# Socio-Emotional Moderators of MOOC Adoption in Professional E-Training: Extending UTAUT with Social Perceptiveness and Group Work Effectiveness

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**ABSTRACT:**
The adoption of Massive Open Online Courses (MOOCs) as a vehicle for professional e-training has grown substantially, yet completion rates among working professionals remain persistently low and adoption intentions are difficult to predict using conventional technology acceptance models alone. The Unified Theory of Acceptance and Use of Technology (UTAUT) has been the dominant framework in this area, but its predominantly structural and cognitive orientation leaves the socio-emotional dimensions of professional digital learning underexplored. This study extends the UTAUT model by introducing Social Perceptiveness (SP) and Group Work Effectiveness (GWE) as novel moderating variables, and by disaggregating the Facilitating Conditions construct into two contextually relevant sub-dimensions: Continuous Availability and Time Flexibility. Using a quantitative design combining a seven-point Likert-scale survey with the behavioral "Reading the Mind in the Eyes" (RME) test, data were collected from 253 professionals enrolled in or having recently completed a MOOC. Analysis was conducted using IBM SPSS, including Cronbach's alpha reliability testing, Pearson correlation, multiple linear regression, and moderation analysis. Results show that Effort Expectancy (EE) and the extended Facilitating Conditions construct are the strongest predictors of Behavioral Intention (BI). GWE significantly moderates the EE–BI relationship, and SP significantly moderates the Social Influence (SI)–BI relationship. These findings contribute to UTAUT scholarship by integrating socio-emotional constructs into a technology-acceptance framework tailored to professional e-learning, and offer actionable guidance for MOOC designers, training managers, and human resource practitioners.

Keywords: MOOCs; professional e-training; UTAUT; Social Perceptiveness; Group Work Effectiveness; Behavioral Intention; digital learning adoption; emotional intelligence.

## 1. Introduction

### 1.1 Background and Motivation

Training has long been recognised as a strategic asset through which organisations secure competitive advantage, sustain workforce development, and retain talent. The shift from exclusively face-to-face training toward blended and fully digital modalities has accelerated over the past decade, driven by technological advances, cost pressures, and the operational disruptions caused by the COVID-19 pandemic (Serrat, 2010; Sood, 2016). Within this broader transformation, Massive Open Online Courses (MOOCs) have attracted significant institutional and corporate interest as scalable, cost-effective mechanisms for professional development. Research and Markets (2025) projects that the global MOOC market will continue to grow through 2034, with organizations increasingly embedding these platforms into corporate upskilling strategies.

MOOCs offer working professionals access to structured educational content produced by globally recognised universities and institutions, typically at little or no direct cost (Daniel, 2012; Yuan & Powell, 2013). Their asynchronous design—combining video lectures, auto-graded assessments, discussion forums, and peer-review mechanisms—provides flexibility that is particularly appealing to professionals navigating demanding schedules (McCluskey, 2020; Liu et al., 2015). The COVID-19 pandemic markedly accelerated MOOC enrollment as both individuals and institutions sought to ensure continuity of learning under conditions of physical restriction (McCluskey, 2020; Impey & Formanek, 2021).

Despite this promise, the empirical record on MOOC engagement is sobering. Dropout rates in non-professional contexts have been documented at or above 90% in multiple investigations (Onah et al., 2014), and completion rates among professionals remain low, with adoption rates in certain organisational populations reported below 5% (Kumar, 2022; Ang et al., 2020). This persistent gap between MOOC availability and actual sustained engagement signals that factors beyond access and platform functionality shape whether professionals choose to enrol in and complete these courses. Mousavinasab et al. (2024) have recently highlighted the emerging role of generative artificial intelligence in addressing some of MOOC's endemic weaknesses, including low learner engagement and insufficient personalisation; however, the interpersonal and socio-emotional dimensions of professional adoption remain underexplored.

While empirical work on technology-enhanced learning in higher education is substantial, considerably less attention has been directed at its role in professional learning environments (Anderson et al., 2020). Within that narrower professional context, most adoption studies have relied on the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), concentrating on structural predictors such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. This cognitive-structural orientation, while analytically productive, overlooks the reality that MOOCs are not merely technical platforms—they are interactive social environments in which learners are exposed to discussion forums, peer assessments, collaborative assignments, and community-driven norms. Professionals' capacity to navigate these social dimensions may meaningfully shape their adoption decisions, yet this proposition has received no dedicated empirical treatment.

### 1.2 Significance of the Problem

The persistence of low completion and adoption rates despite the proliferation of MOOC platforms represents both a practical problem for organisations investing in digital training and a theoretical challenge for adoption research. Gamage et al. (2015) note that MOOC success is shaped not only by platform quality and institutional reputation, but also by the collaborative and social dimensions of the learning experience—dimensions that standard adoption frameworks have yet to fully capture. Anand Shankar Raja and Kallarakal (2020) documented that contextual disruptions such as

the COVID-19 pandemic catalysed adoption, suggesting that structural forces alone are insufficient to explain long-term engagement.

This study proposes that two constructs from adjacent research traditions—Social Perceptiveness (SP), grounded in emotional intelligence theory, and Group Work Effectiveness (GWE), grounded in collective intelligence research—may serve as meaningful moderators of adoption pathways in professional MOOC contexts. In addition, it argues that the standard UTAUT operationalisation of Facilitating Conditions requires disaggregation in workplace learning settings, where the specific dimensions of continuous platform availability and temporal flexibility are functionally distinct and independently salient.

1.3 Research Objectives

This study is guided by five objectives:

Objective 1: To critically review literature on MOOC adoption, workplace e-training, emotional intelligence, collective intelligence, and theoretical models of technology acceptance.

Objective 2: To investigate the moderating roles of SP and GWE on key UTAUT relationships in a professional e-training context.

Objective 3: To establish and justify a methodological framework appropriate to testing the proposed model.

Objective 4: To implement data collection procedures targeting professionals with active MOOC experience.

Objective 5: To develop an extended MOOC adoption framework that incorporates socio-emotional moderators and a context-refined operationalisation of Facilitating Conditions.

