by platform reliability and culturally responsive design.

1. INTRODUCTION AND ANALYTICAL CONTEXT

1.1 The HyFlex Model in Context

The Hybrid-Flexible (HyFlex) model of course design, first developed at San Francisco State University, offers students the ability to choose between face-to-face and online participation within the same course structure (Beatty, 2019). The foundational principle is that students in any modality should have comparable learning experiences, equivalent assessment opportunities, and meaningful access to course content (Abdelmalak & Parra, 2016). As higher education institutions have expanded their adoption of flexible delivery formats, a growing body of research has examined HyFlex outcomes, with studies reporting positive student satisfaction and reduced stress levels (Bockorny et al., 2024; Choi et al., 2024), though challenges remain, particularly around reduced peer interaction and uneven engagement across modalities (Howell et al., 2025).

Increasingly, higher education institutions worldwide have embraced HyFlex course designs and online delivery models in response to competitive market pressures, including cost efficiency, physical space constraints, quality enhancement, and the integration of emerging technologies (Yang et al., 2025). Within this evolving educational landscape, both faculty and students are required to adapt to hybrid learning environments that amalgamate digital and face-to-face modalities. Such transformations have not only reshaped teaching and learning practices but may also have reconfigured students' learning experiences and faculty members' professional identities (Islam et al., 2026).

The integration of artificial intelligence into HyFlex environments represents a more recent development, one that extends the model beyond its original design parameters (Liu et al., 2026). While the HyFlex literature has examined learner choice and equivalency (Xiao et al., 2025), the addition of AI-mediated instructional components raises questions about student acceptance, technology resistance, and the conditions under which AI tools support or complicate the learning experience. Large-scale implementations remain relatively rare, and evidence on how diverse student populations respond to AI-augmented HyFlex learning is still emerging (Yang et al., 2025).

1.2 AI-Enhanced HyFlex at Taylor's University

During the April to July 2025 semester, Taylor's University in Malaysia deployed an AI-augmented HyFlex learning model across 60 undergraduate modules spanning multiple faculties. Two AI-mediated features were introduced alongside the standard HyFlex infrastructure. First, AI avatar lecture videos were developed in which digital replicas of lecturers delivered pre-recorded content, allowing students to access lectures asynchronously. Second, the Noodle Factory AI learning assistant provided interactive quizzes, one-on-one tutoring, and personalised feedback intended to supplement in-class instruction.

A total of 1,168 students completed a structured survey capturing demographic information, self-reported AI interaction behaviours, perceptions of both AI features, and open-ended reflections on their HyFlex learning experience. The student body was internationally diverse, drawn from more than 28 countries, creating a setting in which cultural and linguistic backgrounds may shape how students engage with and evaluate technology-mediated instruction.

1.3 Conceptual Framework

This study draws on three established theoretical perspectives. The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption (Davis, 1989). Its extension, the Unified Theory of Acceptance and Use of Technology (UTAUT), incorporates social influence and facilitating conditions as additional predictors, recognising that technology acceptance operates within institutional and social contexts (Venkatesh et al., 2003). Both frameworks provide a lens for interpreting student evaluations of the specific AI-mediated features deployed at Taylor's University.

Self-Determination Theory (SDT) emphasises autonomy, competence, and relatedness as fundamental psychological needs that shape motivation and engagement (Ryan & Deci, 2000). The HyFlex model's emphasis on learner choice aligns with the autonomy component, while AI tutoring tools may support competence through personalised feedback. However, the replacement of human instructors with AI avatars may undermine relatedness, a tension that the data allow us to examine.

Finally, cultural dimensions theory provides a framework for understanding cross-national variation in technology reception. Hofstede's (2001) dimensions of collectivism, uncertainty avoidance, and power distance have been shown to influence educational technology acceptance (Straub et al., 1997; Teo & Huang, 2019), while Hall's (1976) distinction between high-context and low-context communication styles may shape how students from different cultural backgrounds articulate criticism and appreciation.

1.4 Research Questions

The study addresses four research questions:

RQ1: What are the dominant themes in student perceptions of AI-enhanced HyFlex learning, and what is the overall sentiment distribution?

RQ2: How do student perceptions vary across nationality groups (Malaysian, Chinese, Other)?

RQ3: How does academic progression shape the nature and sophistication of student feedback?

RQ4: What are the specific technology acceptance and resistance patterns for AI-mediated features?

2. METHODOLOGICAL FRAMEWORK AND ANALYTICAL APPROACH

2.1 Study Context and Research Design

This study examines student perceptions of an AI-augmented Hybrid-Flexible (HyFlex) learning model deployed at Taylor's University, Malaysia, during the April to July 2025 semester. The HyFlex approach, as defined by Beatty (2019), allows students to choose between face-to-face and online participation within the same course, with the aim of increasing accessibility and learner autonomy. At Taylor's University, this model was further augmented with two AI-mediated features: AI avatar lecture videos, in which digital replicas of lecturers delivered pre-recorded content, and the Noodle Factory AI learning assistant, which provided interactive quizzes, one-on-one tutoring, and personalised feedback.

