LEX LOCALIS-JOURNAL OF LOCAL SELF-GOVERNMENT
ISSN:1581-5374 E-ISSN:1855-363X
VOL. 23, NO. S6(2025)

SOCIAL PERCEPTIVENESS AND TEAMWORK EFFECTIVENESS AS DETERMINANTS OF MOOCS ADOPTION IN PROFESSIONAL E-TRAINING

Dr. Luciana C. Chaanine[1*], Dr. Angelika Kokkinaki[2]

[1*]Assistant Professor Lebanese International University School of Business, Lebanon
Email: Luciana.Chaanine@liu.edu.lb
[2]Professor University of Nicosia, Cyprus Email: kokkinaki.a@unic.ac.cy

Abstract
With the swiftly changing world and the technological advances that we have been witnessing, organizations have been using digital platforms to upskill employees. The Massive Open Online Courses adoption aligns with the broad concept of e-training and the integration of these online learning systems into training initiatives has been increasing. Several factors have been recognized for their influencing effect on the adoption of MOOCs in professional environments, and the most widely utilized models in such cases was the Unified Theory of Acceptance and Use of; however, no research has attempted to investigate social perceptiveness and teamwork effectiveness potential effect on the adoption of MOOCS as a form of e-training. This study extends the UTAUT through the incorporation of these two novel factors as key determinants in MOOCs modules and courses adoption. The research uses a quantitative design aiming to provide insights for several stakeholders, especially for organizations and providers of MOOCs to benefit from e-training and professional learning through MOOCs and digital platforms.

Keywords: MOOCs, e-training, adoption determinants, UTAUT, Social perceptiveness, social dimension

1. Introduction
1.1 Background
Training is widely regarded as a vital activity through which a company can secure continuous development, sustain long-term growth and reinforce the value of employees as the company's greatest and core assets. Innovative training and e-training have emerged as modern training methods complementing and sometimes surpassing traditional training that is no longer the sole efficient type of training (Serrat, 2010). These new types can help the employees as they increase their engagement and satisfaction and help them in self-actualization (Sood, 2016).
Research and Markets published a recent report entitled "Massive Open Online courses (MOOCs) Market Opportunity, Growth Drivers and Forecast 2025-2034". The report investigates the increasingly important role of these courses in the professional setting and their contributions to the up-skilling of the workforce. According to the report, MOOCs have been providing "on-demand learning solutions", and companies tend to integrate them into corporate strategies when it comes to e-training (Research and Markets, 2025).
Mousavinasab et al (2024) in their paper entitled "Towards Enhanced E-learning Within MOOCs: Exploring the Capabilities of Generative Artificial Intelligence" investigate how the artificial intelligence can help in addressing some of the weaknesses faced by MOOCs. The research claims that there are ten capabilities for generative Artificial Intelligence, namely adaptive learning and individualized support, that can enhance e-training experience for MOOCs users.
Digital learning has witnessed a transformative revolution with MOOCs since they have succeeded in providing flexibility and accessibility for their users, especially for the professionals with hectic schedules who are still interested in pursuing lifelong learning and ongoing education (McCluskey, 2020). Nonetheless, adoption rates among professionals remain inconsistent and falling below 5% with many learners facing significant challenges, with high drop-out rates and completion rates (Kumar 2022; Ang et al., 2020; Onah et al., 2014). Millions of learners across the globe have used MOOCs, and their adoption significantly increased during the COVID-19 pandemic in 2019 (McCluskey, 2020; Impey & Formanek, 2021).
While much empirical work has investigated the effect of technology-enhanced learning on higher education, less has considered its role in professional learning environments (Anderson, Gifford &

Wildman, 2020). While earlier studies focused on technology acceptance theories, little attention has been given to social determinants such as social perceptiveness and teamwork effectiveness.

Significance of the Problem

With technological advancements the world has been witnessing and the impact of a pandemic on traditional face to face learning and training, the shift towards digital solutions became a must and thus leading to an increase in the usage of elearning and a surge in the MOOC's market (Impey, 2020). MOOCs emerged as a key e-learning tools and became an effective means to access knowledge and pursue learning in both academic and professional settings. In response to the disruptions in education during lockdowns and as part of crisis management solutions, MOOCs were adopted to ensure the continuity in learning (Anand Shankar Raja & Kallarakal, 2020).