1.4 Research Hypotheses

The following hypotheses are derived from the extended UTAUT framework:

H1: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) each positively affect professionals' Behavioral Intention (BI) to adopt MOOCs.

H2: GWE positively moderates the PE–BI relationship, such that higher GWE amplifies PE's effect on BI.

H3: GWE positively moderates the EE–BI relationship, such that higher GWE amplifies EE's effect on BI.

H4: GWE positively moderates the SI–BI relationship, such that higher GWE amplifies SI's effect on BI.

H5: SP positively moderates the EE–BI relationship, such that higher SP strengthens EE's effect on BI.

H6: SP positively moderates the SI–BI relationship, such that higher SP strengthens SI's effect on BI.

## 2. Literature Review

2.1 Massive Open Online Courses: Origins, Characteristics, and Professional Use

MOOCs are large-scale online learning environments defined by three principal characteristics: open enrollment without formal prerequisites, massive scalability enabled by digital infrastructure, and structured content delivery through video, assessments, and interaction (Daniel, 2012; Yuan & Powell, 2013). The acronym was first coined in 2008, and the early MOOC movement drew on connectivist principles of distributed networked learning (McAuley et al., 2010; Siemens, 2004). Rollins (2018) situates MOOCs at the intersection of a technical foundation rooted in digital literacy and an ideological commitment to universal access to education. Chattopadhyay (2014) further notes that MOOCs foster 21st-century skills including collaboration, critical thinking, and self-direction.

The field has matured considerably. Ferguson et al. (2019) characterise the trajectory of MOOCs from experimental initiatives to mainstream tools, highlighting their growing contributions to open and lifelong learning and their alignment with the United Nations Sustainable Development Goals relating to quality education (Ossiannilsson, 2021). MOOCs have also been linked to the development of workplace-relevant competencies such as time management and self-

regulated learning (Observatory of Educational Innovation, 2020), and their role in continuous professional development and career progression has been explicitly recognised (Cornock, 2023).

Within professional organisations, MOOCs have been integrated into corporate learning management systems for purposes including technical upskilling, leadership development, regulatory compliance, and onboarding. Research and Markets (2025) identifies on-demand learning flexibility as the primary driver of corporate MOOC adoption. Mousavinasab et al. (2024) introduce a further dimension by documenting ten capabilities of generative artificial intelligence that can augment the MOOC experience, among them adaptive personalisation and automated feedback—both of which address limitations that have historically depressed professional completion rates.

### 2.2 Technology Acceptance Frameworks and UTAUT

Technology acceptance research has generated a rich body of literature, from Davis's (1989) Technology Acceptance Model through the eight-model synthesis that produced UTAUT (Venkatesh et al., 2003). UTAUT proposes that four core constructs—Performance Expectancy (the degree to which using the technology is expected to improve job performance), Effort Expectancy (the degree of ease associated with use), Social Influence (the perceived expectations of relevant others), and Facilitating Conditions (the perceived availability of technical and organisational support)—collectively explain a substantial share of variance in behavioral intention and actual use. The model also incorporates four moderating variables: gender, age, experience, and voluntariness of use.

UTAUT has been applied extensively in e-learning and MOOC adoption research. Al-Rahmi et al. (2019) found strong support for effort expectancy and social influence in the context of mobile learning adoption among higher education students. El-Masri and Tarhini (2017) extended the model with hedonic motivation in cross-national e-learning settings. Cultural dimensions have been examined by Al-Gahtani et al. (2007) and Venkatesh and Zhang (2010), while Mulik et al. (2018) and Nordin et al. (2015) applied UTAUT specifically to MOOC adoption, confirming the relevance of its core constructs in this context. Yuen et al. (2010) explored moderating effects of leadership and organisational context on technology adoption in educational settings.

Despite these contributions, existing applications share a common limitation: they treat adoption as a predominantly cognitive and structural phenomenon, largely bypassing the socio-emotional mechanisms through which professionals interpret and respond to the social environment of a digital learning platform. This study addresses that gap by incorporating SP and GWE as theoretically justified moderators.

### 2.3 Emotional Intelligence and Social Perceptiveness

Emotional intelligence (EI), as foundationally conceptualised by Salovey and Mayer (1990), is defined as the capacity to accurately perceive, use, understand, and regulate emotions in oneself and others. Their four-branch hierarchical model places emotion perception—the ability to read emotional signals in faces, voices, postures, and situations—as the foundational competence upon which higher-order emotional skills are constructed.

Social Perceptiveness is situated within this first branch of EI and refers specifically to the ability to accurately infer others' emotional states, intentions, and interpersonal dispositions from nonverbal and contextual cues (Hall & Bernieri, 2001). The construct is theoretically and empirically intertwined with what developmental psychologists term "theory of mind"—the capacity to attribute mental states such as beliefs, desires, and emotions to others, and to use those attributions to explain and predict their behaviour (Baron-Cohen, 1997; Apperly, 2012). Heyes (2014) describes a related but distinct capacity of "submentalising," emphasising the automaticity of social inference in everyday interaction.

Baron-Cohen et al. (1997) operationalised theory of mind through the "Reading the Mind in the Eyes" (RME) test, a 36-item behavioural instrument in which participants identify the emotional state most accurately depicted by standardised photographs of the eye region. Each item pairs a photograph with four descriptors, of which only one is correct. The RME test has been validated across clinical and non-clinical populations and has been used as an objective, bias-resistant measure of interpersonal sensitivity in organizational and experimental research contexts. Crucially for the present study, Engel et al. (2014) demonstrated that RME performance predicts collective intelligence equally well in online and face-to-face group settings, providing a direct empirical bridge between individual social perceptiveness and group performance in digital environments.

In workplace and educational settings, higher SP is associated with more effective communication, stronger responsiveness to peer feedback, and enhanced conflict resolution (Richards & Pryce, 2006). These properties suggest that individuals with higher SP may be more attuned to the social norms and peer expectations that circulate in MOOC communities, and consequently more responsive to the social influence signals that populate their adoption environment. No prior study has tested whether SP moderates technology acceptance, a gap explicitly noted in the literature and addressed by this research.

