Performance Expectancy and Facilitating Conditions as the Primary Drivers of e-Learning Adoption in Health Economics Education

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ABSTRACT

Introduction. E-learning systems, particularly Massive Open Online Courses (MOOCs), provide substantial supplementary support for complex disciplines such as health economics. However, effective adoption continues to face significant technical, infrastructure, and user-centric challenges. This research investigates the determinants of MOOC adoption among undergraduate students through the UTAUT framework.

Methodology. A correlational, cross-sectional survey design was implemented. Data were collected via a self-administered online survey from 123 undergraduate students enrolled in a Health Economics course at a public university in the Klang Valley, Selangor, Malaysia. Results. An adjusted multivariate linear regression model was used to evaluate the drivers of students' behavioural intention to utilise the platform. The survey instrument demonstrated strong psychometric properties, with all four constructs showing good to excellent internal consistency (α ranging from .79 to .91). The structural model explained 80.1% of the variance in students' behavioural intention. Performance expectancy emerged as the most powerful determinant of adoption intention ($\beta = 0.760$, $p < 0.001$), followed by facilitating conditions ($\beta = 0.280$; $p = 0.007$). Effort expectancy and social influence were not statistically significant predictors within this model. These findings suggest that students are highly motivated to adopt digital platforms when these tools provide clear utility that enhances their conceptual understanding of the course. Although platform simplicity and peer perceptions are relevant, these factors do not independently influence the adoption intentions of students to the same extent as utility and infrastructure. Conclusion. In conclusion, digital learning tools are likely to transform student motivation into active adoption only when institutional support is securely guaranteed and immediate academic value is unequivocally present.

Keywords: e-Learning, Massive Online Open Courses, Unified Theory of Acceptance and Use of Technology, Behavioural Intention, Health Economics

INTRODUCTION

E-learning systems have become a critical component of higher education by offering flexible and innovative learning opportunities; however, their effective adoption continues to face significant challenges, particularly in developing countries (Abbad, 2021). Students frequently encounter technical and infrastructure barriers, such as poor internet connectivity, system failures, and limited device access (Sahoo et al., 2023). Furthermore, user-centric issues such as poor digital skills, low self-efficacy, and a lack of motivation negatively impact student engagement with these platforms (Fadhil, 2022; Sasongko et al., 2025).

In the specific context of Massive Open Online Courses (MOOCs), common hurdles include high dropout rates, limited interactivity, and difficulties integrating online content with traditional coursework (Mishra et al., 2023). To overcome these barriers, traditional teaching methods in higher education increasingly require the supplementary support of e-learning systems and MOOCs to provide flexible, accessible, and innovative digital environments. Integrating MOOCs into traditional coursework, such as through blended learning models or MOOC-based flipped classrooms, has shown significant promise in mitigating traditional classroom limitations, enhancing student engagement, and improving overall learning outcomes. In complex, interdisciplinary fields such as Health Economics, which bridges economic modelling, healthcare policy, and medical sciences, these digital platforms are particularly crucial. They offer cost-effective, sustainable, and highly efficient avenues for learning that help overcome the constraints of time and physical distance for both medical and economics students.

To evaluate the adoption of these platforms and understand what drives student engagement, researchers frequently rely on the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates multiple determinants of technology acceptance to assess behavioural intentions and actual use. However, although the UTAUT framework is widely applied to MOOCs, most research has focused on general populations or on specific, well-researched regions, limiting the generalizability of the findings. Recent studies emphasise that localised cultural dimensions, institutional readiness, and specific socio-economic contexts heavily shape technology acceptance. Consequently, there remains a critical need for comprehensive frameworks that address these contextual dynamics, particularly among specialised demographics such as Health Economics students in the Klang Valley, Malaysia. Understanding how unique local digital infrastructure and regional healthcare-economy pressures shape this educational landscape is essential for localised MOOC integration.