According to Gamage, et al., (2015), MOOCs success can be affected by several factors such as the reputation of the providers of these courses, collaboration with big universities, the discussion forums…; Nonetheless, many users were unable to complete the courses and dropout rates persistently remained high. This research studies key factors, among which are social factors, in an effort to generate practical recommendations and guidelines and propose future research to enhance the acceptance of MOOCs by professionals and succeed in effectively integrating these courses in professional e-training environments.

1.2 Literature Review

Massive Open Online Courses

According to Daniel (2012), MOOCs are online learning platforms that have functioned as disruptive innovation that leveraged the internet to deliver educational content to a massive audience worldwide. They have played a major role in expanding access to education allowing learners to enroll in courses at little or no cost in whatever university, institution or organization all around the world. They are well known for their open nature and scalability. MOOCs are typically asynchronous types of learning with quizzes, assignments, and discussion forums to facilitate learning.

Yuan & Powell (2013) have also highlighted open access, scalability and use of digital technologies as the key characteristics of MOOCs. In many cases, they have also become part of formal education systems with credibility and quality, with some universities offering credit for MOOCs completion.

MOOCs emerged in the late 2000s after growing demands for accessible and affordable education. The acronym "MOOC" was first coined in 2008. According to McAuley et al. (2010), for a successful engagement in the learning process through MOOCs, the users need to be actively engaged along with being self organized and goal oriented. Rollins (2018) believed that MOOCs, and in addition to their technical foundation related to digital literacy and distance learning, they also have an ideological foundation with their universal access. Chattopadhyay (2014) study has associated MOOCs with fostering skills like collaboration that are considered important skills in the 21st-century skills.

MOOCs, E-training and Lifelong Learning

Ferguson et al. (2019), in their article entitled "Open Learning and Learning at Scale: The Legacy of MOOCs", compare and contrast MOOCs limitations and its contribution to open and lifelong learning. They describe their historical evolution and state that, no longer experimental, MOOCs have now become mainstream tools in education and training.

MOOCs' role is expending as it now covers "promoting global equity and social transformation". These courses have been contributing in fairly providing access to good quality education, and this aligns with the SDGs of the United Nations (Ossiannilson, 2021).

In addition to the above, MOOCs can help in building certain skills such as time management and self-regulated learning (Observatory of Educational Innovation, 2020). This article stresses the role of MOOCs in improving employability while nurturing a mindset of lifelong and autonomous learning.

According to Cornock (2023), MOOCs are now increasingly used in continuous learning and lifelong learning and are integrated within career development.

Emotional Intelligence (EI) and Social Perceptiveness

Emotional Intelligence (EI)'s first conceptualization was introduced by Salovey and Mayer (1990); the scholars defined it as being able to identify, regulate, comprehend, and use emotions effectively. Understanding emotions is a fundamental element in their approach, also known as the Four-Branch approach of Emotional Intelligence and is strongly linked to social perceptiveness.

According to research, individuals who have high emotional intelligence can better manage stress and strive for improved performance (Richards & Pryce, 2006). Under emotional intelligence, Social Perceptiveness is associated with "Theory of Mind" which is among abilities that can be precisely quantified (Engel et al., 2014).

In social sciences, particularly in psychology, sociology, and organizational behavior contexts, social perceptiveness is emulative of the concepts of emotional intelligence (EI). It is generally associated with the ability to read, with sufficient accuracy, body language, voice tone and situational context to obtain an understanding of what someone feels, is motivated by, or intends to do. Hall & Bernieri (2001) have discussed nonverbal decoding, empathy, and situational awareness in social perception. The linking between social perceptiveness and EI is reflected in the epistemological and theoretical interrelations with empathy, nonverbal communication, and situational awareness, and continues to be very important for the effective interaction between people. Social perceptiveness, such as in the workplace, in education, and health care, can enhance the ability of individuals to work together more satisfactorily, communicate during conflict resolution, and render patient-centered care. Theoretical emphasis is on social cognition and symbolic interactionism concerning how people respond to social influence. No studies have attempted to investigate whether can social perceptiveness can affect technology acceptance.