### 2.4 Collective Intelligence and Group Work Effectiveness

Collective intelligence refers to the emergent cognitive capacity of a group that systematically exceeds the aggregate intelligence of its individual members when measured across diverse tasks (Woolley et al., 2010). Mayo and Woolley (2016) emphasise that collective performance is less a function of individual cognitive ability and more a function of coordination quality, inclusive communication, and interpersonal attunement within the group. Teams characterised by high collective intelligence tend to outperform expectations on complex tasks precisely because members are more responsive to each other's contributions.

Group Work Effectiveness (GWE), as employed in this study, operationalises the individual's perception of their team's collaborative functioning—the degree to which members coordinate productively, communicate openly, and sustain shared accountability. Babiker et al. (2014) provide converging evidence from healthcare and multidisciplinary professional settings that team interdependence and collaborative culture substantially shape individual performance outcomes. Larson (2010) demonstrates that small-group synergy depends critically on coordination quality rather than raw cognitive capacity. Makary and Daniel (2016) further illustrate the consequences of collaborative failure, identifying inadequate professional communication as a leading contributor to organisational error.

In digital learning contexts, the relevance of GWE is well supported. Wan et al. (2020) found that collaborative engagement with MOOC content—including discussion forum participation and peer assessment—is a positive predictor of course completion. Ekblaw (2016) demonstrated that structured group projects in online courses enhance individual motivation and persistence. These findings suggest that professionals embedded in high-GWE environments may be better positioned to engage with the collaborative affordances of MOOC platforms, and to re-interpret the effort involved in digital learning participation as a shared rather than purely individual burden.

## 3. Theoretical Framework

### 3.1 Connectivism as a Foundation for Digital Learning

Connectivism, introduced by Siemens (2004, 2005), proposes a theory of learning calibrated to the networked, distributed information environment of the contemporary digital age. The theory holds that knowledge resides not within individual minds but across networks of connected people, tools, and digital resources, and that learning consists in the formation and

traversal of connections within these networks. Siemens (2004) notes that network participants share a common interest that links them together, facilitating collaborative thinking and interaction. A key tenet of the theory is that both cognitive and affective processes contribute to learning—a position that directly supports the inclusion of socio-emotional variables such as SP and GWE in a model of digital learning adoption.

Siemens (2005) further argues that the static acquisition of content is insufficient in a rapidly evolving information environment; learners must develop the capacity to locate, evaluate, and connect knowledge across shifting digital sources. This emphasis on network navigation and social connectivity makes connectivism particularly apt as a theoretical anchor for a study of MOOC adoption, where learner engagement is distributed across discussion forums, peer communities, and collaborative assignments.

3.2 Extended UTAUT Framework

This study extends the original UTAUT model (Venkatesh et al., 2003) in two theoretically justified directions.

First, the Facilitating Conditions (FC) construct is disaggregated into two contextually distinct sub-dimensions: (a) Continuous Availability, defined as the extent to which professionals perceive the MOOC platform to be accessible at any time and on any device without service interruption; and (b) Time Flexibility, defined as the degree to which the learning format accommodates the variable and often fragmented scheduling constraints of working adults. This disaggregation is supported by Liu et al. (2015), who identified these dimensions as independently salient for professional learners, and by Castaño-Muñoz et al. (2018), who found temporal flexibility to be a decisive adoption factor in a large-scale Spanish professional development study.

Second, the model introduces SP and GWE as moderating variables. SP is proposed to moderate the SI–BI and EE–BI relationships on the theoretical premise that interpersonal sensitivity shapes how receptive individuals are to social adoption cues and how they cognitively appraise the demands of online learning environments. GWE is proposed to moderate the PE–BI, EE–BI, and SI–BI relationships on the premise that professionals embedded in high-functioning collaborative environments are better equipped to leverage MOOCs' social and collaborative features, reducing perceived effort and amplifying perceived value.

## 4. Methodology

4.1 Research Philosophy and Design

This research adopts a positivist epistemological stance and a deductive research design, wherein theory-derived hypotheses are tested against primary empirical data. The deductive reasoning chain proceeds as follows: UTAUT as technology acceptance framework → theoretical extensions incorporating SP and GWE → hypotheses → seven-point Likert-scale survey and RME behavioral test → statistical analysis → confirmation or refutation of hypotheses. This approach is consistent with the dominant methodological tradition in technology acceptance research (Venkatesh et al., 2003; Al-Rahmi et al., 2019) and enables systematic, replicable testing of the proposed model.

The study combines survey-based attitudinal measurement with a behavioral assessment component. This design choice was deliberate: measuring SP exclusively through self-report items would be vulnerable to social desirability bias and limited discriminant validity. By incorporating the RME behavioral test, the study introduces an objective, validated measure of interpersonal sensitivity that is independent of respondents' self-assessment tendencies.

4.2 Sample and Recruitment

The target population consisted of professionals who were currently enrolled in, or had recently completed, at least one MOOC on any major platform. Participants were recruited through professional social media networks (primarily LinkedIn), direct messaging functions within MOOC platforms, and targeted email outreach. All participants provided written informed consent prior to completing the instrument.

Sample size was determined using a standard probability sampling formula with a margin of error of ±6%, which falls within the widely accepted range of ±4% to ±8% for studies targeting large professional populations (Medina & Portilla, 2015). This calculation indicated a minimum of approximately 250 respondents. The final sample comprised 253 professionals representing multiple countries and occupational sectors, providing adequate statistical power for the planned regression and moderation analyses.

4.3 Measurement Instrument

The questionnaire was structured in three parts, following established survey design principles (Oppenheim, 1992; Brace, 2004; Tourangeau et al., 2000).

Part 1 collected demographic data, including gender, age range, educational level, professional sector, and MOOC participation history.

