

Student Perceptions of Artificial Intelligence and Metaverse-Enabled Remote Learning in New Zealand Tertiary Education

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Abstract

The increasing development of emerging digital technologies is creating new possibilities for remote tertiary education. Artificial Intelligence and Metaverse technologies offer potential for personalised learning, intelligent support, immersive interaction, and collaboration; however, their educational value depends partly on how students perceive their usefulness, accessibility, supporting conditions, and motivational potential. This study examined New Zealand tertiary students' perceptions of prospective Artificial Intelligence- and Metaverse-enabled remote learning environments and investigated whether selected technology-acceptance and motivational factors were associated with perceived learning engagement. A mono-method quantitative, cross-sectional survey design was adopted. Data were collected through an online questionnaire comprising 20 Likert-scale items representing six constructs: performance expectancy, facilitating conditions, motivation, perceived ease of use, perceived usefulness, and perceived learning engagement. A total of 356 responses were retained for analysis. Descriptive statistics, reliability analysis, Pearson correlation, exploratory chi-square analysis, and multiple linear regression were conducted. The regression model was statistically significant and explained 33.8% of the variance in perceived learning engagement ($R^2 = .338$; adjusted $R^2 = .329$; $F = 35.773$, $p < .001$). Perceived usefulness ($\beta = .279$, $p < .001$), motivation ($\beta = .218$, $p < .001$), and facilitating conditions ($\beta = .179$, $p < .001$) were statistically significant predictors of perceived learning engagement. Performance expectancy ($\beta = .065$, $p = .223$) and perceived ease of use ($\beta = .089$, $p = .058$) were not statistically significant predictors. An exploratory chi-square analysis also identified a statistically significant association between age and perceptions of virtual teamwork ($p = .001$). The findings provide preliminary evidence that perceived usefulness, motivation, and facilitating conditions are important considerations in understanding student engagement with prospective advanced remote learning environments. Given the cross-sectional design and purposive non-probability sampling, the findings indicate statistical associations rather than causal effects and should be interpreted within the study sample.

Keywords: artificial intelligence, Metaverse, remote learning, tertiary education, technology acceptance, motivation, learning engagement, New Zealand

1. Introduction

1.1 Digital Transformation of Tertiary Education

Digital technologies have become an established component of contemporary tertiary education. The rapid expansion of online and blended learning has increased flexibility in where, when, and how students participate in education. The evolution of distance learning has increasingly moved education towards digitally mediated environments, creating a foundation for contemporary forms of remote and online learning (Tamuli, 2023). The COVID-19 pandemic accelerated this transition, requiring tertiary institutions to adopt digital platforms and communication technologies at unprecedented speed. In New Zealand, students experienced rapid changes in teaching and learning arrangements, with online platforms becoming an important mechanism for maintaining educational continuity (Clarke & Munro, 2021).

Although the rapid transition demonstrated the value of digital delivery, it also highlighted limitations associated with conventional online learning. Digital learning environments can provide flexibility and accessibility, but students may experience reduced interpersonal interaction, limited opportunities for experiential learning, and difficulties maintaining sustained engagement. These concerns have contributed to continuing interest in technologies that may provide richer forms of interaction and support.

The next stage of digital transformation is therefore increasingly concerned not only with moving existing teaching activities online, but also with reconsidering how digital environments can support learning. Artificial Intelligence (AI) and Metaverse technologies represent two distinct, although potentially complementary, developments within this broader transformation. AI can provide adaptive and data-driven forms of support, whereas Metaverse environments can provide immersive, spatial, and socially interactive experiences. Their educational value should therefore be considered in relation to learning purposes rather than technological novelty alone.

1.2 Artificial Intelligence and Metaverse Technologies in Education

Artificial Intelligence refers broadly to computational systems capable of performing tasks associated with human cognitive functions, including prediction, classification, language processing, recommendation, and adaptive decision-making. Within education, AI has been associated with personalised learning, intelligent tutoring, automated feedback, learning analytics, and adaptive support (Villegas-Ch et al., 2020; Wei et al., 2021; Tuczyński, 2024). Recent research on students' perceptions of AI integration also highlights the importance of considering how learners understand and respond to AI within higher education (Slimi et al., 2025).

The Metaverse represents a different technological proposition. Rather than primarily providing computational intelligence, Metaverse-enabled environments emphasise persistent, immersive, and interactive digital spaces. Virtual Reality (VR), Augmented Reality (AR), avatars, virtual laboratories, and shared three-dimensional environments can potentially support experiential and collaborative learning (Pradana & Elisa, 2023; Rane et al., 2023).

These technologies should not, however, be treated as synonymous. AI concerns computational intelligence and adaptive support, while the Metaverse concerns immersive and interactive digital environments. They may be integrated into the same educational ecosystem, but they offer different capabilities and raise different questions concerning adoption, accessibility, pedagogy, and student experience.

Recent scholarship indicates that educational technology adoption is shaped by multiple interacting factors rather than technology characteristics alone. Granić (2022), in a systematic review of educational technology adoption, highlights the relevance of technology-acceptance perspectives for understanding the adoption of educational technologies. Similarly, Maghaydah et al. (2024) synthesise research on Metaverse adoption in education and identify adoption-related factors that extend beyond the technology itself. These perspectives support examining students' perceptions of educational value, usability, and the availability of appropriate support when considering emerging learning technologies. This provides a useful foundation for examining student perceptions of emerging technologies before widespread institutional implementation.