The survey was administered across multiple faculties, drawing responses from 1,168 students enrolled in courses that had adopted the HyFlex model. The study adopted a convergent parallel mixed-methods design (Creswell & Plano Clark, 2018), collecting quantitative data through Likert-scale perception items and qualitative data through an open-ended response question within the same instrument. This design permits the simultaneous collection and subsequent integration of both data strands, allowing qualitative findings to contextualise and, where appropriate, complicate the quantitative patterns.

Four research questions guided the analysis. RQ1 asked what dominant themes characterise student perceptions and what the overall sentiment distribution is. RQ2 examined how perceptions vary across nationality groups. RQ3 investigated whether academic progression shapes the nature of student feedback. RQ4 focused on the specific technology acceptance and resistance patterns for AI-mediated features.

2.2 Survey Instrument and Data Collection

The survey instrument comprised 22 items organised into four sections. Section A collected demographic information through five items: Student ID, Nationality, Module Name, Faculty or School, and Semester of enrolment. Section B included eight items measuring students' self-reported AI interaction behaviours using a binary response format. Sample items include: “I use AI to get quick answers or direct explanations to academic problems” and “I learn complex topics by discussing them with AI.”

Section C contained eight Likert-scale perception items, four addressing AI avatar videos and four addressing the Noodle Factory AI learning assistant. A sample avatar item reads: “The use of AI Avatars in videos supports my learning and helps me retain information better.” A sample Noodle Factory item reads: “The quizzes provided by the Noodle Factory learning assistant effectively helped me check and confirm my understanding of the module's topics.” The response scale used a four-point forced-choice format (Strongly Disagree = 1, Disagree = 2, Agree = 4, Strongly Agree = 5) with no neutral midpoint. This deliberate omission of a midpoint was a design decision intended to encourage definitive responses. The numeric coding preserves a gap at the scale centre (no value of 3) to maintain symmetry. Internal consistency for the 8-item perception scale was high (Cronbach's alpha = 0.933, n = 1,168).

Section D consisted of a single open-ended item: “Please share your experience with HyFlex Learning (Interactive Synchronous Learning) for this module throughout the semester. You may include what you found helpful or enjoyable, and suggest any improvements that could make the learning experience better for future semesters.” The survey was administered via SurveyMonkey during the semester, with participation being voluntary and anonymous. Institutional ethical approval was obtained prior to data collection.

2.3 Sample Characteristics and Response Rate

A total of 1,168 students completed the survey. Open-ended responses were filtered to retain only meaningful contributions: empty responses, single-word answers, and responses of fewer than 10 characters were excluded. This yielded 476 responses suitable for analysis, representing a 40.8% response rate. Fifty-eight students appeared in multiple modules due to cross-enrolment; because each response pertained to a specific module experience, the analysis was conducted at the response level rather than the student level.

Students were grouped by nationality into three categories: Malaysia (n = 237, 49.8%), China (n = 134, 28.2%), and Other (n = 105, 22.1%), the latter comprising

students from 28 countries. Academic progression was categorised as Early (Semesters 1 and 2, n = 232), Mid (Semesters 3 and 4, n = 166), and Advanced (Semester 5 and above, n = 78). Four module categories were identified: Education (n = 58), Hospitality (n = 35), Event/Tourism (n = 34), and Other (n = 349). Table 1 presents the full sample characteristics.

Table 1. Sample characteristics (N = 476)

Characteristic	**n**	%
Nationality group		
Malaysia	237	49.8
China	134	28.2
Other (28 countries)	105	22.1
Academic level		
Early (Semester 1-2)	232	48.7
Mid (Semester 3-4)	166	34.9
Advanced (Semester 5+)	78	16.4
Module category		
Education	58	12.2
Hospitality	35	7.4
Event/Tourism	34	7.1
Other	349	73.3

Note. Response-level analysis; 58 students appeared in more than one module.

2.4 Analytical Approach

2.4.1 Sentiment analysis

Sentiment analysis of the open-ended responses was conducted using the AFINN lexicon (Nielsen, 2011), implemented via the tidytext package in R. The AFINN lexicon assigns integer valence scores ranging from -5 (most negative) to +5 (most positive) to a curated list of 2,477 English words. For each response, sentiment-bearing words were identified and their scores averaged to produce a single mean sentiment value per response. This approach was chosen for its transparency and reproducibility, as each classification can be traced to specific lexical matches.

Responses were classified into three categories based on the mean AFINN score: Positive (mean > 0.5), Negative (mean < -0.5), and Neutral (otherwise). A sensitivity analysis was conducted at alternative thresholds (0.25, 0.75, and 1.00) to

assess the stability of the classification. Cohen's d was computed as a one-sample effect size, comparing the mean sentiment score against a neutral baseline of zero (Cohen, 1988). It should be noted that lexicon-based methods do not capture negation, sarcasm, or contextual irony, and individual classifications should be interpreted with this limitation in mind.

2.4.2 Thematic analysis

Thematic analysis followed the six-phase reflexive approach outlined by Braun and Clarke (2006, 2021). The research team developed a codebook defining five themes grounded in the study's conceptual framework: Technology Effectiveness, Learning Quality, Social Interaction, Flexibility and Convenience, and Improvement Needs. Each theme was operationally defined with inclusion criteria, and sub-theme categories were specified for Flexibility (five sub-themes including Temporal Flexibility and Spatial Flexibility) and for technology feature evaluation (five features: AI Avatar, Interactive Tools, Recorded Sessions, Online Classes, and Platform Stability), each coded with a positive, neutral, or negative valence.