Part 2 administered the Reading the Mind in the Eyes (RME) test (Baron-Cohen et al., 1997) and self-report items measuring perceived Social Perceptiveness and Group Work Effectiveness. The RME test comprises 36 standardised photographs of the eye region, each paired with four emotion descriptor terms. Respondents selected the term they judged most accurately to depict the emotional state of the individual in the photograph; only one option per item is correct. This instrument has been validated across cultural and clinical contexts and serves as a widely recognised objective measure of theory-of-mind capacity and interpersonal sensitivity.

Part 3 measured UTAUT-related constructs using items adapted from validated prior scales. Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions (original and extended), and Behavioral Intention were each assessed with multiple items rated on a seven-point Likert scale (1 = Strongly Disagree; 7 = Strongly Agree). The full instrument contained 35 adapted items, each limited to a maximum of 20 words to ensure clarity and comprehensibility (Oppenheim, 1992). Items were adapted from prior research to align with the specific context of professional MOOC adoption, consistent with recommendations for ensuring content validity through contextual localisation (Luarn & Lin, 2005). A glossary of technical and domain-specific terms was appended to reduce ambiguity and minimise interpretive distortion (De Leeuw & De Heer, 2002).

Considerable care was devoted to questionnaire design and testing, consistent with scholars who identify this stage as critical yet "under-discussed, underused, and underreported" in quantitative research (Prescott & Soeken, 1989, p. 60). Item length, sequencing, and framing were reviewed to avoid leading questions that could compromise response integrity (Brace, 2004; Tourangeau et al., 2000). References were drawn from reputable academic databases including EBSCO, Elsevier Scopus, and Google Scholar.

4.4 Pilot Study

A pilot study involving 21 professionals was conducted prior to the main distribution. Pilot participants identified several terms as insufficiently defined, including technical constructs from the UTAUT framework that were unfamiliar to non-specialist professionals. Based on this feedback, definitions for key terms were added to the instrument as a separate glossary, and several items were reworded to improve clarity. This preparatory phase followed Agresti and Finlay's (2009) guidance on ensuring that the essential features of a dataset are accurately captured through well-calibrated instruments.

4.5 Analytical Strategy

Data were processed and analysed using IBM SPSS Statistics. The analytical sequence comprised five stages. First, Cronbach's alpha was calculated for each scale to assess internal consistency, following Tavakol and Dennick's (2011) criterion that alpha values at or above .70 are adequate. Second, descriptive statistics characterised the sample on all key variables. Third, a Pearson correlation matrix was computed to examine bivariate relationships among variables and to identify potential multicollinearity. As noted by Hew et al. (2015),

multicollinearity—indicated by Variance Inflation Factor (VIF) values at or above 10—can distort regression estimates and must be checked before proceeding. Fourth, multiple linear regression was estimated with Behavioral Intention as the dependent variable and the five predictor variables as independent variables. Fifth, moderation analyses were conducted to test the conditioning effects of GWE and SP on selected predictor–outcome relationships. The predictive equation derived from the regression model was used to quantify each predictor's independent contribution to adoption intention.

## 5. Results

### 5.1 Reliability Analysis

Internal consistency was assessed using Cronbach's alpha. As shown in Table 1, all scales met or exceeded the .70 threshold (Tavakol & Dennick, 2011), with five of eight scales achieving alpha values above .85. The EE scale demonstrated exceptional internal consistency (α = .919), and the BI scale was also excellent (α = .906). The RME test, functioning as a behavioural rather than attitudinal instrument, returned a coefficient of .717, which is acceptable for a 36-item perceptual task. The GWE scale demonstrated the lowest but still acceptable reliability (α = .714).

Table 1. Internal Consistency Coefficients for All Measurement Scales

| Scale | Cronbach's α | No. of Items |
|---|---|---|
| PE | .861 | 5 |
| EE | .919 | 5 |
| SI | .869 | 5 |
| FC | .803 | 10 |
| BI | .906 | 3 |
| SP | .893 | 6 |
| GWE | .714 | 5 |
| RME Photographs | .717 | 36 |

Note. PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; BI = Behavioral Intention; SP = Social Perceptiveness; GWE = Group Work Effectiveness; RME = Reading the Mind in the Eyes test.

### 5.2 Descriptive Analysis and Multicollinearity Screening

Prior to regression analysis, descriptive statistics were computed to characterise the professional sample. A Pearson correlation matrix was then produced to examine bivariate relationships and to screen for multicollinearity (Pallant, 2007). Results confirmed that each predictor variable maintained a meaningful positive correlation with Behavioral Intention. Variance Inflation Factor (VIF) values were below 10 for all predictors, confirming the absence of problematic multicollinearity (Hew et al., 2015) and satisfying the prerequisite for multiple linear regression analysis.

### 5.3 Multiple Linear Regression

A multiple linear regression model was estimated with Behavioral Intention (BI) as the dependent variable and Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions Original (FC Original), and Facilitating Conditions Extended (FC Extended) as independent variables. The full model was statistically significant ($F(5, 247) = 40.087$, $p < .001$). The adjusted $R^2$ value of .437 indicates that the five predictors jointly account for approximately 43.7% of the variance in professionals' behavioral intention to adopt MOOCs (Table 2)

Table 2. Multiple Linear Regression — Model Summary

| Model | R | $R^2$ | Adj. $R^2$ | Std. Error | $R^2$ Change | F Change | df1 |
|---|---|---|---|---|---|---|---|
| 1 | .669 | .448 | .437 | .752 | .448 | 40.087 | 5 |

The ANOVA results confirming overall model significance are presented in Table 3.

Table 3. Analysis of Variance (ANOVA)

| Model | Source | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 113.199 | 5 | 22.640 | 40.087 | .000 |
| | Residual | 139.497 | 247 | .565 | | |
| | Total | 252.696 | 252 | | | |

Note. Dependent Variable: BI. Predictors: (Constant), FC Extended, SI, PE, FC Original, EE.

Inspection of the individual regression coefficients (Table 4) reveals that two predictors reached statistical significance at the conventional $\alpha = .05$ level: Effort Expectancy ($B = .323$, $\beta = .335$, $t = 5.057$, $p < .001$) and the extended Facilitating Conditions construct ($B = .347$, $\beta = .311$, $t = 4.564$, $p < .001$). Performance Expectancy approached but did not attain the significance threshold ($B = .106$, $p = .079$). Social Influence ($B = .029$, $p = .425$) and the original Facilitating Conditions variable ($B = .023$, $p = .744$) were not statistically significant as main effects.