Table 1. Summary of Recent Research on Digital Transformation and Emerging Technologies in Tertiary Education

Study	Research focus	Key findings or contribution	Relevance to the present study
Clarke and Munro (2021)	New Zealand students' experiences of online learning during COVID-19	Examines student experiences during the rapid transition to online learning.	Establishes the New Zealand context for digitally mediated tertiary education.
Granić (2022)	Educational technology adoption	Reviews technology-adoption research and the relevance of technology-acceptance perspectives.	Supports examining students' technology-related perceptions.
Sushama et al. (2022)	AI-based remote learning	Discusses the potential role of AI in remote education.	Provides background for investigating AI-enabled learning environments.
Pradana and Elisa (2023)	Metaverse in education	Reviews educational opportunities and challenges associated with Metaverse technologies.	Supports consideration of immersive and interactive learning environments.
Muthmainnah et al. (2023)	Metaverse, student engagement, academic performance, and motivation	Examines relationships between Metaverse technology, engagement, academic performance, and motivation.	Provides context for examining motivation and perceived engagement.
Maghaydah et al. (2024)	Metaverse adoption in education	Synthesises factors affecting adoption and proposes directions for future research.	Informs consideration of perceived value, usability, and facilitating conditions.
Slimi et al. (2025)	Students' perceptions of AI integration in higher education	Examines students' perceptions of integrating AI into higher education.	Supports the learner-centred focus of the present study.
Hu and Xiao (2025)	Factors influencing online learning engagement	Synthesises factors associated with engagement, including motivation, digital experience, interaction, and support.	Provides a basis for examining motivational and environmental factors associated with engagement.
Present study	Student perceptions of prospective AI- and Metaverse-enabled remote learning in New Zealand tertiary education	Examines five technology-acceptance and motivational predictors of perceived learning engagement using survey data from 356 participants.	Extends this research by examining the combined prospective context and identifying perceived usefulness, motivation, and facilitating conditions as statistically significant predictors in the study sample.

Table 1 summarises relevant research on digital transformation, educational technology adoption, AI-enabled learning, Metaverse-enabled learning, and online learning engagement. Existing studies provide insights into technology adoption and the potential educational applications of emerging technologies. However, the literature also highlights the importance of student perceptions, motivation, and supporting conditions in digital learning environments. Building on this research, the current study examines the relationships between selected technology-acceptance and motivational factors and perceived learning engagement in the context of prospective AI- and Metaverse-enabled remote learning among New Zealand tertiary students.

1.3 Research Motivation and Purpose

This study is motivated by the continuing development of technology-mediated tertiary education and the emergence of AI and Metaverse applications as possible components of future remote learning environments. While these technologies have considerable potential, their educational value cannot be inferred solely from technical capability. Student perceptions provide an important perspective because students are direct participants in learning environments and their perceptions of usefulness, accessibility, support, and motivation may be associated with their willingness to engage.

The study therefore focuses on prospective rather than established implementation. Participants were asked about perceptions of advanced digital learning environments rather than being evaluated after sustained exposure to a specific AI- or Metaverse-enabled institutional platform.

The purpose of the research is to examine whether selected technology-acceptance and motivational constructs are associated with students' perceived learning engagement in the context of prospective AI- and Metaverse-enabled remote learning. This focus is consistent with the view that the educational value of emerging technologies should be considered not only in terms of technical capability, but also in relation to students' perceptions and experiences (Slimi et al., 2025).

1.4 Research Problem, Objectives, and Questions

Although research on AI and Metaverse technologies in education is expanding, important questions remain concerning how students perceive these technologies in tertiary remote-learning contexts. Existing studies have examined technological possibilities, adoption, engagement, motivation, and academic outcomes, but evidence remains uneven across educational contexts.

A further issue is that the educational literature sometimes treats emerging technologies as inherently transformative. Such framing can obscure the importance of students' perceptions and contextual conditions. However, the potential of a technology to provide new learning experiences does not, by itself, establish its educational effectiveness or guarantee student engagement. Research on educational technology adoption emphasises the relevance of technology-acceptance perspectives (Granić, 2022), while research on Metaverse adoption identifies factors that must be considered when evaluating implementation in educational settings (Maghaydah et al., 2024). Furthermore, Hu and Xiao (2025), in their systematic review of online learning engagement, identify multiple learner-related and environmental factors associated with engagement, including motivation, interaction, collaboration, and instructor support.

The present study therefore adopts a more cautious approach by examining relationships between established technology-acceptance and motivational constructs and perceived learning engagement.

The study aims to:

- (1) Examine students' perceptions of prospective AI- and Metaverse-enabled remote learning environments.
- (2) Examine relationships between technology-acceptance and motivational factors and perceived learning engagement.
- (3) Identify which technology-acceptance and motivational factors significantly predict perceived learning engagement.

The research questions are:

RQ1. How do New Zealand tertiary students perceive prospective Artificial Intelligence- and Metaverse-enabled remote learning environments?

RQ2. What relationships exist between technology-acceptance and motivational factors and perceived learning engagement?

RQ3. Which technology-acceptance and motivational factors significantly predict students' perceived learning engagement?

1.5 Significance of the Study

The study contributes to research on emerging educational technologies by examining student perceptions before assuming that large-scale implementation has occurred. It extends technology-acceptance research into the combined context of prospective AI- and Metaverse-enabled remote learning while retaining a clear distinction between the two technological domains.

The study is also relevant to the growing literature on online learning engagement. Hu and Xiao (2025), based on a systematic review of 55 empirical studies, identified motivation, digital experience, self-efficacy, platform and equipment characteristics, collaboration, interaction, and instructor support among factors associated with online learning engagement. Their findings reinforce the importance of examining engagement as a multidimensional educational outcome rather than attributing it solely to the presence of a particular technology.

For tertiary educators and institutional decision-makers, the study provides evidence concerning which student-perceived factors are statistically associated with engagement. Such evidence may assist institutions in evaluating future technology investments, designing student-centred digital environments, and identifying areas requiring institutional support.

2. Literature Review

2.1 Artificial Intelligence in Remote Learning

AI has several potential applications within remote tertiary education. Research on AI-based remote learning has highlighted its potential to support technology-mediated and flexible educational experiences (Sushama et al., 2022). Adaptive learning systems can use information about student performance to adjust content or recommendations, while intelligent tutoring systems can provide targeted guidance. AI-enabled analytics may also assist educators in identifying patterns of participation and academic progress (Villegas-Ch et al., 2020; Wei et al., 2021).