The coding was performed using a large language model (Claude, Anthropic) as a coding assistant, with the researchers providing the codebook definitions, reviewing outputs, and resolving ambiguous cases. This approach was adopted to process the full corpus of 476 responses systematically while maintaining fidelity to the predefined theme definitions. Each response could be assigned to multiple themes (mention-based coding) as well as a single primary theme (exclusive assignment). The use of AI-assisted coding represents a departure from traditional manual coding and its implications are addressed in the Limitations section.

2.4.3 Statistical testing

Group differences in sentiment were assessed using Pearson's chi-square test of independence (sentiment category by nationality group; sentiment category by academic level) and one-way analysis of variance (ANOVA) comparing mean sentiment scores across nationality groups. All tests were evaluated at an alpha level of .05. Effect sizes are reported where applicable.

2.4.4 Mixed-methods integration

Following the convergent design framework proposed by Creswell and Plano Clark (2018), quantitative and qualitative findings were integrated through a joint display table. The display juxtaposes quantitative results (sentiment distribution, statistical tests) with qualitative evidence (thematic patterns, representative student

quotations) across each research question. Integration was assessed for convergence, complementarity, and divergence between the two data strands.

3. RESULTS

This section presents findings organised by the four research questions, followed by an integrated mixed-methods synthesis. All percentages for thematic prevalence are mention-based (a single response could address multiple themes) unless otherwise stated. Student quotations are presented verbatim with minor formatting adjustments for readability; each has been verified against the original survey data.

3.1 RQ1: What Are the Dominant Themes and the Overall Sentiment Distribution?

The overall sentiment distribution of the 476 analysed responses was predominantly positive. As shown in Table 2, 60.7% of responses (n = 289) were classified as positive, 31.1% (n = 148) as neutral, and 8.2% (n = 39) as negative. The mean AFINN score was 1.06 (SD = 1.26), yielding a Cohen's d of 0.84, which represents a large effect size by conventional benchmarks (Cohen, 1988). This suggests that student responses tended to carry positive sentiment, though the sizeable neutral category (31.1%) indicates that a substantial minority of students offered neither clearly positive nor negative evaluations.

A sensitivity analysis confirmed that the majority-positive pattern held across alternative classification thresholds: at a threshold of 0.25, 66.0% of responses were classified as positive; at 0.75, 57.8%; and at 1.00, 51.5%. Although the proportion varied with threshold stringency, a positive majority was observed at every tested level.

Table 2. Overall sentiment distribution (N = 476)

Sentiment Category	n	%
Positive	289	60.7
Neutral	148	31.1
Negative	39	8.2
Total	476	100.0

Note. AFINN lexicon (Nielsen, 2011). M = 1.06, SD = 1.26, Cohen's d = 0.84. Classification threshold: |mean| > 0.5.

Thematic analysis revealed five distinct themes. Technology Effectiveness was the most prevalent, mentioned in 37.6% of responses, followed by Learning Qual-

ity (20.4%), Social Interaction (20.0%), Flexibility and Convenience (18.7%), and Improvement Needs (10.7%). Table 3 presents the full distribution. The dominance of Technology Effectiveness as a theme indicates that students were primarily concerned with evaluating the specific technological tools they encountered, rather than broader pedagogical or logistical aspects of the HyFlex model.

Table 3. Theme prevalence (mention-based, N = 476)

Theme	n	% of Responses
Flexibility and Convenience	89	18.7
Technology Effectiveness	179	37.6
Learning Quality	97	20.4
Social Interaction	95	20.0
Improvement Needs	51	10.7

Note. Responses could mention multiple themes; percentages do not sum to 100%.

Student responses illustrate the thematic landscape. Technology-related evaluations ranged from appreciation for interactive features to frustration with platform issues:

"It is not like other AI tools that can directly summarize the courseware. When watching AI video teaching, I prefer AI to help me directly summarize the key points of the course, which is more convenient and faster. However, one thing Noodle Factory does well is the review and test part, which can help me quickly grasp the key points of the course." (Malaysia student, Other, Early (1-2), positive sentiment)

"I hope that lecture can be not in pre- recorded form cause is not helpful and the video did not explain in details just bring through the topic i would rather to have online lecture or face-to- face lecture this two is more helpful. thanks " (Malaysia student, Other, Mid (3-4), positive sentiment)

"I find that the hyflex lessons are less time consuming as I can be in the comfort of my own home and join class, but I do think face to face classes are more engaging. I would prefer hyflex learning over face to face though and I just hope there's a stricter rule for the completion so we don't feel like we're going to be okay even if we don't do it" (Other student, Education, Early (1-2), positive sentiment)