Table 4. Unstandardised and Standardised Regression Coefficients

| Predictor | B | Std. Error | β | t | Sig. |
|---|---|---|---|---|---|
| (Constant) | 1.262 | .374 | — | 3.378 | .001 |
| PE | .106 | .060 | .102 | 1.764 | .079 |
| EE | .323 | .064 | .335 | 5.057 | .000 |
| SI | .029 | .036 | .041 | .799 | .425 |
| FC (Original) | .023 | .069 | .020 | .327 | .744 |
| FC (Extended) | .347 | .076 | .311 | 4.564 | .000 |

Note. Dependent Variable: BI. *p < .05; ***p < .001.

The regression equation derived from these results is:

$$BI = 1.262 + 0.323(EE) + 0.347(FC\ Extended)$$

This equation indicates that each one-unit increase in Effort Expectancy corresponds to a .323-unit increase in Behavioral Intention, and each one-unit increase in the extended Facilitating Conditions construct corresponds to a .347-unit increase in Behavioral Intention, holding all other predictors constant.

5.4 Hypothesis Testing

H1 was supported at the model level. The regression model was statistically significant, and two of the four UTAUT core constructs—EE and extended FC—exerted significant positive effects on Behavioral Intention. This confirms that the structural adoption antecedents collectively predict professionals' MOOC adoption intention.

H2 was not supported. GWE did not significantly moderate the PE–BI relationship.

H3 was supported. GWE significantly moderated the EE–BI relationship. Professionals in high-GWE environments demonstrated a stronger

conversion of ease-of-use perceptions into adoption intention, suggesting that supportive collaborative settings mitigate the subjective effort cost of MOOC engagement. This aligns with Wan et al. (2020), who found that collaborative course engagement predicts completion, and with Ingram (2000), who documented performance benefits of effective teamwork in organisational settings.

H4 was not supported. GWE did not significantly moderate the SI–BI relationship.

H5 was not supported. SP did not significantly moderate the EE–BI relationship.

H6 was supported. SP significantly moderated the SI–BI relationship. Professionals who performed more accurately on the RME test demonstrated a stronger association between perceived social expectations and their own adoption intention, indicating that individuals with greater interpersonal sensitivity are more responsive to peer adoption signals. This finding extends Mulik et al. (2018) and Nordin et al. (2015), who identified Social Influence as a significant predictor, by demonstrating that the effect varies systematically with individual differences in SP.

A summary of hypothesis outcomes is presented in Table 5.

Table 5. Summary of Hypothesis Testing Outcomes

| H | Statement | Outcome | Note |
|---|---|---|---|
| H1 | PE, EE, SI, and FC positively affect BI to adopt MOOCs | Supported | EE and FC (Extended) significant |
| H2 | GWE moderates the PE–BI relationship | Not supported | — |
| H3 | GWE moderates the EE–BI relationship | Supported | Positive moderation confirmed |
| H4 | GWE moderates the SI–BI relationship | Not supported | — |
| H5 | SP moderates the EE–BI relationship | Not supported | — |
| H6 | SP moderates the SI–BI relationship | Supported | Positive moderation confirmed |

As a supplementary finding, an independent samples t-test applied to RME performance scores revealed that female participants significantly outperformed male participants, consistent with established findings on gender differences in emotion recognition (Hall & Bernieri, 2001).

## 6. Discussion

### 6.1 Interpreting the Main Effects: Effort and Access as Primary Drivers

The emergence of Effort Expectancy and the extended Facilitating Conditions construct as the dominant predictors of adoption intention is consistent with the realities of professional learning. Working adults operate under significant time pressure and cognitive load; the usability and accessibility of a learning platform are not peripheral features but central preconditions for sustained engagement. Professionals appear to evaluate MOOCs in pragmatic terms—if a platform is difficult to use or inaccessible at convenient times, no amount of perceived performance benefit or peer encouragement will translate into adoption commitment.

The non-significance of Social Influence as a main effect is noteworthy. It does not imply that social context is irrelevant—the supported moderation of SP on the SI–BI relationship demonstrates that social influence does operate, but its effect is conditioned by individual

interpersonal sensitivity. Professionals as a group may be less susceptible to undifferentiated normative pressure than student populations, making the direct effect of social influence weaker; however, those with higher SP are meaningfully more responsive to it.

The non-significance of Performance Expectancy ($p = .079$), while approaching significance, suggests that professionals in the study sample did not primarily evaluate MOOCs in terms of their expected impact on job outcomes—a finding that contrasts with some prior UTAUT applications but may reflect the specific character of voluntary, self-directed professional learning, where the utility calculus is more nuanced and long-term.

### 6.2 The Role of Group Work Effectiveness

The supported moderation of GWE on the EE–BI relationship carries important theoretical and practical implications. Theoretically, it demonstrates that the relationship between perceived ease of use and adoption intention is not fixed but varies with the quality of the collaborative environment in which a professional is embedded. A working professional who perceives their team as cohesive, communicative, and mutually accountable appears to approach the cognitive and practical demands of a new digital learning platform more favourably—the group context reduces the subjective burden of individual effort.

Practically, this suggests that organisational MOOC deployment strategies may achieve better outcomes when they embed platform participation within team-level learning initiatives rather than positioning it as an exclusively individual activity. MOOC designers might consider incorporating structured collaborative elements—group challenges, peer mentoring assignments, team-based projects—that activate the moderating potential of GWE. Organisations with teams that demonstrate lower cohesion might benefit from targeted preparatory workshops before MOOC rollout, to build the collaborative infrastructure that makes digital learning adoption more likely.

### 6.3 The Role of Social Perceptiveness

The supported moderation of SP on the SI–BI relationship reveals a more granular mechanism than prior UTAUT-based studies have captured. Social Influence does not exert a uniform effect on adoption intention across professionals; its potency is amplified among individuals who are more skilled at reading interpersonal cues and interpreting social signals. High-SP professionals appear to be more attuned to the adoption behaviours and learning intentions of their professional communities, and this attunement translates more directly into their own motivation to adopt.