AI can additionally support personalised feedback and learning recommendations. These capabilities may be relevant to remote learners because students often work with greater independence and may require timely support. Recent literature on the use of AI in distance education further illustrates the growing role of AI within digitally mediated learning environments (Tuczyński, 2024).

However, technological capability does not necessarily translate into educational value. Students may evaluate an AI-enabled system according to whether it is useful for their learning, whether it is easy to use, whether appropriate support is available, and whether it contributes to a meaningful learning experience. This learner-centred perspective is supported by research examining students' perceptions of AI integration in higher education (Slimi et al., 2025).

2.2 Metaverse-Enabled Remote Learning

The Metaverse offers an alternative approach to remote learning by creating immersive environments in which students can interact through avatars, virtual objects, and shared three-dimensional spaces. Such environments may be particularly relevant for activities involving simulation, practice, collaboration, and experiential learning.

Pradana and Elisa (2023) identify opportunities for Metaverse technologies to support interaction and immersive learning while also noting challenges concerning infrastructure, accessibility, and implementation. Muthmainnah et al. (2023) similarly reported relationships between Metaverse technology, student engagement, academic performance, and learning motivation in their empirical study.

2.3 Technology Acceptance in Educational Technology

The Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) provide established frameworks for understanding technology-related perceptions and behaviour (Davis, 1989; Venkatesh et al., 2003).

TAM places particular emphasis on perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which an individual believes that using a technology will improve task performance, while perceived ease of use concerns the perceived effort associated with using the technology (Davis, 1989).

UTAUT extends technology-acceptance research by incorporating constructs including performance expectancy and facilitating conditions. Performance expectancy concerns the expected benefits of technology use, while facilitating conditions concern the extent to which users perceive that organisational and technical resources are available to support use (Marikyan & Papagiannidis, 2025).

Educational technology adoption research demonstrates the continuing relevance of these constructs across educational contexts (Granić, 2022). Research on online learning systems has also extended TAM by considering motivational influences, supporting the inclusion of motivation alongside technology-acceptance constructs in the present study (Zhang et al., 2008). The present study therefore combines selected TAM and UTAUT constructs with motivation to examine their relationships with perceived learning engagement.

2.4 Relationships between Technology Acceptance, Motivation, and Learning Engagement

The literature suggests several theoretically plausible relationships between the independent variables and perceived learning engagement. The Technology Acceptance Model identifies perceived usefulness and perceived ease of use as central constructs in understanding technology acceptance (Davis, 1989), while the Unified Theory of Acceptance and Use of Technology incorporates performance expectancy and facilitating conditions into its explanation of technology acceptance and use (Venkatesh et al., 2003). In educational settings, Zhang et al. (2008) extended the Technology Acceptance Model by incorporating intrinsic motivation in online learning systems. In addition, Hu and Xiao (2025) identified motivation, digital experience, collaboration, interaction, and instructor support as factors associated with online learning engagement. Taken together, these studies provide a theoretical and empirical basis for investigating whether technology-acceptance factors and motivation are associated with perceived engagement in prospective AI- and Metaverse-enabled remote learning environments.

Perceived usefulness may be associated with engagement because students who believe that a technology contributes meaningfully to learning may be more inclined to invest effort in activities supported by that technology.

Performance expectancy may similarly be related to engagement where students expect technology use to improve learning performance. However, performance expectancy and perceived usefulness can overlap conceptually, making their relative contribution uncertain when both are included in a multivariable model.

Facilitating conditions may support engagement by reducing practical barriers to participation. Appropriate infrastructure, technical assistance, access to devices, and institutional guidance may make participation more feasible.

Perceived ease of use may reduce the effort required to interact with a digital learning environment. Nevertheless, ease of use may not necessarily be sufficient to produce engagement if students do not perceive the technology as educationally useful.

Motivation represents a more learner-centred factor. Students who report greater motivation may also report greater engagement, although the cross-sectional design does not establish the direction of this relationship.

2.5 Research Gap and Conceptual Positioning

Three gaps inform the present study.

First, much of the literature examines individual technologies or specific applications, whereas the present study considers prospective AI- and Metaverse-enabled remote learning as an emerging educational context while distinguishing between the technologies conceptually. For instance, Sushama et al. (2022) investigate AI-based remote learning, and Pradana and Elisa (2023) review applications of Metaverse technologies in education. Similarly, Slimi et al. (2025) explore students' perceptions of AI integration in higher education, while Maghaydah et al. (2024) analyse the factors influencing Metaverse adoption in educational settings. Collectively, these studies offer valuable insights into distinct technological domains. Building on this literature, the present study examines student perceptions within the combined context of prospective AI and Metaverse-enabled remote learning, while recognising that these technologies are conceptually and functionally distinct rather than interchangeable.

Second, research on online learning engagement increasingly recognises multiple learner and environmental influences. Hu and Xiao (2025) demonstrate that engagement is associated with a broad range of factors, including motivation, technology, interaction, collaboration, and support. The present study narrows this broader field to selected technology-acceptance and motivational constructs.

Third, relatively little empirical work has examined these relationships specifically from the perspective of New Zealand tertiary students. The present study addresses this contextual gap by examining survey responses from 356 participants recruited from the New Zealand tertiary education context. Given the purposive, non-probability sampling strategy, the findings should be interpreted within the study sample rather than as representative of all New Zealand tertiary students.

2.6 Hypotheses Development

H1: Performance Expectancy

Students who perceive that emerging digital technologies can improve their learning performance may report greater learning engagement.

H1: Performance expectancy is positively associated with perceived learning engagement.

H2: Facilitating Conditions

Adequate technical, institutional, and organisational support may facilitate participation in digitally mediated learning.

H2: Facilitating conditions are positively associated with perceived learning engagement.

H3: Motivation

Motivational readiness is expected to be positively related to students' willingness to invest effort in learning.

H3: Motivation is positively associated with perceived learning engagement.

H4: Perceived Ease of Use

Technologies perceived as easier to use may impose fewer barriers to participation.

H4: Perceived ease of use is positively associated with perceived learning engagement.