"Theory of Mind" is also known as "mindalizing" (Apperly, 2012) or "mind reading" (Heyes, 2014); it allows people to deduce the mental states of others. It involves the capacity to examine behavior by using ideas such as objectives and emotions. The "theory of mind" is crucial for social perceptiveness (Baron-Cohen, 1997).

Teamwork and collective intelligence

According to Mayo and Woolley (2016), the idea that a smart team is only a group of intelligent people is out of date and instead, the main goals should focus on understanding what makes a team collectively clever and how to encourage efficient coordination and collaboration among its members. Babiker et al. (2014) point out that while individual efforts in business contexts frequently fall short of expectations, interdisciplinary teams are essential for long-term success. According to Larson (2010), performance can be greatly improved by teamwork. According to Makary and Daniel (2016), one of the reasons for mistakes is inadequate professional communication.

Aim of the research

This study integrates Social Perceptiveness and the Effectiveness of Group Work as moderators in the context of MOOCs and e-training—two elements that no prior studies, to the authors' knowledge, have examined. A systematic search through Google Scholar and EBSCO, using the keywords "Social Perceptiveness" AND "MOOCs," yielded no results. When using the keywords "Group Work Effectiveness" AND "MOOCs" in the search, only nine articles appeared in the results, but none of these articles used GWE as a moderator to test its effect. Add to this, these studies did not use the UTAUT model nor did they collect their primary data from professionals.

One of this study's contribution is the expansion of original UTAUT model and the inclusion of SP and GWE as additional moderating variables. Moreover, the research offers a different perspective on studying the existing construct, the Facilitating Conditions, by going into deep analysis and splitting it into two sub-dimensions:

1. Continuous uninterrupted availability (having 24/7 access to the MOOC platform)
2. Time Flexibility (adaptability in each learner's schedule).

The inclusion of these two sub-dimensions in this study was supported by previous studies. These two sub-constructs have been identified as significant factors that facilitate the acceptance of MOOCs (Liu et al., 2015); this echoes other research mainly that of Castaño-Muñoz et al. (201. The main underpinning of this theory is used to formulate research questions and hypotheses as follows:

H1: Facilitating Conditions (FC), Performance Expectancy(PE), Effort Expectancy(EE), & Social Influence (SI) have positive effects on the Behavioral Intention(BI) to use MOOCs in professional setting.

H2: In professional settings, the Group work effectiveness (GWE) has positive moderating impact on the PE-BI relationship. Higher GWE makes PE's impact on behavioral intention higher.

H3: In professional settings, the Group work effectiveness (GWE) has positive moderating impact on the EE-BI relationship. Higher GWE, makes EE's impact on behavioral intention higher.

H4: In professional settings, the Group work effectiveness (GWE) has positive moderating impact on the SI-BI relationship. Higher GWE makes SI's impact on behavioral intention higher.

H5: In professional settings, Social perceptiveness (SP) positively moderates the EE-BI relationship; the higher the SP, the more powerful the EE's impact is on behavioral intention.

H6: In professional settings, the Social perceptiveness (SP) positively moderates the SI-BI relationship; the higher the SP, the more powerful the SI's impact is on behavioral intention.

2. Theoretical Framework

2.1 Connectivism as a Theoretical Framework for Learning

Connectivism has been historically used as a theoretical framework in an attempt to understand the novel kinds of learning especially where knowledge is diffused across digital networks and accessed through online communities. Siemens (2004) states that these communities have some sort of common interest and that is what links them together to facilitate collaborative thinking and interaction among learners. An important concept in connectivism is that knowledge resides within a variety of perspectives and in networked systems.

The theory stipulates that both emotions and reasoning form knowledge since learning occurs through both cognitive and affective processes. According to Siemens (2005), the static acquisition of knowledge is not enough; one needs to learn how to get knowledge particularly in the swiftly evolving information-driven age of technology.

2.2 UTAUT Model

This research is theoretically grounded in UTAUT model (Venkatesh et al., 2003). This model describes a user's process to accept and interact with information systems and technologies. Venkatesh et al. created it in 2003, from the incorporation of TAM- and the integration of some aspects from eight previous models of technology acceptance. The Key Components of UTAUT can be grouped in core constructs, moderators and outcome variables.