This has concrete implications for organisational communication and peer advocacy strategies. Visible social modelling of MOOC participation—through peer endorsements, internal testimonials, and collaborative platform features—is likely to be particularly persuasive when directed at employees with demonstrably high interpersonal sensitivity. Conversely, professionals with lower SP may benefit from more structured social scaffolding, such as blended learning formats that supplement online content with facilitated face-to-face interaction, reducing reliance on the social signal interpretation capacity that underpins the SI–BI relationship.

The use of the RME behavioral test alongside self-report SP items also represents a methodological contribution. The dual-measurement approach reduces reliance on potentially biased self-assessment and provides a more robust operationalisation of interpersonal sensitivity, consistent with Baron-Cohen et al.'s (1997) evidence for the test's discriminant validity and Engel et al.'s (2014) demonstration of its predictive relevance in online collaborative contexts.

### 6.4 Theoretical Contributions

This study contributes to UTAUT scholarship in three respects. First, it demonstrates that socio-emotional individual differences—specifically SP and GWE—condition how structural adoption antecedents translate into behavioral intention,

expanding the model's explanatory scope beyond its traditional cognitive-structural boundaries. Second, it provides empirical support for disaggregating the Facilitating Conditions construct in professional e-learning contexts, with continuous availability and time flexibility emerging as functionally distinct and independently predictive sub-dimensions. Third, the incorporation of the RME behavioral test as an objective SP measure introduces a methodological approach not previously employed in technology acceptance research, strengthening construct validity and reducing self-report bias.

More broadly, the research advances a more integrative understanding of MOOC adoption—one that bridges structural access conditions, cognitive ease-of-use appraisals, and socio-emotional interpretation capacities. It also supports a shift in how MOOC effectiveness is assessed, proposing that quantitative outcome metrics be supplemented with qualitative indicators of collaborative engagement, such as discussion participation rates, peer review quality, and group assignment outcomes.

6.5 Practical Implications

For MOOC platform designers, findings support investment in intuitive interfaces, reliable 24/7 access, and scheduling flexibility. In addition, the GWE findings suggest that embedding structured collaborative mechanisms—peer mentoring, group tasks, visible participation norms—may activate team-level support that reduces the effort barrier to adoption. Platforms currently designed primarily for individual self-directed learning may benefit from architectural features that acknowledge the organisational team context in which professional learners are embedded.

For human resource practitioners and training managers, the research suggests that MOOC deployment should be approached as an organisational-level initiative rather than an individual employee responsibility. Training managers may achieve better adoption outcomes by framing MOOC participation within team development narratives, creating peer learning cohorts, and using SP assessments to identify employees who are likely to respond strongly to peer advocacy strategies. HR dashboards that track not only enrollment but collaborative engagement metrics—forum participation, peer assessment activity—may provide a more complete picture of MOOC effectiveness than completion rates alone.

## 7. Limitations and Future Research

This study has several limitations that qualify its findings and point toward productive future directions. First, the cross-sectional design precludes causal inference; while the moderation findings are theoretically coherent and statistically significant, longitudinal data would be needed to establish causal relationships between the predictor variables and actual MOOC completion behaviour over time.

Second, the dependent variable is Behavioral Intention rather than observed completion or sustained usage. Intention-behaviour gaps are well documented in technology adoption research; future studies should incorporate behavioural usage data or platform-level completion records to test whether the relationships identified here translate into actual engagement.

Third, while the sample includes professionals from multiple countries and sectors, it does not enable controlled sector-specific or culture-specific analysis. Given the established sensitivity of both social influence processes and interpersonal competency constructs to cultural variation (Al-Gahtani et al., 2007; Venkatesh & Zhang, 2010), future research should systematically test the proposed model across homogeneous cultural and industry groups.

Fourth, participant self-selection in online recruitment may introduce bias, as respondents who are already engaged with MOOCs may differ systematically from those who have declined to participate. Future studies should explore sampling strategies that capture non-adopters alongside active users.

Finally, the non-supported hypotheses (H2, H4, H5) represent important findings in their own

right. Future research should investigate under what conditions—in terms of platform type, team structure, or sector—these moderation effects might emerge, and whether more granular operationalisations of SP and GWE would produce different results.

## 8. Conclusion

This study extends the UTAUT model by introducing Social Perceptiveness (SP) and Group Work Effectiveness (GWE) as novel moderating variables in the context of professional MOOC adoption, and by disaggregating the Facilitating Conditions construct into the contextually distinct sub-dimensions of Continuous Availability and Time Flexibility. Using data from 253 professionals, the study demonstrates that adoption intention is most powerfully driven by Effort Expectancy and the extended Facilitating Conditions construct, and that GWE and SP each moderate specific adoption pathways in theoretically coherent ways.

The findings make a clear theoretical case for incorporating socio-emotional individual differences into technology acceptance frameworks. Adoption is not a purely cognitive or structural decision; it is shaped by the interpersonal dynamics of the professional environment and by the social interpretation capacities of individual learners. The supported moderation effects of GWE on the EE–BI relationship and SP on the SI–BI relationship demonstrate that the professional context of MOOC use must be understood as a socially embedded rather than individually isolated phenomenon.

For practitioners, the study provides a concrete framework for more effective MOOC deployment: design platforms for accessibility and scheduling flexibility, embed participation within collaborative team contexts, and leverage peer advocacy strategies in ways that are sensitive to the interpersonal competencies of the target audience. Future research should test the model longitudinally, across cultural contexts, and with direct behavioural engagement data, to consolidate and extend these findings.

## References

Aday, L. A. (2006). Designing and conducting health surveys: A comprehensive guide (3rd ed.). Jossey-Bass.

Agresti, A., & Finlay, B. (2009). Statistical methods for the social sciences (4th ed.). Pearson Prentice Hall.