H5: Perceived Usefulness

Students who perceive advanced digital learning technologies as useful for their learning may report stronger engagement.

H5: Perceived usefulness is positively associated with perceived learning engagement.

3. Methodology

3.1 Methodological Choice and Research Strategy

A mono-method quantitative strategy was employed using a cross-sectional online questionnaire.

The cross-sectional design enabled data to be collected from a relatively large group of tertiary students within a defined period. It was appropriate for examining associations among perceptions at a particular point in time.

3.2 Research Context and Participants

The target population consisted of tertiary students in New Zealand. The estimated population was approximately 388,840 students.

The target population was tertiary students in New Zealand. The analytic file contains 356 records, each indicating agreement to participate and containing complete responses to the 20 Likert-type items. Participants were recruited purposively through institutional and online communication channels, including email, online groups, and QR codes, as described in the study records. Because this was a non-probability sample, it should not be described as nationally representative. The number of people invited to participate and the number who opened or started the questionnaire were not available in the materials reviewed; therefore, a response rate cannot be calculated from the available records.

A conventional sample-size benchmark of 384 responses was used during planning as a reference point for a large population (Cochran, 1977). The final exported file contains 356 records. This benchmark is not evidence of representativeness, and the achieved sample size does not remove the limitations associated with purposive, non-probability recruitment.

Participants were recruited through institutional and online communication channels, including email, online groups, and QR-code-based recruitment.

3.3 Data Collection Procedure

Data were collected through an online questionnaire administered using Google Forms. The timestamps in the exported file range from 21 August to 16 September 2025, a span of 27 calendar days.

Participants received information about the purpose of the study and completed the questionnaire voluntarily. The questionnaire used structured Likert-scale items to measure the six study constructs.

Responses were exported for analysis using Microsoft Excel and SPSS.

3.4 Measurement of Variables

Six constructs were measured using 20 Likert-scale items:

The 20 questionnaire items were organized into six constructs for analysis: perceived ease of use (PEOU), perceived usefulness (PU), motivation (MOT), facilitating conditions (FC), performance expectancy (PE), and perceived learning engagement (ENG). Each construct was measured by three to four items, all rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), as coded in the exported dataset. Construct scores were computed as the mean of each respondent's ratings across the items assigned to that construct, so that higher scores indicate stronger agreement with the construct being measured.

The constructs represent five predictor variables and one outcome variable. Performance expectancy (PE) captures expected improvement in learning-related performance; facilitating conditions (FC) captures perceived access to resources and support; motivation (MOT) captures students' motivational orientation toward participation; perceived ease of use (PEOU) captures the perceived effort involved in using the proposed environment; perceived usefulness (PU) captures its expected educational value; and perceived learning engagement (ENG) captures self-reported willingness and involvement in learning activities. PE and FC are aligned conceptually with UTAUT (Venkatesh et al., 2003), while PU and PEOU are core TAM constructs (Davis, 1989); motivation is included because motivational factors have been considered in online-learning technology acceptance (Zhang et al., 2008) and learning engagement (Hu & Xiao, 2025).

- (1) Performance expectancy (PE) – students' perceptions that the proposed technologies could improve learning-related performance.
- (2) Facilitating conditions (FC) – perceptions concerning the availability of technical, institutional, and organisational support.
- (3) Motivation (MOT) – students' motivational orientation toward participation in the learning environment.
- (4) Perceived ease of use (PEOU) – perceptions of the effort required to use the proposed technologies.
- (5) Perceived usefulness (PU) – perceptions that the technologies would provide useful educational value.
- (6) Perceived learning engagement (ENG) – students' perceived willingness and involvement in learning activities.

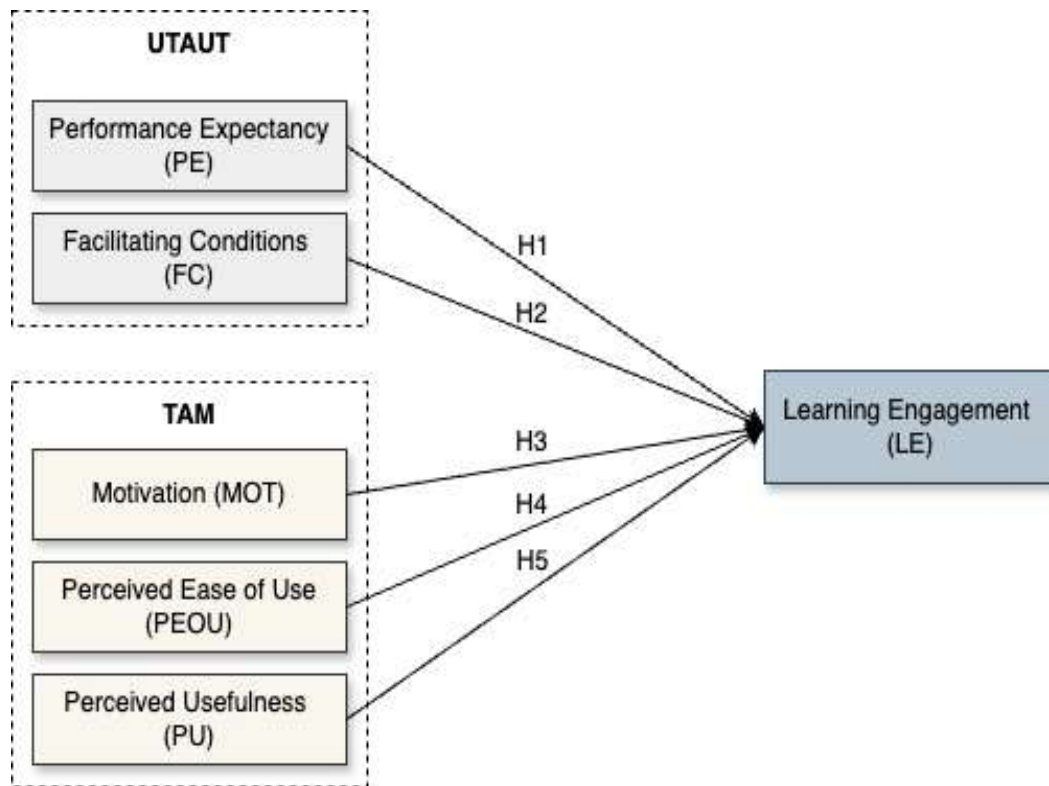


Figure 1. Conceptual Model Diagram (Source: Author)

3.5 Data Analysis

Several statistical techniques were applied.