The **core constructs** are formed of the following variables:

Performance Expectancy (PE): Extent to which someone uses technology and believes that its result will be positive on job performance.

Effort Expectancy (EE): How much difficulty an individual associates with using technology.

Social Influence (SI): How much an individual believes that acquaintances around him/her expect him/her to use this technology.

Facilitating Conditions (FC): How much an individual thinks it is easy to get organizational and technical support while using technology.

UTAUT has been applied in different fields, mainly Information systems adoption, Healthcare technology and educational technology (e.g., e-learning platforms, MOOCs). For instance,Al-Rahmi, et al. (2019) used UTAUT in their research to understand learners' adoption of Mobile Learning Systems in Higher Education.

3. Methodology

This research adopts a deductive approach, whereby the research model is developed from already established theories. Specifically, it draws on technology acceptance frameworks and previous studies to build the model and formulate the hypotheses. To test these hypotheses, data will be gathered through a questionnaire and an experiment, followed by analysis to either validate or refute the proposed assumptions.

The Research Deductive Reasoning of this Thesis is as follows: UTAUT as technology Acceptance Framework -> Hypotheses -> Seven point Likert-scale survey -> Confirmation of factor

This study aims to accomplish the following goals:

Objective 1 – Conduct a comprehensive literature review addressing key cognitive dimensions of elearning, lifelong learning, SP, GWE, and theoretical models of elearning adoption.

Objective 2 – Investigate the role of Emotional Intelligence and Collective Intelligence—specifically SP and GWE—as moderating factors influencing e-learning adoption.

Objective 3 – Establish the methodological framework necessary to address the primary research questions outlined in this research.

Objective 4 – Implement experimental procedures with professionals using MOOCs as an e-learning platform.

Objective 5 – Develop an extend e-learning adoption model by incorporating enhancements to the Facilitating Conditions variable and integrating SP and GWE as moderating factors.

This research is based on a survey and an experiment conducted over time within a deductive method for theory development. The experiment recruited professionals from all over the world who were taking or had completed a MOOC (Massive Open Online Course). Thus, the study was organized around a framework which included the following components:

- The assessment of Social Perceptiveness as one of the components of Emotion Intelligence through the "Mind in the Eye" test.
- The assessment of participants' acceptance of technology.
- The assessment of perception of GWE as a measure of Collective Intelligence.

Participants were recruited through emails and social media posts and direct messaging service of the MOOC platform. The respondents' answers were collected using Google forms to host the online questionnaire, with all respondents providing written consent. The responses collected were 253. The data was analyzed by a social science statistical software SPSS.

The questionnaire consists of three parts:

- Part 1 gathers demographic info about respondents.
- Part 2 has a test that was administered online about social perceptiveness and a combination of statements about group work effectiveness. "Reading the Mind in the Eyes" RME Test is divided into 36 photos. Each photo has a pair of eyes with four words that describe the photo, and only one of these words is the correct answer to how the person in the photo feels (Baron-Cohen, et al., 1997).
- Part 3 deals with Technology acceptance.

In this research, the quantitative method is employed to evaluate the research model & explore relationships between the behavioral intention of professionals when it comes to attending MOOCs and the variables:PE, EE, SI, and FC, with the latter expanded to address specific contextual elements. Additionally, the model investigates the moderation roles of SP and GWE on relationships between the dependent and selected independent variables. As mentioned earlier, primary data was gathered through a survey using Google Forms and analyzed using SPSS. The resulting statistical outputs were used to determine whether the proposed hypotheses are accepted or rejected. Several variables within the model were adapted from previous studies and contextualized for the specific case of MOOCs being a form of e-training.

Prior to data collection, this research allocated considerable attention to the careful design and testing of the questionnaire. According to Prescott & Soeken, (1989, p. 60) this is a critical step that is often "under-discussed, underused, and underreported". Numerous scholars have emphasized the significance of survey design, highlighting its essential role in ensuring the validity of data collection and the reliability of subsequent analysis (Tourangeau et al., 2000; Aday, 2006). The section that follows outlines the preparatory measures undertaken during this key phase, which preceded the formal distribution of the questionnaire and the implementation of the experiment.