Al-Gahtani, S. S., Hubona, G. S., & Wang, J. (2007). Information technology (IT) in Saudi Arabia: Culture and the acceptance and use of IT. Information & Management, 44(8), 681–691. https://doi.org/10.1016/j.im.2007.09.002

Al-Rahmi, W. M., Yahaya, N., Alturki, U., Alrobai, A., Aldraiweesh, A., Omar Umar, I., & Asiri, M. J. (2019). Using UTAUT to understand students' adoption of mobile learning systems in higher education. IEEE Access, 7, 174673–174686. https://doi.org/10.1109/ACCESS.2019.2957206

Anand Shankar Raja, M. K., & Kallarakal, T. K. (2020). Investigating learner perception on the effectiveness of MOOCs. Procedia Computer Science, 172, 843–847. https://doi.org/10.1016/j.procs.2020.05.122

Anderson, V., Gifford, J., & Wildman, J. (2020). An evaluation of social learning and learner outcomes in a massive open online course (MOOC): A healthcare sector case study. Human Resource Development International, 23(3), 208–237. https://doi.org/10.1080/13678868.2019.1620880

Ang, K. L. M., Ge, F. L., & Seng, K. P. (2020). Big educational data analytics: Survey, architecture and challenges. IEEE Access, 8, 116392–116414. https://doi.org/10.1109/ACCESS.2020.2994561

Apperly, I. (2012). What is "theory of mind"? Concepts, cognitive processes and individual differences. Quarterly Journal of Experimental Psychology, 65(5), 825–839. https://doi.org/10.1080/17470218.2012.670235

Babiker, M., Fischbacher-Smith, M., & Fischbacher-Smith, D. (2014). Health care professional development: Working as a team to improve patient care. Sudanese Journal of Paediatrics, 14(2), 9–16.

Baron-Cohen, S. (1997). Mindblindness: An essay on autism and theory of mind. MIT Press.

Baron-Cohen, S., Wheelwright, S., Hill, J., Raste, Y., & Plumb, I. (1997). The "Reading the Mind in the Eyes" test revised version: A study with normal adults, and adults with Asperger syndrome or high-functioning autism. Journal of Child Psychology and Psychiatry, 42(2), 241–251. https://doi.org/10.1111/1469-7610.00715

Brace, I. (2004). Questionnaire design: How to plan, structure and write survey material for effective market research. Kogan Page.

Castaño-Muñoz, J., Kalz, M., Kreijns, K., & Punie, Y. (2018). Who is taking MOOCs for teachers' professional development on the use of ICT? A cross-sectional study from Spain. Technology, Pedagogy and Education, 27(5), 607–624. https://doi.org/10.1080/1475939X.2018.1528997

Chattopadhyay, S. (2014). 11 Differences between a MOOC and an online course. Retrieved from http://idreflections.blogspot.com/2014/06/11-differences-between-mooc-and-online.html

Cornock, M. (2023). The evolving role of open online courses in lifelong learning journeys. MattCornock.co.uk. https://mattcornock.co.uk/online-learning-digital-education/the-evolving-role-of-open-online-courses-in-lifelong-learning-journeys-the-mooc-isnt-dead/

Daniel, J. (2012). Making sense of MOOCs: Musings in a maze of myth, paradox, and possibility. Journal of Interactive Media in Education, 2012(3), 1–20. https://doi.org/10.5334/2012-18

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

De Leeuw, E., & De Heer, W. (2002). Trends in household survey nonresponse: A longitudinal and international comparison. In R. M. Groves, D. A. Dillman, J. L. Eltinge, & R. J. A. Little (Eds.), Survey nonresponse (pp. 41–54). Wiley.

Ekblaw, R. (2016). Effective use of group projects in online learning. Contemporary Issues in Education Research, 9(3), 121–128. https://doi.org/10.19030/cier.v9i3.9710

El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of e-learning systems in Qatar and USA: Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Educational Technology Research and Development, 65(3), 743–767. https://doi.org/10.1007/s11423-016-9508-8

Engel, D., Woolley, A. W., Jing, L. X., Chabris, C. F., & Malone, T. W. (2014). Reading the mind in the eyes or reading between the lines? Theory of mind predicts collective intelligence equally well online and face-to-face. PLOS ONE, 9(12), e115212. https://doi.org/10.1371/journal.pone.0115212

Ferguson, R., Coughlan, T., Egelandsdal, K., Gaved, M., Herodotou, C., Scanlon, E., & Sharples, M. (2019). Open learning and learning at scale: The legacy of MOOCs. Journal of Interactive Media in Education, 2019(1), 1–14. https://doi.org/10.5334/jime.948

Gamage, D., Fernando, S., & Perera, I. (2015). Factors affecting successful implementation of eLearning in Sri Lankan universities. International Journal of Modern Education and Computer Science, 7(6), 49–56. https://doi.org/10.5815/ijmecs.2015.06.07

Hall, J. A., & Bernieri, F. J. (Eds.). (2001). Interpersonal sensitivity: Theory and measurement. Lawrence Erlbaum Associates.

Hew, J. J., Leong, L. Y., Ooi, K. B., & Chong, A. Y. L. (2015). What catalyses mobile apps usage intention: An empirical analysis. Industrial Management & Data Systems, 115(7), 1269–1291. https://doi.org/10.1108/IMDS-01-2015-0028

Heyes, C. (2014). Submentalizing: I am not really reading your mind. Perspectives on Psychological Science, 9(2), 131–143. https://doi.org/10.1177/1745691613518076

Impey, C. (2020). Bringing science to the masses: MOOCs and the public face of science. Science Communication, 42(2), 247–258. https://doi.org/10.1177/1075547019896972

Impey, C., & Formanek, M. (2021). MOOCS and 100 days of COVID: Enrollment surges in massive open online astronomy courses during the pandemic. Social Sciences & Humanities Open, 4(1), 100177. https://doi.org/10.1016/j.ssaho.2021.100177

Ingram, H. (2000). Linking teamwork with performance. Team Performance Management, 6(1/2), 5–10. https://doi.org/10.1108/13527590010343258

Kumar, M. (2022). MOOCs in learning: Pros, cons, and tips. eLearning Industry. https://elearningindustry.com/are-moocs-worth-it-pros-cons-and-tips-to-maximize-learning-outcomes

Larson, J. R. (2010). In search of synergy in small group performance. Psychology Press.