3.5.1 Descriptive Statistics

Means, medians, modes, and measures of dispersion were used to summarise the study constructs and participant characteristics.

3.5.2 Reliability Analysis

Internal consistency was assessed using Cronbach's alpha (Cronbach, 1951). The existing analysis summary indicates that all six constructs exceeded .70; however, the exact alpha coefficients were not available in the verified material used for this revision.

3.5.3 Pearson Correlation

Pearson correlation coefficients were calculated to examine bivariate relationships among the constructs.

3.5.4 Multiple Linear Regression

Multiple linear regression was used to determine whether performance expectancy, facilitating conditions, motivation, perceived ease of use, and perceived usefulness statistically predicted perceived learning engagement when considered simultaneously.

The regression model was specified as:

$$\text{ENG} = \beta_0 + \beta_1\text{PE} + \beta_2\text{FC} + \beta_3\text{MOT} + \beta_4\text{PEOU} + \beta_5\text{PU} + \varepsilon$$

where ENG represents perceived learning engagement and the remaining terms represent the five predictor variables.

3.5.5 Exploratory Chi-square Analysis

Four cross-tabulation and chi-square analyses were conducted to explore associations involving demographic variables and selected categorical questionnaire responses.

Because four chi-square tests were conducted, a Bonferroni-adjusted significance level of $\alpha = .0125$ was considered when interpreting these exploratory analyses.

4. Results

4.1 Data Screening and Sample

The exported dataset contained 356 records. All 356 records indicated "I Agree" to the participation question and had complete responses to the 20 Likert-type items. No response-rate estimate could be calculated because the number of people invited to participate was not available in the materials reviewed.

The achieved sample was slightly below the conventional benchmark of 384 responses used during the planning stage. Given the purposive non-probability sampling strategy, this difference should not be interpreted as a simple distinction between an adequate and inadequate sample. Rather, the achieved sample represents the participants successfully recruited for the study and provides the basis for the reported analyses.

4.2 Descriptive Characteristics

The sample included students from different demographic groups and fields of study.

The demographic profile of the exported records is summarised in Table 2. These counts and percentages describe the file as provided; because the file shows unusually structured response patterns across subsets of records, the demographic profile and inferential analyses should be treated as provisional until the source records are verified.

Table 2. Demographic characteristics of the exported records (N = 356)

Characteristic	Category	n	%
Age group	18–24	73	20.5%
	25–34	106	29.8%
	35–44	85	23.9%
	45–54	65	18.3%
	55 and above	27	7.6%
Gender	Female	165	46.3%
	Male	152	42.7%
	Other	39	11.0%
Ethnic group	Asian	193	54.2%
	European	69	19.4%
	Māori	47	13.2%
	Pacific Peoples	47	13.2%
Current level of study	Bachelor's degree	111	31.2%
	Postgraduate diploma	77	21.6%
	Master's degree	68	19.1%
	Certificate or diploma	66	18.5%
	Doctorate (PhD)	34	9.6%
Field of study	Information Technology	105	29.5%
	Business	81	22.8%
	Engineering	53	14.9%
	Health Sciences	47	13.2%
	Education	37	10.4%
	Arts / Humanities	33	9.3%

Note. Percentages are calculated from the 356 records in the exported file and may not sum to 100.0% because of rounding.

The demographic analyses were used primarily to describe the sample and to provide exploratory examination of selected categorical relationships. They were not intended to establish demographic causes of engagement.

4.3 Descriptive Analysis of Study Constructs

The construct means were generally close to the midpoint of the five-point Likert scale.

Table 3 reports the descriptive statistics for the six construct scores.

Table 3. Descriptive statistics for study constructs (N = 356)

Construct	Mean	SD	Median	Observed range	Mode
Performance expectancy	3.0552	0.9509	3	1–5	3
Perceived ease of use	3.0122	0.9292	3	1–5	3
Motivation	2.9260	0.9853	3	1–5	3
Facilitating conditions	2.9747	0.9643	3	1–5	3
Perceived usefulness	2.9726	0.8604	3	1–5	3
Perceived learning engagement	2.9649	0.8983	3	1–5	3

All six construct scores had a median and mode of 3, and each observed range covered the recorded 1–5 scale.

The six construct means ranged from 2.9260 to 3.0552 on the recorded 1–5 scale and their medians were 3. These values cluster around the numerical midpoint; the interpretation as neutral should be confirmed against the original response-anchor labels. Because participants were asked about prospective technologies rather than reporting sustained use of a specific implemented platform, the results describe expectations and perceptions, not demonstrated learning outcomes.

4.4 Reliability Analysis

The earlier analysis summary reported that all six constructs exceeded the .70 threshold. The exact coefficients were not available in the material verified for this revision, so the individual alpha values should be added from the final SPSS output before submission. Until those values and item mappings are checked, this reliability statement should be treated as provisional.

The reliability findings support the use of the composite construct measures in the subsequent correlation and regression analyses.

4.5 Correlation Analysis

The Pearson correlation analysis identified positive relationships among the principal constructs.

Correlation coefficients ranged approximately from $r = .242$ to $r = .495$, with the observed relationships statistically significant.

Perceived learning engagement demonstrated the strongest bivariate relationship with perceived usefulness ($r \approx .479$), followed by motivation ($r \approx .400$), facilitating conditions ($r \approx .385$), performance expectancy ($r \approx .358$), and perceived ease of use ($r \approx .284$).

These findings indicate that the five predictors were positively related to perceived learning engagement at the bivariate level.