"I find Hyflex to be interesting, although it's very flexible and convenient, however I prefer physical learning instead. I feel like this is a good alternative to learn your modules but I feel like it's not enough. I still physically learning as I get

to convey my emotions and talk to a person. I highly value in person learning rather than online." (Malaysia student, Other, Mid (3-4), positive sentiment)
"I found HyFlex Learning flexible and convenient. It was helpful to attend both online and in-person depending on my situation. I enjoyed the real-time interaction during online classes and the recorded sessions for review. However, improving audio and video quality would make the experience better." (China student, Other, Mid (3-4), positive sentiment)

3.2 RQ2: How Do Student Perceptions Vary Across Nationality Groups?

No statistically significant association was found between nationality group and sentiment category, $\chi^2(4) = 6.53$, $p = .1628$, nor between nationality group and mean sentiment score, $F(2, 473) = 1.687$, $p = .186$. A descriptive trend was nonetheless observable: Chinese students appeared somewhat more positive (66.4%) than students from Other nationalities (60.0%) or Malaysia (57.8%). However, this pattern did not reach conventional levels of significance and should be interpreted with caution.

Negative sentiment rates varied descriptively across groups: China 3.7%, Malaysia 9.3%, and Other 11.4%. Chinese students expressed notably less negative sentiment, though again this difference was not statistically significant.

Table 4. Sentiment distribution by nationality group

Group	n	Positive %	Neutral %	Negative %	M	SD
China	134	66.4	29.9	3.7	1.22	1.1
Malaysia	237	57.8	32.9	9.3	1.02	1.34
Other	105	60.0	28.6	11.4	0.943	1.24

Note. $\chi^2(4) = 6.53$, $p = .1628$. $F(2, 473) = 1.687$, $p = .186$.

Table 5. Theme prevalence by nationality group (mention-based)

Theme	China (n = 133)	Malaysia (n = 237)	Other (n = 106)
Technology Effectiveness	30 (22.6%)	97 (40.9%)	52 (49.1%)
Learning Quality	36 (27.1%)	44 (18.6%)	17 (16.0%)
Social Interaction	8 (6.0%)	57 (24.1%)	30 (28.3%)
Flexibility and Convenience	36 (27.1%)	32 (13.5%)	21 (19.8%)
Improvement Needs	9 (6.8%)	30 (12.7%)	12 (11.3%)

Note. Percentages are within-group. Responses could mention multiple themes.

Qualitative differences in thematic emphasis were apparent despite the absence of significant quantitative differences. Chinese students placed relatively greater emphasis on Learning Quality (27.1%) and Flexibility (27.1%), while Malaysian students were most concerned with Technology Effectiveness (40.9%) and Social Interaction (24.1%). Students from Other nationalities showed the strongest focus on Technology Effectiveness (49.1%).

The qualitative data reveal how cultural and educational backgrounds may shape the focus of student feedback, even when overall sentiment levels appear comparable:

"I found the HyFlex Learning experience very helpful as it offered flexibility to attend classes both online and in person. The interactive synchronous format kept me engaged, especially during discussions and group work. One area for improvement could be better coordination between in-class and online students to ensure equal participation. Overall, it was a convenient and effective way to learn." (China student, Other, Early (1-2), positive sentiment)

"Was looking forward to the module, but the entire hyflex but just made it feel extremely unimportant. Despite my best efforts, answers input in the quizzes are marked incorrectly due to the inability of the ai to detect 'different' answers from those not structured as preprogrammed. I feel this hyflex limits this module and should only be used as a support system to a traditional lecture." (Malaysia student, Other, Early (1-2), neutral sentiment)

"It's helpful, but somehow it ends up making me confused about which one to open first, because there are just so many steps, both on MyTIMES and HyFlex. I think that's also why many students are still unsure how to access everything. Since our lectures are online, it depends on each student's situation. If the lectures were face-to-face, I believe students would be more focused and less confused.\" (Other student, Other, Early (1-2), neutral sentiment)

"i hate it. it just feels like ai slop to cut corners. the avatars are so painfully obviously ai. they're monotonous, their voices don't even match the lecturers, it's terrible. the quizzes are wrong sometimes. bring back the weekly quizzes on mytimes instead. and for q6, i don't use ai for any of this. i only use noodle factory for the compulsory weekly quizzes." (Malaysia student, Other, Early (1-2), negative sentiment)

3.3 RQ3: How Does Academic Progression Shape Student Feedback?

Academic level was not significantly associated with sentiment distribution, $\chi^2(4) = 1.22$, $p = .8754$. Positive sentiment rates were broadly similar across all three groups: Early (59.5%), Mid (60.2%), and Advanced (65.4%). Mean sentiment scores

followed a slight upward trend from Early (M = 1.0) to Advanced (M = 1.14), but the differences were negligible.

Table 6. Sentiment and theme prevalence by academic level

Measure	Early (n = 232)	Mid (n = 166)	Advanced (n = 78)
Positive sentiment %	59.5	60.2	65.4
Neutral sentiment %	32.8	30.7	26.9
Negative sentiment %	7.8	9.0	7.7
Mean sentiment	1.0	1.1	1.14
Technology Effectiveness	88 (37.9%)	55 (33.1%)	36 (46.2%)
Learning Quality	44 (19.0%)	40 (24.1%)	13 (16.7%)
Social Interaction	57 (24.6%)	21 (12.7%)	17 (21.8%)
Flexibility and Convenience	41 (17.7%)	34 (20.5%)	14 (17.9%)
Improvement Needs	26 (11.2%)	14 (8.4%)	11 (14.1%)

Note. $\chi^2(4) = 1.22$, $p = .8754$. Sentiment from AFINN analysis; themes from mention-based coding.