LITERATURE REVIEW

Behavioural intention (BI) in e-learning refers to individuals' willingness to adopt and use e-learning systems. BI in e-learning is shaped by a combination of cognitive, social, and contextual factors. The development of the research framework of this study is guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003). The UTAUT model provides a comprehensive framework for understanding the factors influencing undergraduate students' acceptance and use of Massive Open Online Courses (MOOCs). By addressing key factors and demographic influences, higher learning institutions can enhance the design and delivery of MOOCs, ultimately improving student engagement and learning outcomes. Building upon this framework, this study investigates the determinants of Massive Open Online Courses (MOOCs) adoption in the Health Economics course among undergraduate students. Figure 1.0 shows the research framework of this study. The hypothesised relationship between the variables is discussed in the following section.

Performance Expectancy (PE) and Behavioural Intention

PE is defined as the degree to which an individual believes the system will help them attain gains in job/academic performance (Venkatesh et al.,2003). In this study, PE refers to the extent to which undergraduate students believe that incorporating MOOCs into their studies will enhance their academic performance and understanding of Health Economics. Prior literature consistently highlights PE as the most robust predictor of behavioural intention to adopt educational technologies (Xue et al., 2024; Altalhi, 2021).

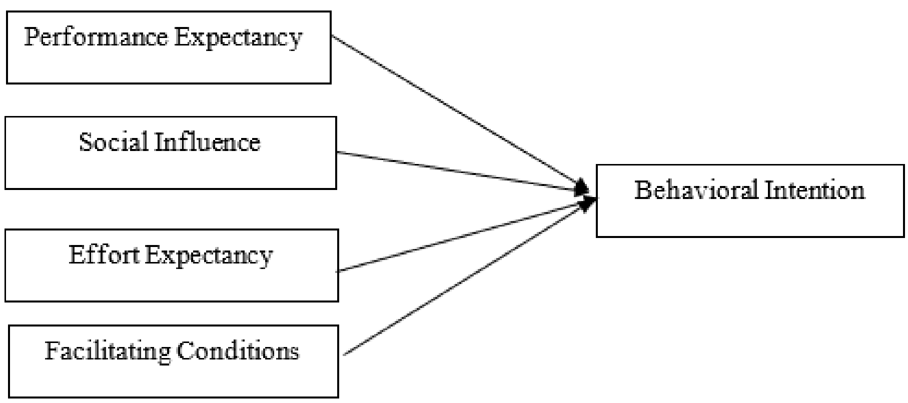

Figure 1: Research Framework of the Study

In specialised and quantitative fields like health economics, students face complex theoretical concepts and data analysis. If a MOOC is perceived to improve their grades directly, clarify dense economic concepts, or offer valuable supplementary resources, their intention to utilise it increases substantially (Wan et al., 2020). Therefore, the following hypothesis is developed:

H1: Performance expectancy positively and significantly influences undergraduate students' behavioural intention.

Effort Expectancy (EE) and Behavioural Intention

EE refers to the ease of use of the system (Venkatesh et al., 2003). In this study, EE is operationalised to evaluate the perceived ease of navigating and using the MOOC platform. When digital platforms have simplified user interfaces and low cognitive barriers, students are more willing to engage with online learning materials (Chen, 2021; Kharis et al., 2026). While technical ease of use is necessary to prevent early dropouts, it often serves as a baseline requirement rather than the primary driver of long-term academic adoption. Thus, it is hypothesised that:

H2: Effort expectancy positively influences undergraduate students' behavioural intention.

Social Influence (SI) and Behavioural Intention

Venkatesh et al. (2003) defined SI as the degree to which an individual perceives that "important others" believe they should use the system. In this study, SI captures the pressure or encouragement students feel from influential figures, such as lecturers and classmates, to utilise MOOCs. In university ecosystems, peer recommendations and institutional mandates can steer students toward digital tools (Mishra et al., 2023; Pham et al., 2025). Therefore, the following hypothesis is proposed:

H3: Social influence positively influences undergraduate students' behavioural intention.