However, bivariate correlations do not indicate whether each predictor makes a unique contribution when the predictors are considered simultaneously. Multiple regression was therefore used for the principal hypothesis-testing analysis.

Table 4 shows positive, statistically significant correlations among all study constructs.

Table 4. Pearson Correlations Among the Study Constructs

Variable	Statistic	PEOU	PU	MOT	FC	PE	ENG
PEOU	Pearson Correlation	1	.272**	.260**	.242**	.287**	.284**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001
	N	356	356	356	356	356	356
PU	Pearson Correlation	.272**	1	.354**	.373**	.495**	.479**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001
	N	356	356	356	356	356	356
MOT	Pearson Correlation	.260**	.354**	1	.242**	.250**	.400**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001
	N	356	356	356	356	356	356
FC	Pearson Correlation	.242**	.373**	.242**	1	.422**	.385**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001
	N	356	356	356	356	356	356
PE	Pearson Correlation	.287**	.495**	.250**	.422**	1	.358**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001
	N	356	356	356	356	356	356
ENG	Pearson Correlation	.284**	.479**	.400**	.385**	.358**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	
	N	356	356	356	356	356	356

4.6 Exploratory Cross-Tabulation and Chi-Square Analysis

Four exploratory chi-square analyses were conducted.

A statistically significant association was identified between age and perceptions of virtual teamwork, with $p = .001$. This relationship remains statistically significant under the Bonferroni-adjusted threshold of .0125.

The remaining three exploratory relationships were not statistically significant:

- (1) Gender and perceptions of game-like AI tutoring: not significant.
- (2) Level of study and perceptions of institutional guidance: not significant.
- (3) Field of study and perceptions of adaptive intelligent tutors: not significant.

These analyses should be interpreted cautiously because they were exploratory, involved categorical variables, and were not the principal basis for testing the study hypotheses.

4.7 Multiple Linear Regression

Multiple linear regression was conducted with perceived learning engagement as the dependent variable and performance expectancy, facilitating conditions, motivation, perceived ease of use, and perceived usefulness as predictors.

The overall regression model was statistically significant:

$R^2 = .338$; adjusted $R^2 = .329$; $F = 35.773$; $p < .001$.

The model therefore explained approximately 33.8% of the observed variance in perceived learning engagement within the sample.

The standardised regression coefficients and hypothesis outcomes are reported in Table 5.

Table 5. Standardised regression coefficients (β), p-values, and hypothesis test outcomes for predictors of perceived learning engagement

Predictor	β	p-value	Hypothesis
Performance expectancy	.065	.223	H1 not supported
Facilitating conditions	.179	< .001	H2 supported
Motivation	.218	< .001	H3 supported
Perceived ease of use	.089	.058	H4 not supported
Perceived usefulness	.279	< .001	H5 supported

Perceived usefulness was the strongest statistically significant predictor in the model ($\beta = .279$, $p < .001$), followed by motivation ($\beta = .218$, $p < .001$) and facilitating conditions ($\beta = .179$, $p < .001$).

Performance expectancy did not make a statistically significant unique contribution ($\beta = .065$, $p = .223$).

Perceived ease of use was also not statistically significant at the .05 level ($\beta = .089$, $p = .058$). Although its coefficient was positive, the result does not meet the prespecified significance criterion.

Table 6. The outcome of each hypothesis test derived from the multiple linear regression model presented in Section 4.7

Hypothesis	Statement	Result
H1	Performance expectancy is positively associated with perceived learning engagement.	Not supported
H2	Facilitating conditions are positively associated with perceived learning engagement.	Supported
H3	Motivation is positively associated with perceived learning engagement.	Supported
H4	Perceived ease of use is positively associated with perceived learning engagement.	Not supported
H5	Perceived usefulness is positively associated with perceived learning engagement.	Supported

Three of the five hypotheses were supported in the multivariable regression model.

5. Discussion

5.1 Overview of Findings

The study examined whether selected technology-acceptance and motivational factors were associated with perceived learning engagement in prospective AI- and Metaverse-enabled remote learning environments.

The principal finding is that perceived usefulness, motivation, and facilitating conditions were statistically significant predictors of perceived learning engagement. Performance expectancy and perceived ease of use were not statistically significant predictors in the multivariable model.

For RQ2, all five predictors showed positive bivariate relationships with perceived learning engagement, with perceived usefulness showing the strongest reported correlation ($r \approx .479$), followed by motivation ($r \approx .400$) and facilitating conditions ($r \approx .385$). These results indicate that each construct was related to engagement when considered pairwise. They do not, by themselves, show that each variable contributes independently once overlap among predictors is considered. This distinction is consistent with the use of TAM and UTAUT constructs to describe related but conceptually distinct perceptions (Davis, 1989; Venkatesh et al., 2003).

For RQ3, the regression results identify perceived usefulness ($\beta = .279$, $p < .001$), motivation ($\beta = .218$, $p < .001$), and facilitating conditions ($\beta = .179$, $p < .001$) as statistically significant predictors in the specified model. Performance expectancy ($\beta = .065$, $p = .223$) and perceived ease of use ($\beta = .089$, $p = .058$) were not statistically significant at the .05 level. The pattern is compatible with research that considers usefulness and motivational factors relevant to educational technology acceptance and engagement (Granić, 2022; Zhang et al., 2008; Hu & Xiao, 2025). Nevertheless, the results do not establish that the significant factors cause engagement, and the non-significant coefficients should not be interpreted as evidence that performance expectations or usability are unimportant in other contexts.

Viewed against RQ1, all six construct means range from 2.9260 to 3.0552 on the recorded 1–5 scale, with medians and modes of 3. The scores therefore cluster around the numerical midpoint. Whether that midpoint should be labelled “neutral” depends on the original response-anchor wording, which should be verified. Because respondents considered prospective environments rather than reporting sustained use of a deployed platform, the results represent expectations and perceptions, not evidence of learning gains following implementation. This distinction is important when interpreting literature on AI in remote learning (Sushama et al., 2022), Metaverse-enabled education (Pradana & Elisa, 2023), and student perceptions of AI integration (Slimi et al., 2025).