While quantitative sentiment did not vary significantly, qualitative differences in thematic emphasis were apparent. Advanced students showed an elevated focus on Technology Effectiveness (46.2%) and Improvement Needs (14.1%), suggesting that academic progression may shape the specificity and constructiveness of feedback without necessarily altering its overall valence. Early-semester students, by contrast, were more likely to mention Social Interaction concerns (24.6%), possibly reflecting the adjustment challenges of newer students.

The following responses illustrate how feedback character may shift with academic experience:

"HyFlex learning was flexible and effective. I appreciated the recordings and live interaction. To improve, better online engagement and technical support are needed for a more balanced experience." (China student, Other, Early (1-2), positive sentiment)

"As a school with such prestige, it is saddening to see it begin to replace the lecturers and tutors with generative AI. As a student, it seems more of a way to lay off costs rather than for the benefit of students. Please reconsider the use of generative Ai as it sets a bad precedent to students and education as a whole. Question 6 doesn't even have an option to deny the use of ai." (Malaysia student, Other, Mid (3-4), neutral sentiment)

"The concept of Hyflex said that we can take our lecture anytime of the week but we are still required to attend an online night session that was at a very ineffective timing. I think this contradicts with the purpose and I think it's better

for real-time lectures to be optional. Apart from that, the AI video I find is really effective because lecturer will summarise the important knowledge into videos of 10 mins which saves a lot of time and is easier to understand" (Malaysia student, Other, Advanced (5+), positive sentiment)

3.4 RQ4: What Are the Technology Acceptance and Resistance Patterns?

A fine-grained analysis of technology-specific mentions reveals sharply differentiated acceptance patterns across the five AI-mediated features. Table 7 presents the evaluation of each feature by students who mentioned it.

Table 7. Technology feature evaluation by students who mentioned each feature

Feature	Mentions	Positive	Neutral	Negative
AI Avatar Videos	77	19 (24.7%)	6 (7.8%)	52 (67.5%)
Online Classes	36	14 (38.9%)	1 (2.8%)	21 (58.3%)
Interactive Tools (Noodle Factory)	77	49 (63.6%)	5 (6.5%)	23 (29.9%)
Recorded Sessions	31	29 (93.5%)	1 (3.2%)	1 (3.2%)
Platform Stability	23	0 (0.0%)	0 (0.0%)	23 (100.0%)

Note. Based on valence coding of technology feature mentions within coded responses.

AI avatar videos were the most contested feature. Of the 77 responses that mentioned avatars, 67.5% expressed negative evaluations, with only 24.7% positive. Student objections centred on the perceived artificiality of the AI-generated voice, the absence of real-time interaction, and a sense that avatar lectures represented a diminished learning experience compared with human-led instruction. This pattern of resistance may reflect perceived ease-of-use barriers as conceptualised in the Technology Acceptance Model (Davis, 1989).

The interactive tools (primarily Noodle Factory quizzes and tutoring) received a more favourable reception: 63.6% of the 77 mentions were positive, though 29.9% were negative, with complaints focusing on answer recognition and technical reliability. Recorded sessions were overwhelmingly well received, with 93.5% of 31 mentions being positive; students valued the ability to revisit content at their own pace. Online classes drew a majority-negative response (58.3% of 36 mentions), and platform stability was universally criticised (100.0% of 23 mentions reporting technical difficulties).

Acceptance patterns also varied across module categories, suggesting that implementation context may shape student reception. Table 8 presents the sentiment distribution by module type.

Table 8. Sentiment by module category

Module Category	n	Positive %	Mean Sentiment
Education	58	74.1	1.41
Event/Tourism	34	70.6	1.2
Other	349	59.6	1.03
Hospitality	35	40.0	0.582

Note. Module categories derived from curriculum classification.

Education modules showed the highest positive sentiment (74.1%, M = 1.41), while Hospitality modules had the lowest (40.0%, M = 0.582). This variation may reflect differences in how AI features were integrated into course delivery across disciplines, though further investigation would be needed to identify the specific pedagogical factors involved.

The following quotations illustrate the range of student responses to specific technological features:

"I don't like it, I would rather having lecturer to teach me instead. I don't feel like learning, the AI lecture video is horrible, the AI video always have the same sentence structure of xxx is not only, but also xxxx, and it is so annoying yet the content is not impactful and good. In short, I just don't like it, I don't feel like the experience reciprocates with the fees I have paid." (Malaysia student, Other, Advanced (5+), neutral sentiment)

"I feel like this concept is beneficial, especially for lectures. this is so lecturers can focus more on tutorial classes. this also makes sure that the lecturer doesn't miss out on any information. i also like it better as the voices are much clearer and i can go back and watch the AI videos again." (Malaysia student, Event/Tourism, Mid (3-4), positive sentiment)