Facilitating Conditions (FC) and Behavioural Intention

FC is defined as the belief that an organisational and technical infrastructure exists to support system use (Venkatesh et al., 2003). In the context of this study, FC refers to the availability of technological infrastructure, reliable internet access, and institutional support systems necessary for using MOOCs effectively. Unlike broader e-learning environments where FC is sometimes viewed merely as a predictor of direct usage, the unique context of specialised undergraduate coursework positions FC as a critical determinant of behavioural intention (Fianu et al., 2018; Arkorful et al., 2022). MOOCs often require stable connectivity to run simulations, view lecture videos, or access external websites. If a public university in the Klang Valley provides seamless integration, students' intention to adopt the platform skyrockets (Tayag & Tayag, 2020). Conversely, poor infrastructure acts as an immediate barrier to entry. Therefore, the following hypothesis is proposed:

H4: Facilitating conditions positively and significantly influence undergraduate students' behavioural intention.

METHODOLOGY

This study employed a quantitative, cross-sectional survey design to investigate the determinants of Massive Open Online Courses (MOOCs) adoption among undergraduate students. The theoretical framework was guided by the Unified Theory of Acceptance and Use of Technology (UTAUT). The target population comprised undergraduate students enrolled in a health economics course at a public university located in the Klang Valley, Malaysia. The inclusion criteria are 1) enrolled in the health economics course and 2) successful completion of all core components within the course. The course is chosen because the MOOC is embedded in the e-learning component as one of the teaching methodologies.

The study utilised non-probability, convenience sampling, and the sample size was calculated using G*Power software. The test used an alpha of 0.05, a power of 0.80, and a medium effect size of ($f^2 = 0.15$). 80% is considered the minimum acceptable power in most social science studies (David Gefen, 2011), so the desired sample size was 85. Approximately 123 samples were successfully collected during the data collection activity on the second cycle of the academic term (2025/2026). Informed consent was obtained prior to the distribution of the questionnaire.

Data were gathered via a self-administered questionnaire distributed online via Microsoft Forms to all respondents, available in English. The survey link was primarily disseminated through class WhatsApp groups to facilitate easy access for participants. The questionnaire consisted of six sections: Demographic profile, behaviour intention, performance expectancy, social influence, effort expectancy, and facilitating conditions. In total, 24 items adapted from Abbad (2020) were measured on a five-point Likert-type scale (1 = strongly disagree, 5 = strongly agree). Statistical analyses were conducted using R (R Core Team, 2026) within RStudio (RStudio, 2026).

RESULTS

Demographic profiles

The sample was heavily concentrated in early adulthood, with most respondents aged 22 (n = 54, 44%) or 23 (n = 40, 33%). Most respondents were female (n = 109, 89%) and had strong academic backgrounds, with 68 (55%) attaining a CGPA of 3.50 or higher. A total of 116 (94%) respondents confirmed reliable internet access at home, establishing a well-equipped baseline for the digital platform. 93% of respondents reported prior experience with online courses, making them familiar with online learning platforms and their variability.

A preliminary analysis of the study was performed using Cronbach's alpha (α) coefficients (N = 123). All scales demonstrated acceptable to excellent reliability, exceeding the conventional 0.70 threshold. Specifically, the reliability coefficients were (α = .84) for the 5-item Social Influence scale, (α = .88) for the 4-item Performance Expectancy scale, (α = .79) for the 5-item Effort Expectancy scale, and (α = .91) and (α = .76) for the 4-item Facilitating Conditions scale and the 5-item Behavioural Intention scale, respectively.

All scales exceeded the standard 0.70 reliability threshold, which enables the researcher to confidently state that the data accurately reflect students' true perceptions of MOOC acceptance. Multicollinearity did not pose a significant concern for the model, as all Variance Inflation Factor (VIF) values remained well below the conventional threshold of 5.0 (social influence = 3.58, performance expectancy = 4.22, effort expectancy = 4.11, facilitating condition = 2.57).