This pattern is important because it suggests that the educational value students associate with emerging technologies may be more closely connected with engagement than technological simplicity alone.

5.2 Perceived Usefulness and Perceived Learning Engagement

Perceived usefulness was the strongest statistically significant predictor in the regression model.

This finding is consistent with the central role assigned to perceived usefulness in technology-acceptance research. Granić (2022) found that technology-adoption research frequently incorporates usefulness-related perceptions when examining educational technology acceptance.

The finding also has relevance to online learning engagement research. Hu and Xiao (2025) identify technology and learning-environment characteristics among the factors associated with engagement, reinforcing the view that engagement is connected to students’ perceptions of the learning environment rather than to technology in isolation.

For the present study, the result suggests that students may be more likely to perceive themselves as engaged when they regard advanced digital learning environments as educationally valuable. Importantly, this does not mean that usefulness causes engagement. The cross-sectional design only establishes that the variables were statistically associated within the regression model.

This interpretation is also consistent with the broader argument that engagement is associated with features of the learning environment and the support available to learners, rather than technology alone (Hu & Xiao, 2025). The present study adds a sample-specific result to that literature by showing that perceived usefulness remained statistically significant when the other four predictors were included in the same regression model. The distinction between bivariate association and a unique regression contribution should remain explicit when comparing these findings with prior studies that may use different outcomes, technologies, samples, or analytical methods.

5.3 Motivation and Perceived Learning Engagement

Motivation was the second strongest statistically significant predictor.

This finding is consistent with literature identifying motivation as an important learner-related factor in online engagement. Hu and Xiao (2025) identify motivation among the major learner-side factors associated with online learning engagement.

The finding also aligns with research examining engagement and motivation among university students. Calafell et al. (2024) investigated engagement and motivation alongside academic performance among students undertaking teacher-training degrees, reinforcing the relevance of motivational factors within tertiary education.

In the context of emerging technologies, this result suggests that technological innovation should not be treated as a substitute for sound motivational and pedagogical design. A technologically sophisticated learning environment may still provide limited educational value if students do not have meaningful reasons to participate.

The result therefore supports a learner-centred rather than technology-centred interpretation of digital transformation.

5.4 Facilitating Conditions and Perceived Learning Engagement

Facilitating conditions were also a statistically significant predictor.

This finding highlights the importance of the environment surrounding technology use. Students may require appropriate devices, connectivity, technical assistance, institutional guidance, and accessible learning resources to participate effectively in technology-mediated education.

This interpretation is consistent with Hu and Xiao’s (2025) review, which identified digital platforms and equipment, instructor support, collaboration, interaction, and learning-environment characteristics among factors associated with online learning engagement.

The result also has practical significance for tertiary institutions considering advanced digital technologies. Investment in technology without corresponding investment in infrastructure and support may limit the educational value perceived by students.

5.5 Non-significant Predictors: Performance Expectancy and Perceived Ease of Use

5.5.1 Performance Expectancy

Performance expectancy was not a statistically significant predictor in the regression model.

This result should not be interpreted as evidence that students consider performance improvements unimportant. Rather, performance expectancy did not make a statistically significant unique contribution to perceived learning engagement after the other predictors were included.

The positive bivariate correlation between performance expectancy and engagement indicates that the constructs were related at the correlation level. The absence of significance in the regression model suggests that its unique contribution may be less pronounced once usefulness, motivation, and facilitating conditions are considered simultaneously.

No additional explanation, such as students being primarily motivated by grades or intrinsic rather than extrinsic reasons, should be inferred because the study did not directly measure those mechanisms.

5.5.2 Perceived Ease of Use

Perceived ease of use was positively associated with engagement at the bivariate level but did not reach statistical significance in the regression model ($\beta = .089$, $p = .058$).

The result is close to, but above, the conventional .05 threshold. It is therefore more appropriate to describe the relationship as positive but not statistically significant under the study's prespecified criterion, rather than describing it as a meaningful or confirmed predictor.

The study also did not measure students' digital proficiency. Consequently, explanations based on presumed digital competence should not be advanced.

A further limitation is that the manuscript does not currently report item-level descriptive statistics or the full operationalisation of every construct. Future revisions should make the measurement basis transparent so readers can judge comparability with prior TAM, UTAUT, motivation, and engagement studies. Any additional references should be added only where they support a specific claim and should be checked for complete bibliographic details and consistency between in-text citations and the reference list.

5.6 Exploratory Demographic Findings

The significant relationship between age and perceptions of virtual teamwork was the only exploratory demographic association that remained statistically significant after consideration of the Bonferroni-adjusted threshold.

This finding may indicate that perceptions of particular forms of virtual collaboration differ across age groups, but the present analysis does not establish why such differences exist.

The non-significant relationships involving gender, level of study, and field of study indicate that these variables did not demonstrate statistically detectable associations with the selected technology perceptions in the exploratory analyses.

These findings should not be interpreted as evidence that demographic characteristics have no relationship with technology adoption more broadly. They reflect only the specific variables and sample examined in this study.

5.7 Theoretical Implications

The study provides three main theoretical implications.

First, the findings support the continued relevance of technology-acceptance perspectives in emerging educational technology research. Granić (2022) demonstrates the breadth of educational technology adoption research based on technology-acceptance models, and the present study extends this approach to a prospective AI- and Metaverse-enabled remote-learning context.

Second, the findings indicate that technology acceptance and motivation should not necessarily be considered independent domains. Motivation emerged as a significant predictor alongside usefulness and facilitating conditions, suggesting that learner-related factors remain important when evaluating advanced educational technologies.

Third, the findings reinforce the importance of conceptualising learning engagement as a multidimensional educational outcome influenced by both learner and environmental factors. This is consistent with the synthesis provided by Hu and Xiao (2025) and with empirical work linking engagement to acceptance and other online-learning characteristics (Sharif Nia et al., 2023).