"When using HyFlex learning, I found it helpful that the platform could provide instant feedback to improve my answers, especially in essay writing. However, I often experienced issues with the system not signing me in properly, and it took a long time to access the platform. This delay was frustrating and demotivating, especially during online classes when time and focus are important." (Malaysia student, Education, Early (1-2), positive sentiment)

"HyFlex offer us to have flexible schedules on when to watch lecture videos. We can watch whenever we are available. However, I still prefer physical lecture classes because it offers an environment where I needed to be focused on the module and impact me for having classes without blanking out" (Malaysia student, Other, Mid (3-4), positive sentiment)

"I appreciate using AI for my own reading and personalised reviews. However, I think it is not really beneficial as AI only covers minimal and surfaced content

of the class. I would prefer live sessions where I could learn and absorb information better. Moreover, my Noodle Factory gives me a lot of problem whenever I want to log in or use the application." (Malaysia student, Other, Early (1-2), positive sentiment)

"To be honest, I found the HyFlex learning experience this semester quite frustrating and ineffective. The idea of flexible learning is good in theory, but in practice, it didn't work well for this module. The interaction between online and in-person students felt very disconnected, and online participation was often sidelined or ignored." (Malaysia student, Other, Early (1-2), neutral sentiment)

3.5 Mixed-Methods Integration

Table 9 presents a joint display integrating quantitative and qualitative findings across the study's four research dimensions, following the convergent design framework of Creswell and Plano Clark (2018). The integration reveals patterns of convergence, complementarity, and divergence between the two data strands.

Table 9. Joint display: Integration of quantitative and qualitative evidence

Dimension	Quantitative Finding	Qualitative Evidence	Integration Assessment
Overall sentiment	60.7% positive; d = 0.84; 31.1% neutral	Technology Effectiveness dominant theme (37.6%); students focus on evaluating specific features	Convergent: positive majority aligns with appreciation for interactive tools and recordings; the 31.1% neutral share tempers the effect size
Cross-national	No significant difference (p = .1628)	Chinese students emphasise flexibility and learning quality; Malaysian students focus on technology and social interaction	Complementary: similar sentiment levels mask qualitative differences in what students attend to
Academic progression	No significant difference (p = .8754)	Advanced students show elevated Technology Effectiveness (46.2%) and Improvement Needs (14.1%)	Complementary: progression may shape feedback specificity without altering valence
AI features	AI Avatar 67.5% negative; Recorded Sessions 93.5% positive	Students object to avatar artificiality but value replay functionality	Convergent: human-like AI features face resistance; utility features gain acceptance
Module variation	Education 74.1% vs. Hospitality 40.0%	Implementation context shapes reception across disciplines	Divergent: discipline-level differences suggest context matters more than technology itself

Note. Following Creswell and Plano Clark (2018) convergent design integration.

The integration reveals three key patterns. First, quantitative and qualitative findings converge on the overall positive-but-nuanced character of student perceptions and on the polarised reception of AI avatar technology. Second, the qualitative data complement the null quantitative findings for cross-national and academic progression effects by revealing thematic differences that sentiment scores alone do not capture. Third, module-level variation suggests that the context of implementation, not merely the technology itself, shapes student reception, a finding that emerges most clearly from the qualitative data but is supported by the quantitative sentiment differences across module categories.

Two responses illustrate the convergence-divergence dynamic. The first exemplifies a case where quantitative and qualitative signals align:

"The HyFlex Learning experience for this module provided a flexible and inclusive approach. I found the live interaction, through Teams video conferencing, helpful in keeping me engaged and connected with both the lecturer and my peers. The ability to revisit recorded sessions was particularly useful for reviewing difficult topics. Overall, the HyFlex model supported my learning effectively." (Other student, Other, Advanced (5+), positive sentiment)

The second illustrates a case of divergence, where the AFINN score classified the response as positive despite substantive criticism in the text:

"Don't like the hybrid teaching method of AI usage with online courses. Would prefer not to have this type of hybrid learning, not recommended. The AI alone is helpful, online classes are ok but the hybrid combination is a no-go. Please don't use this hybrid method again, would prefer face to face classes with usage of this AI, or more interactive online classes. Other than that, it's good" (Other student, Other, Early (1-2), positive sentiment)

4. DISCUSSION

The findings reveal a nuanced picture of student engagement with AI-augmented HyFlex learning. While the overall sentiment was positive, the data pointed to important variations in what students attend to and how they evaluate specific technological features. This section interprets the results through the study's theoretical framework and considers their implications for practice.

4.1 Overall Reception and Technology Focus

The 60.7% positive sentiment rate, with a large effect size (Cohen's $d = 0.84$), aligns with broader findings in the HyFlex literature, where student satisfaction tends to be favourable when learner choice is preserved (Bockorny et al., 2024; Choi et

al., 2024). From the perspective of the Technology Acceptance Model, this suggests that students perceived the HyFlex platform as broadly useful and accessible (Davis, 1989). However, the sizeable neutral category (31.1%) tempers this interpretation, indicating that a substantial share of students remained ambivalent.