As for the secondary data, this research conducted a literature review, drawing extensively on scholarly works related to the theories in Technology Acceptance, MOOCs, in addition to constructs within Emotional Intelligence—specifically SP—as well as constructs related to Collective Intelligence, mainly Group Work Effectiveness.

The objective of reviewing the existing literature review was to collect robust secondary data about technology acceptance, with emphasis on factors that have effects on the intentions of professionals to join & complete MOOCs as a form of e-training. The references were chosen from reputable academic databases including EBSCO, Elsevier's Scopus, Google Scholar focus on factors influencing the adoption and completion of MOOCs. As for the primary data, it was collected primarily through the questionnaire. Several recommendations were taken into consideration at the time of designing the questionnaire. For instance, relevance and brevity were insured in the items since almost all the statements in the questionnaire were concise, accurate and deliver their intended meanings. Following Oppenheim's (1992) guidance, most items in the questionnaire were limited to a maximum of 20 words to ensure that these statements are clear and comprehensible by the respondents.

According to Brace (2004), to develop a well-designed questionnaire, the researcher needs to take into account several things particularly the length of the questions and their order. This research followed these guidelines to provide consistency throughout the instrument. Additionally, the researchers added a glossary for all potentially ambiguous words in an attempt to minimize confusion and misinterpretations since this can distort respondents' responses (DeLeeuw & DeHeer, 2002). Moreover, the statements were carefully phrased to avoid any framing that could suggest an answer or lead respondents toward a specific answer as this would risk the integrity of the primary data. The questionnaire included 35 items customized from prior research; they were carefully modified to align with the specific context of this research since this can help to ensure the validity of the content, and this comes in line with scholars' recommendations (Luarn & Lin, 2005).

Concerning the sample chosen, and since the target population is quite large, the researchers found it acceptable to work within a reasonable margin of error. Due to time and resources constraints, a margin of error of ±6% was selected, which falls within the generally accepted range of ±4% to ±8% (Medina & Portilla, 2015). Based on this and after applying the formula of appropriate sampling size, the number of required respondents was set to approximately 250. Inferential statistical techniques were employed to use hypotheses testing and draw conclusions, and SPSS was utilized as the tool to process and interpret the data.

4. Results

A pilot study was performed with a sample of 21 respondents before the official release of the questionnaire. Based on their feedback, instances were identified where certain terms were not clearly understood. As a result, definitions for key terms were added to the questionnaire to enhance clarity and ensure consistent interpretation among participants.

Cronbach's alpha tests the "extent to which all the items in a test measure the same construct and hence it is connected to the interrelatedness of the items within the test" (Tavakol & Dennic, 2011, p.53). Thus, the researchers calculated Cronbach's alpha; the results proved the reliability of factors and model, and thus it was decided that the model is appropriate for this research.

Table 1 Reliability Analysis

Scale	Cronbach's Alpha 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 Photos	.717	36

To better understand the demographic and behavioral characteristics of the professionals who participated in this study, the researchers conducted a Descriptive analysis. As Agresti and Finlay (2009) state, descriptive statics help the researchers to present the essential features of dataset which helps them to identify any trends and patterns withing the responses.

According to Pallant (2007), before conducting any statistical analysis, it is essential to verify that the data is free from multicollinearity. As noted by Hew et al. (2015), multicollinearity happens when there is a strong interrelation between the independent variables making it difficult to study the unique impact of each of these variables on the dependent variable. That's why it is important to detect and address multicollinearity when it exists to ensure that the regression outcomes will be reliable. The researchers performed the Pearson Correlation test to determine if there is any case of multicollinearity in the collected data, and the findings indicated that each variable has a relation with the dependent variable and that there is linear relationships among them. With this result, the prerequisite to conduct a multiple linear regression analysis is fulfilled.

For the purpose of assessing the holistic effect of all the factors on the behavioral intention to use and complete the MOOCs, the researchers conducted a Multiple linear regression analysis since this test will examine the combined effect of all independent factors. Using SPSS, R-squared was calculated to determine the amount of variance in the dependent variable as explained by the model. The adjusted R-squared value was 0.437, indicating that approximately 43.7% of the variation in Behavioral Intention of professionals to use MOOCs can be attributed to the set of independent variables included in the model.