5.8 Practical Implications

The findings provide several implications for tertiary institutions.

Educational usefulness should be prioritised. Emerging technologies should be introduced where they address identifiable learning needs rather than merely because they are technologically novel.

Motivation should be incorporated into digital-learning design. Learning activities should provide meaningful goals, opportunities for participation, and relevant learning experiences.

Facilitating conditions should accompany technology adoption. Institutional implementation should include infrastructure, technical support, staff capability, student orientation, and accessible resources.

Staff capability should be developed alongside technological capability. Educators require support to integrate AI and immersive environments pedagogically rather than simply technically.

Evaluation should precede large-scale implementation. Institutions should pilot technologies, collect student feedback, evaluate learning outcomes, and assess accessibility before committing to widespread adoption.

5.9 Limitations and Future Research

The findings should be interpreted in light of several limitations.

In addition, the exported response file contains highly structured patterns in some demographic and item-response sequences.

The cross-sectional design prevents causal inference. Longitudinal research could examine whether perceptions change following actual exposure to AI- and Metaverse-enabled learning.

The purposive non-probability sample limits generalisability. Future studies could employ probability sampling or larger multi-institutional samples across New Zealand.

The study measured perceived engagement rather than behavioural engagement. Future research could combine questionnaire responses with learning-platform activity, attendance, completion, interaction, and achievement data.

The study also examined broad constructs rather than individual technology features. Future research could separately investigate AI tutoring, personalised feedback, adaptive learning, virtual laboratories, avatar-based collaboration, immersive simulation, and other specific capabilities.

Experimental or quasi-experimental studies could further determine whether particular implementations produce measurable differences in engagement or learning outcomes.

6. Conclusion and Recommendations

6.1 Conclusions in Relation to the Research Questions

6.1.1 RQ1: How do Students Perceive Prospective AI- and Metaverse-enabled Remote Learning Environments?

Students reported broadly moderate or neutral perceptions across the measured constructs, with construct means generally close to the midpoint of the Likert scale.

These findings should be interpreted within the prospective context of the study. Participants were not evaluating an established institutional system after sustained use. Their responses therefore provide evidence about expectations and perceptions rather than demonstrated outcomes of implementation.

6.1.2 RQ2: What Relationships Exist between Technology-acceptance and Motivational Factors and Perceived Learning Engagement?

Positive bivariate relationships were observed between all five predictors and perceived learning engagement.

The strongest bivariate relationship was between perceived usefulness and perceived learning engagement, followed by motivation, facilitating conditions, performance expectancy, and perceived ease of use.

These relationships are consistent with literature indicating that engagement in online learning is associated with both learner and environmental factors (Hu & Xiao, 2025; Sharif Nia et al., 2023).

6.1.3 RQ3: Which Factors Significantly Predict Perceived Learning Engagement?

Multiple regression showed that perceived usefulness, motivation, and facilitating conditions were statistically significant predictors of perceived learning engagement.

Performance expectancy and perceived ease of use were not statistically significant predictors under the study's .05 criterion.

The model explained 33.8% of the variance in perceived learning engagement. This represents the explanatory performance of the specified model within the sample and should not be interpreted as evidence of population-level generalisability.

6.2 Overall Contribution of the Study

6.2.1 Empirical Contribution

The study provides empirical evidence from New Zealand tertiary students concerning perceptions of prospective AI- and Metaverse-enabled remote learning.

The results identify three constructs—perceived usefulness, motivation, and facilitating conditions—as statistically significant predictors of perceived learning engagement within the study model.

6.2.2 Theoretical Contribution

The study demonstrates the usefulness of combining selected TAM and UTAUT constructs with motivation when examining student perceptions of emerging educational technologies.

It also contributes to the growing literature that treats online learning engagement as the product of multiple learner and environmental considerations rather than as an automatic consequence of technological innovation.

6.2.3 Practical Contribution

For tertiary institutions, the findings suggest that successful digital transformation requires more than technological acquisition.

Students need to perceive educational value, remain motivated to participate, and have appropriate institutional and technical support.

6.3 Recommendations for Tertiary Education Practice

Recommendation 1: Prioritise Educational Usefulness

Institutions should prioritise technologies that provide identifiable educational benefits. Technology selection should be guided by learning objectives, student needs, curriculum requirements, and evidence of educational value.

Recommendation 2: Design for Meaningful Student Engagement

AI and Metaverse technologies should be integrated into learning activities that encourage participation, collaboration, reflection, problem-solving, and authentic learning.

Recommendation 3: Strengthen Facilitating Conditions

Institutions should provide adequate infrastructure, device access, technical assistance, student orientation, and staff support before scaling emerging technologies.

Recommendation 4: Develop Staff Capability

Professional development should focus not only on how technologies operate but also on how they can be integrated appropriately into curriculum and assessment.

Recommendation 5: Evaluate Before Scaling

Institutions should conduct structured pilots and evaluate student perceptions, engagement, accessibility, learning outcomes, staff workload, and implementation challenges before undertaking large-scale adoption.

Recommendation 6: Maintain Usability and Accessibility

Although perceived ease of use was not a statistically significant predictor in this study, usability remains an important implementation consideration. Technologies should be accessible, understandable, and appropriate for students with different levels of technological access and experience.

Recommendation 7: Consider Equity and Responsible Implementation

Institutions should evaluate whether emerging technologies introduce additional financial, technological, accessibility, privacy, or participation barriers.

6.4 Future Research

Future research should examine actual rather than prospective use of AI- and Metaverse-enabled learning environments.

Longitudinal studies could investigate how student perceptions develop following exposure to these technologies. Experimental studies could compare conventional online learning with specific AI- or Metaverse-supported interventions.

Future research could also employ mixed methods to combine quantitative measures with student interviews and focus groups. Behavioural engagement measures obtained from learning-management systems could complement self-reported engagement.

Finally, future studies should examine specific AI and Metaverse features separately. Such research would allow more precise conclusions concerning which technological capabilities are associated with particular aspects of learning engagement.

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