A particularly notable finding is that Technology Effectiveness (37.6%) emerged as the dominant theme, rather than Flexibility and Convenience (18.7%). This suggests that students were primarily evaluating the specific technological tools they encountered, not the flexibility of the delivery format itself. The dominance of technology-related concerns is consistent with TAM's emphasis on perceived usefulness and ease of use as primary determinants of acceptance (Davis, 1989; Venkatesh et al., 2003). For practitioners, this implies that the success of HyFlex models may hinge less on the structural flexibility they offer than on the quality and perceived utility of the specific tools deployed.

The flexibility dimension, while not dominant, remains significant. At 18.7% of responses, it reflects an ongoing appreciation for learner autonomy that aligns with Self-Determination Theory (Ryan & Deci, 2000). The ability to choose when and where to engage with course materials appears to reduce perceived stress and support self-regulated learning strategies (Broadbent & Fuller-Tyszkiewicz, 2018), a finding consistent with the learner choice and equivalency principles central to the HyFlex design (Xiao et al., 2025).

4.2 Cross-National Patterns

The descriptive trend in sentiment across nationality groups (Chinese students 66.4% positive, Other 60.0%, Malaysian 57.8%) did not reach statistical significance, $\chi^2(4) = 6.53$, $p = .1628$; $F(2, 473) = 1.687$, $p = .186$. This finding cautions against drawing strong conclusions about nationality-based differences in overall satisfaction. However, the qualitative data reveal meaningful differences in thematic emphasis that the sentiment scores alone do not capture.

Chinese students placed relatively greater emphasis on Learning Quality (27.1%) and Flexibility (27.1%), while Malaysian students were most concerned with Technology Effectiveness (40.9%) and Social Interaction (24.1%). Students from other nationalities showed the strongest focus on Technology Effectiveness (49.1%). These patterns may reflect cultural orientations described by Hofstede (2001): students from collectivist cultural backgrounds may weight social and relational aspects differently, while uncertainty avoidance may shape expectations about technology reliability (Straub et al., 1997; Teo & Huang, 2019).

The qualitative data also suggest differences in communication style that are consistent with Hall's (1976) high-context/low-context distinction. Chinese students tended to embed criticism within overall positive framing, while Malaysian students

adopted a more direct evaluative tone. Students from other nationalities often offered balanced assessments that weighed positive and negative aspects explicitly. These patterns, while qualitative and not generalisable, have implications for how feedback instruments are designed and interpreted in multicultural educational settings (Meyer, 2014).

4.3 Academic Maturation

Academic progression was not significantly associated with sentiment distribution, $\chi^2(4) = 1.22$, $p = .8754$. Positive sentiment rates were broadly similar across Early (59.5%), Mid (60.2%), and Advanced (65.4%) students. This indicates that favourable attitudes toward HyFlex learning are not contingent on academic experience, a finding that speaks to the model's appeal across different stages of undergraduate study.

Nonetheless, qualitative differences in thematic emphasis were apparent. Advanced students showed elevated attention to Technology Effectiveness (46.2%) and Improvement Needs (14.1%), suggesting that academic maturation may shape the specificity and constructiveness of feedback without altering its overall valence. This pattern is consistent with developmental models of critical thinking, which posit that students' progress from dualistic acceptance toward more contextualised and evaluative reasoning as they advance (King & Kitchener, 2004; Bloom, 2010). Early-semester students, by contrast, more frequently mentioned Social Interaction concerns (24.6%), possibly reflecting the adjustment challenges and relational needs of newer students (Yaban & Gaschler, 2025).

4.4 Technology Acceptance Polarisation

The most striking finding concerns the sharply differentiated reception of individual technology features. The AI avatar videos attracted the strongest resistance, with 67.5% of the 77 students who mentioned them expressing negative evaluations and only 24.7% positive. By contrast, recorded sessions were overwhelmingly well received (93.5% positive), and interactive tools (primarily Noodle Factory) received a favourable majority (63.6% positive). This pattern suggests that technology acceptance in HyFlex settings is highly feature-specific rather than blanket.

The avatar resistance may be interpreted through the lens of TAM and UTAUT. The perceived artificiality of the AI-generated voice and the absence of real-time interaction appear to have undermined both perceived usefulness and perceived ease of use (Davis, 1989). From an SDT perspective, the replacement of human instructors with digital replicas may have compromised the relatedness component of motivation, as students reported feeling disconnected from the learning experi-

ence (Ryan & Deci, 2000). This aligns with the broader finding that AI features are most readily accepted when they complement rather than replace human instruction (Abbass, 2019), a principle consistent with the human-in-the-loop frameworks advocated by the U.S. Office of Educational Technology (2023).

The acceptance of recorded sessions and interactive tools, by contrast, suggests that AI features offering clear utility (content replay, self-assessment) without displacing the human instructor face less resistance. The social influence component of UTAUT (Venkatesh et al., 2003) may also play a role: in collectivist educational cultures, the endorsement of specific tools by lecturers and peers may carry particular weight (Holden & Rada, 2011). Platform stability, universally criticised (100.0% negative across all 23 mentions), represents a facilitating condition failure that may independently undermine technology acceptance regardless of feature quality.

Module-level variation further complicates the picture. Education modules showed the highest positive sentiment (74.1%), while Hospitality modules had the lowest (40.0%). This suggests that implementation context, including how AI features are integrated into specific disciplinary pedagogies, shapes student reception in ways that aggregate statistics may obscure.