Table 1. Demographic Profile (N = 123)

Respondent Characteristic	**n (%)**
Age (Years)	
21 or below	22 (18)
22	54 (44)
23 or above	47 (38)
Gender Profile	
Female	109 (89)
Male	14 (11)
Academic Performance (CGPA)	

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2.50 to 2.99	5 (4.1)
3.00 to 3.49	50 (41)
3.50 and above	68 (55)
Prior Online Course Experience	114 (93)
Reliable Home Internet Access	116 (94)

To assess the structural drivers influencing students' behavioural intention to utilize MOOCs for the HSM546 Health Economics and Evaluation course content, an adjusted multivariate linear regression model was executed. The structural model demonstrated exceptional explanatory power, with an R^2 value of 0.801 and an adjusted R^2 of 0.779. This indicates that the included theoretical constructs and sociodemographic controls account for 80.1% of the total variance in student behavioural intentions. The overall model fit was highly significant, $F(12, 110) = 36.8$, $p < 0.001$, confirming its structural validity for individual pathway evaluation.

Table 2: Multivariate Linear Regression Matrix: Drivers of MOOC Behavioural Intention

Predictive Driver / Pathway	**Unstandardized Beta (β)**	**95% CI**	**p-value**
Baseline Constant (Intercept)	-0.42	-0.94, 0.09	0.107
Performance Expectancy (PE)	0.59	0.38, 0.80	**<0.001**
Effort Expectancy (EE)	0.20	-0.02, 0.41	0.069
Social Influence (SI)	-0.02	-0.25, 0.20	0.826
Facilitating Conditions (FC)	0.32	0.13, 0.50	**<0.001**
Age (Categorical Tiers)			
21 and below	—	—	—
22	0.01	-0.20, 0.21	0.94
23 and above	-0.08	-0.30, 0.13	0.34
Gender [Ref: Female]			
Female	—	—	—
Male	0.20	-0.03, 0.44	0.08
Academic Tier [Ref: 2.50 to 2.99]			
3.50 and above	—	—	—
3.00 – 3.49	0.03	-0.12, 0.18	0.71
2.50 – 2.99	0.02	-0.35, 0.40	0.89

Abbreviation: CI = Confidence Interval, $R^2 = 0.771$; Adj. $R^2 = 0.753$; Statistic = 42.3; p-value = <0.001

As shown in Table 2, the individual pathway analysis revealed that performance expectancy (PE) was the primary and most powerful determinant of a student's intention to adopt the platform ($\beta = 0.59$, 95% CI: 0.38 to 0.80, $p < 0.001$). Adjusting for all other covariates, student behavioural intention is predicted to increase by 0.76 units for every single-unit increment in perceived learning utility. Facilitating conditions (FC) emerged as the secondary significant driver ($\beta = 0.32$, 95% CI: 0.13 to 0.50, $p < 0.001$), confirming that structural support, institutional alignment, and technological resources directly foster positive adoption intentions. Conversely, effort expectancy (EE) ($\beta = 0.20$, $p = 0.069$) and social influence (SI) ($\beta = -0.02$, $p = 0.826$) were not statistically significant predictors within this model.

The evaluation of sociodemographic control variables demonstrated that individual background characteristics had a negligible influence on technology adoption intentions. Compared with the baseline reference groups, none of the individual categorical tiers for cumulative grade performance average (CGPA) was statistically significant ($p > 0.05$), indicating that the core drivers of utility and infrastructure operate uniformly across all age brackets and academic capability levels within the cohort. With respect to gender, male students exhibited slightly higher baseline intention metrics compared to their female counterparts ($\beta = 0.21$, 95% CI: -0.01 to 0.44), however, this path narrowly missed the standard threshold for statistical significance ($p = 0.065$), suggesting a marginal trend that may warrant isolated investigation in larger, more evenly balanced sample environments.