Liu, M., Kang, J., & McKelroy, E. (2015). Examining learners' perspective of taking a MOOC: Reasons, excitement, and perception of usefulness. Educational Media International, 52(2), 129–146. https://doi.org/10.1080/09523987.2015.1053948

Luarn, P., & Lin, H.-H. (2005). Toward an understanding of the behavioral intention to use mobile banking. Computers in Human Behavior, 21(6), 873–891. https://doi.org/10.1016/j.chb.2004.03.003

Makary, M. A., & Daniel, M. (2016). Medical error—the third leading cause of death in the US. BMJ, 353, i2139. https://doi.org/10.1136/bmj.i2139

Mayo, A. T., & Woolley, A. W. (2016). Teamwork in health care: Maximizing collective intelligence via inclusive collaboration and open communication. AMA Journal of Ethics, 18(9), 933–940. https://doi.org/10.1001/journalofethics.2016.18.9.stas1-1609

McAuley, A., Stewart, B., Siemens, G., & Cormier, D. (2010). MOOC model for digital practice. University of Prince Edward Island.

McCluskey, M. (2020). Taking a MOOC during COVID-19: What to know. U.S. News & World Report. https://www.usnews.com/higher-education/online-education/articles/taking-a-mooc-during-coronavirus-pandemic-what-to-know

Medina, M., & Portilla, I. (2015). Media market research on immigrant audiences: Lessons learned from a critical analysis of the Spanish media survey. International Journal of Communication, 9, 501–522.

Mousavinasab, E., Thota, C., & MacCallum, K. (2024). Towards enhanced e-learning within MOOCs: Exploring the capabilities of generative artificial intelligence. In PACIS 2024 Proceedings (Paper 11). Association for Information Systems. https://aisel.aisnet.org/pacis2024/track14_educ/track14_educ/11/

Mulik, S., Srivastava, M., & Yajnik, N. (2018). Extending UTAUT model to examine MOOC adoption. NMIMS Management Review, 36(2), 26–44.

Nordin, N., Norman, H., & Embi, M. A. (2015). Technology acceptance of massive open online courses in Malaysia. Malaysian Journal of Distance Education, 17(2), 1–16.

Observatory of Educational Innovation. (2020). MOOCs and their contribution to lifelong learning. Tecnológico de Monterrey. https://observatory.tec.mx/edu-bits-2/mooc-courses-and-their-contribution-to-lifelong-learning

Onah, D. F., Sinclair, J., & Boyatt, R. (2014). Dropout rates of massive open online courses: Behavioural patterns. In EDULEARN14 Proceedings (Vol. 1, pp. 5825–5834). IATED.

Oppenheim, A. N. (1992). Questionnaire design, interviewing and attitude measurement (2nd ed.). Pinter Publishers.

Ossiannilsson, E. (2021). MOOCs for lifelong learning, equity, and liberation. In Proceedings of the EdMedia + Innovate Learning 2021 Conference. https://www.researchgate.net/publication/354127436

Pallant, J. (2007). SPSS survival manual: A step-by-step guide to data analysis using SPSS for Windows (3rd ed.). Open University Press.

Prescott, P. A., & Soeken, K. L. (1989). The potential uses of pilot work. Nursing Research, 38(1), 60–62. https://doi.org/10.1097/00006199-198901000-00013

Research and Markets. (2025, May). Massive Open Online Courses (MOOCs) market opportunity, growth drivers, and forecast 2025–2034. GlobeNewswire. https://www.globenewswire.com/news-release/2025/05/05/3073829/28124/en/Massive-Open-Online-Courses-MOOCs-Market-Opportunity-Growth-Drivers-and-Forecast-2025-2034-Businesses-Turn-to-MOOCs-for-Workforce-Upskilling-and-On-Demand-Learning-Solutions.html

Richards, D., & Pryce, J. (2006). EI: Well-being and performance. Competency & Emotional Intelligence, 13, 41–45.

Rollins, A. (2018). What's a MOOC? History, principles and characteristics. eLearning Industry. https://elearningindustry.com/whats-a-mooc-history-principles-characteristics

Salovey, P., & Mayer, J. D. (1990). Emotional intelligence. Imagination, Cognition and Personality, 9(3), 185–211. https://doi.org/10.2190/DUGG-P24E-52WK-6CDG

Serrat, O. (2010). A primer on organisational learning. Asian Development Bank. https://www.adb.org/publications/primer-organizational-learning

Siemens, G. (2004). Connectivism: A learning theory for the digital age. elearnspace. http://www.elearnspace.org/Articles/connectivism.htm

Siemens, G. (2005). Connectivism: Learning as network-creation. ASTD Learning News, 10(1).

Sood, V. (2016). Massive Open Online Courses: Learners' perspectives. International Journal of Information Dissemination and Technology, 6(1), 49–53.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International Journal of Medical Education, 2, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Tourangeau, R., Rips, L. J., & Rasinski, K. (2000). The psychology of survey response. Cambridge University Press. https://doi.org/10.1017/CBO9780511819322

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. Journal of Global Information Technology Management, 13(1), 5–27. https://doi.org/10.1080/1097198X.2010.10856507

Wan, L., Niu, Z., & Xie, K. (2020). Promoting MOOC completion: The role of peer learning networks. Internet and Higher Education, 46, 100737. https://doi.org/10.1016/j.iheduc.2020.100737

Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., & Malone, T. W. (2010). Evidence for a collective intelligence factor in the performance of human groups. Science, 330(6004), 686–688. https://doi.org/10.1126/science.1193147

Yuan, L., & Powell, S. (2013). MOOCs and open education: Implications for higher education. JISC CETIS. http://publications.cetis.org.uk/2013/667

Yuen, A. H. K., Law, N., & Wong, K. C. (2010). ICT implementation and school leadership: Case studies of ICT integration in teaching and learning. Educational Technology & Society, 13(2), 52–66.