4.5 Implementation Implications

Three practical implications emerge from the findings. First, platform stability must be treated as a precondition for technology acceptance, not an afterthought. The universal criticism of technical infrastructure failures indicates that even well-designed AI features will be poorly received if the underlying platform is unreliable. Institutions adopting HyFlex models should invest in technical infrastructure testing and support before scaling AI-mediated features.

Second, the data support a principle of human-AI complementarity rather than substitution. The sharp contrast between the positive reception of interactive tools and recorded sessions, and the rejection of AI avatars, suggests that students accept AI when it supplements human instruction but resist it when it appears to replace the human instructor. This finding aligns with human-in-the-loop frameworks that position AI as a support tool for teaching rather than an autonomous delivery mechanism (Abbass, 2019; Office of Educational Technology, 2023). From the perspective of SDT, preserving the human element may be necessary to sustain the relatedness component of intrinsic motivation (Ryan & Deci, 2000).

Third, the qualitative differences across nationality groups, while not statistically significant at the aggregate level, suggest that culturally responsive design may improve technology acceptance across diverse student populations. The distinct communication styles observed, from indirect criticism embedded in positive framing to direct evaluative commentary, imply that feedback instruments and course design

processes should accommodate a range of expressive norms (Hall, 1976; Herrera et al., 2012). Institutions serving internationally diverse student bodies may benefit from piloting AI features with students from different cultural backgrounds before full-scale deployment.

5. CONCLUSION

This study examined 476 student responses across 60 modules at Taylor's University to assess perceptions of an AI-augmented HyFlex learning model. The overall sentiment was positive (60.7%), but this aggregate figure conceals important variation. Students were primarily concerned with evaluating specific technological features (Technology Effectiveness, 37.6%), not with the flexibility of the delivery model itself.

Feature-specific acceptance patterns represent the study's most actionable finding. Recorded sessions were overwhelmingly well received (93.5% positive), while AI avatar videos were strongly resisted (67.5% negative). This polarisation suggests that the success of AI integration in HyFlex settings depends not on whether AI is used, but on how it is positioned relative to human instruction. Tools that supplement human teaching are accepted; tools perceived as replacing it face resistance.

Cross-national and academic-progression effects were not statistically significant at the quantitative level, though qualitative differences in thematic emphasis suggest that cultural background and academic experience shape the focus and specificity of student feedback. These findings point to the importance of culturally responsive implementation strategies and ongoing attention to platform stability as preconditions for technology acceptance.

The study contributes to the emerging literature on AI-augmented HyFlex learning by providing empirical evidence from a large, internationally diverse student sample in a Southeast Asian context. Its convergent mixed-methods design allows both the scale of student sentiment and the texture of individual experience to inform conclusions. Future research should examine longitudinal effects, compare pre- and post-implementation perceptions, and investigate whether targeted improvements to AI avatar design can shift the acceptance patterns observed here.

6. LIMITATIONS AND METHODOLOGICAL CONSIDERATIONS

Several limitations should be considered when interpreting these findings. First, the study was conducted at a single institution (Taylor's University, Malaysia), which limits the generalisability of the results to other HyFlex implementations, particularly

those in different cultural and institutional contexts. The specific configuration of AI tools (AI avatars and Noodle Factory) is particular to this setting, and student responses may not transfer to different AI-mediated features.

Second, the open-ended responses were collected in English, which was not the first language for 50.2% of respondents (n = 239). This language constraint may have limited the depth and nuance of non-native speakers' feedback, potentially biasing sentiment scores toward shorter, less expressive responses. Future studies should consider collecting responses in students' preferred languages to address this limitation.

Third, sentiment analysis was conducted using the AFINN lexicon, a dictionary-based approach that does not capture negation, sarcasm, or contextual irony. A response containing positive words used ironically would be misclassified as positive. The sensitivity analysis at multiple thresholds provides some reassurance that the majority-positive finding is not an artefact of threshold choice, but individual classifications should be interpreted with caution.

Fourth, thematic coding was performed using a large language model (Claude, Anthropic) as a coding assistant. While this approach afforded consistency across all 476 responses and maintained fidelity to the predefined Braun and Clarke codebook, it represents a departure from traditional manual coding. LLM-based coding may introduce systematic biases that are not yet well understood, and the approach limits reproducibility to the extent that model outputs may vary across versions or configurations. The transparency of disclosing this method is intended to allow readers to assess its appropriateness.

Fifth, the survey used a four-point forced-choice Likert scale (1, 2, 4, 5) with no neutral midpoint. While this design decision was intended to encourage definitive responses, it may have pushed ambivalent students toward poles they did not strongly endorse. The perception data should be interpreted with this constraint in mind.

Sixth, 58 students appeared in multiple modules due to cross-enrolment, and the analysis was conducted at the response level. While each response pertained to a specific module experience, the non-independence of responses from the same student may inflate the effective sample size and should be considered a potential source of bias. The cross-sectional design also precludes any claims about change over time; a longitudinal design with pre- and post-implementation measures would be needed to assess whether student perceptions shift with extended exposure to AI-augmented HyFlex learning.

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