DISCUSSION

The findings demonstrated that performance expectancy and facilitating conditions emerged as the primary drivers of students' behavioural intention to adopt MOOCs to enhance their learning experience in the health economics course (H1) ($\beta = 0.76$, $p < 0.001$) and (H4) ($\beta = 0.28$, $p = 0.007$). The empirical findings supported the direct positive hypotheses (H1 and H4). A robust pathway indicates that learners are intensely willing to adopt digital platforms if they derive explicit utility that directly enriches their conceptual understanding of the course. Consequently, while digital media may initially be perceived as a novel innovation by certain learners, the MOOC platform must transcend its novelty factor and be established as a functional catalyst capable of delivering clear academic returns. This value-driven focus mirrors recent evidence in broader technology acceptance literature, such as the adoption of artificial intelligence (AI) in the banking industry (Papathomas et al., 2025) and among business professionals in Bangladesh (Emon & Khan, 2025), where digital systems successfully drive individual behavioural intentions by directly optimising operational activities and assisting in complex financial decision-making. This pragmatic orientation is further supported by Liu et al. (2025), who noted that, along with performance expectancy, perceived enjoyment of a technology platform and personal innovativeness significantly shape university students' overall behavioural intentions.

Simultaneously, facilitating conditions, including the availability of structural resources, a stable technical environment, and the explicit alignment of curriculum requirements with the technological approach, strongly influence the respondents' intentions to engage with MOOC learning activities within this health economics curriculum. The critical weight of this institutional support is widely supported in the global literature. For instance, Yang & Qian (2025) found a positive and significant effect ($\beta = 0.445$) of facilitating conditions on behavioural intentions among physical education students in China. This is also supported by another literature review, which states that technological and environmental readiness corroborate the respondents' behavioural intention (Gößwein et al., 2025). However, this structural dependency is not entirely universal across regional landscapes, as evidenced by a contrasting study on e-learning adoption among university students in Indonesia, which determined that facilitating conditions exerted no direct effect on behavioural intention (Nugraha et al., 2025).

On the other hand, the model explicitly rejects both effort expectancy (H2) ($\beta = 0.10$, $p = 0.35$) and social influence (H3) ($\beta = -0.04$, $p = 0.67$). The rejection of H2 is largely explained by the respondent's higher baseline digital literacy. With 93% of respondents possessing prior online course experience and 94% reporting reliable home internet access, platform simplicity functions as a baseline prerequisite rather than an active motivator. This is consistent with the previous study's finding of e-learning usage in the post-pandemic period across universities in Greece (Zacharis & Nikolopoulou, 2022). Similarly, the rejection of H3 suggests that external peer or lecturer pressures are secondary to the standalone academic value required in demanding interdisciplinary subjects. This aligns with recent studies among university learners in China on online learning, which found that external pressure was not the primary driver of the e-learning approach (Chu et al., 2026; Khan et al., 2023).

These findings suggest that digital learning tools will only successfully transform student motivation into active adoption if there is a secure institutional baseline of support and immediate academic value is essential.

CONCLUSION

This study applied the UTAUT framework to evaluate the determinants of MOOCs adoption among undergraduate health economics students. The regression model proved highly robust, predicting 77.1% of the total variance in behavioural intention. The findings identify performance expectancy as the dominant predictor of adoption, demonstrating that learners are highly motivated to embrace digital platforms when these tools deliver explicit utility that enhances their conceptual understanding and academic performance. Furthermore, facilitating conditions play a critical secondary role, confirming that structural support, institutional alignment and technological resources are essential for fostering positive adoption intentions. Interestingly, platform simplicity (effort expectancy) and peer or institutional pressure (social influence) did not exert a statistically significant, standalone impact on behavioural intention, compared with utility and infrastructure. Ultimately, digital educational tools will only transform student motivation into active adoption if comprehensive institutional support is guaranteed and immediate academic value is clearly demonstrated. To build upon the current framework, future research must expand beyond the specialised demographic of health economics students. Given that localised cultural dimensions, socio-economic contexts and varying degrees of institutional readiness heavily influence technology acceptance, investigating a more diverse range of regional landscapes will significantly improve the generalisability of these findings. The study's limitations include a single-course format, respondents from a single institution, and a gender imbalance that hinders generalizability.

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