Table 2 Multiple Linear Regression- Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics		
					R Square Change	F Change	df1
1	.669[a]	.448	.437	.752	.448	40.087	5

Moving to the ANOVA findings:

Table 3 Anova

ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	113.199	5	22.640	40.087	.000[b]
	Residual	139.497	247	.565		
	Total	252.696	252			

a. Dependent Variable: BI
b. Predictors: (Constant), FC_Final, SI, PE, FC Original, EE
We have statistically significant findings here, so the model is statistically significant. As for the coefficients, the results were as follows:

Table 4 Coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(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
	FCOriginal	.023	.069	.020	.327	.744
	FC_Final	.347	.076	.311	4.564	.000

Among these independent variables tested, the EE and extended FC Effort Expectancy and the extended Facilitating Conditions appear to be the most influencial on professionals' intention to attend MOOCs. The multiple regression analysis gave the following predictive equation: $Y = 1.262 + 0.323X_1 + 0.347X_2$
Where:
Y represents the Behavioral Intention to attend MOOCs,
X_1 represents Effort Expectancy,
X_2 represents the extended Facilitating Conditions.
This equation suggests that both factors significantly contribute to predicting professionals' likelihood to attend and complete their MOOCs.
Numerous previous studies have extensively studied different factors' moderating effects on the relationships between Behavioral Intention and the rest of the core constructs of the UTAUT. For instance, Venkatesh et al. (2003) studied age, gender &experiences as moderators. Then other researchers took this as a foundation and built upon it and extended the model by examining various additional moderating variables. For example, some studies have studied culture as a moderator (Al-Gahtani et al., 2007; Venkatesh & Zhang, 2010; Yuen et al., 2010), while others have considered factors such as ethnicity, religion, and language.
This research contributes to this growing body of literature by extending model and examining two novel moderators: Social Perceptiveness, a construct linked to Emotional Intelligence, and Group Work Effectiveness, a construct linked to Collective Intelligence. The research studies them in terms of their effects on the relationships between professionals' intentions and independent variables within the context of MOOCs adoption.
The analyses and testing of the hypotheses showed that H1, H3 and H6 were supported whereas the rest were not.
H1 proposes that the independent factors FC, PE, EE, SI have positive effects on professionals' Behavioral Intention to use MOOCs. The researchers used two scenarios to test this hypothesis: the first one tests the model as a whole and identifies the weak variables that need to be eliminated. For scenario 1, a multiple linear regression was done for this research question. As for the scenario 2, it tests the relationships of each independent variable separately and in it, the researchers resorted to simple linear regression. There were several sequential steps to test the IV/DV relationship and the first step was using summation of all variables instead of using the median statistical function.

As per scenario 1, a multiple linear regression was performed to evaluate the predictive power of independent variables on the dependent variable. The results showed that there was no Multi collinearity with all VIF less than 10. P = .000, the R2 = 0.448, suggesting that the four variables EE, PE, SI and FC explained 44.8% of the variability in the behavior intention. The individual factors were evaluated and, results were as follows in table 3
The effect of PE on BI was not statistically significant, p = 0.079; EE significantly influence BI, p = 0.00 with the results suggesting that for each additional unit of EE, BI increased by 0.323 units. The effect of SI on BI was not statistically significant, B = 0.029, p = 0.425.
FC extended was a significant predictor of BI, p= 000 with the results suggesting that for each additional unit of FC, BI increased by 0. 347 units. The results showed that H1 is supported; this suggests that the conceptual model has a good chance to predict behavioral intention in the context of MOOCs for professionals.
H3 assumes that Group work effectiveness (GWE) positively moderates the EE-BI relationship; the higher the GWE, the more powerful the EE's impact is on behavioral intention. The results showed that H3 is supported; this can indicate that the effectiveness of Working in groups can have a positive impact and engage the participants with MOOCs and thus increasing the likeliness of following and completing these courses. This aligns with Wan et al. (2020)'s results. Similarly, Ingram (2000)'s study has reported improvements of individual and organizational performance.
As for H6, it assumes that Social perceptiveness (SP) positively moderates the SI-BI relationship, and that the higher the SP, the more powerful the SI's impact is on behavioral intention"; thus, one can deduce that individuals who score high in the RME test tend to have greater Social Perceptiveness than those who scored low, and thus are more likely to enroll and finish a MOOC course. The findings suggest that Social Perceptiveness increases the effect of SI on Behavioral Intention in MOOC setting(Mulik et al., 2018; Nordin et al., 2015).
It is worth noting that, before examining the moderating effects of specific variables, the researchers conducted preliminary analyses on the potential moderators—particularly Social Perceptiveness—to ensure the reliability and consistency of the measures used. Given that Social Perceptiveness was assessed using two distinct methods, additional attention was dedicated to this construct. First, Social Perceptiveness was measured through an experimental method, specifically the Reading the Mind in the Eyes Test, which involved 36 standardized photographs used to assess the respondents' ability to interpret emotional states based on subtle facial cues. This widely recognized test provided an objective measure of social perceptiveness. Second, a self-assessment component was included in the questionnaire, wherein respondents rated their own social perceptiveness based on a series of subjective statements. This approach captured the participants' self-perceived social awareness and interpretive abilities.
To explore possible differences based on demographic variables, the researcher conducted an independent samples t-test to explore whether gender has an effect on performance in RME test. Results showed that females had better scores and performed better overall.

5. Discussion & Expected Contributions

5.1 Theoretical Contribution

The research contributes to existing literature through the extension of UTAUT model: it has integrated new social dimensions thus it has developed a refined conceptual framework and at the same time, it has offered a more comprehensive understanding of user behavior in technology acceptance setting.
The key contribution of this research is the testing of Social Perceptiveness as a novel moderating variable in the UTAUT model. The findings indicate that Social Perceptiveness significantly enhances the SI-BI relationship, suggesting that individuals with higher social cue awareness might be more influenced by people's opinions when taking a decision to use a certain technology, specifically MOOCs. So a theoretical contribution would be to align KPIs with the variables from the UTAUT as

this would give a new theoretical way to analyze MOOCs adoption in professional settings. This implies that interpersonal skills and team dynamics can influence the employees' engagement and the potential outcomes of MOOCs and thus, this research integrates soft skills into technology acceptance models.
This also proposes that the theoretical assessment of e-training tools can now be shifted from quantitative to qualitative with the adding of metrics such as collaborative assignment results, participation in discussions, peer review feedback… as being metrics to assess MOOCs effectiveness. Moreover, the research studies factors such as Continuous Availability and Time Flexibility as extensions to the Facilitating Conditions (FC); this is to further investigate FC effect on behavioral intentions. These variables were shown to positively influence user engagement and willingness to participate in MOOCs, which shows the important role of flexible and accessible learning environments when promoting sustained technology use.

5.2 Practical Contribution

The research offers practical recommendations to MOOC designers and HR practitioners. The findings indicate that GWE has a moderating effect on EE-BI relationship in MOOCs setting. MOOCs designers might find this helpful since it proposes adding some collaborative elements into course design to increase the likelihood of learners finishing their MOOCs, for instance, adding group activities since this can increase the perceived ease of use and encourage users' participation. They can for instance prepare workshops for teams with low cohesion.
In addition to this, results related to the second moderating variable, Social Perceptiveness (SP), suggest that individuals with higher levels of SP can have a stronger intention to engage with MOOCs. This suggests using SP as a criterion when creating groups or tailoring the course experiences to better match users' individual skills. They can for instance prepare blended models for learners with low social perceptiveness. Thus the strategic recommendations to HR practitioners would be to draw their attention so that they can include assessments that test social and team-based competences. They should acknowledge the importance of teamwork, and this means they can train managers to stress and emphasize the importance of teamwork while participating in a MOOC. They can also choose MOOCs that include collaborative features and develop HR dashboards that can appraise the behavioral engagements of the professionals using MOOCs.
While these findings are promising, further research is necessary to validate the moderating role of SP and to explore additional factors that may aid in the segmentation and customization of the MOOC experience.

6. Conclusion

This study extends the UTAUT model by introducing Social Perceptiveness (SP) and Group Work Effectiveness (GWE) as novel moderating variables in the adoption of MOOCs for professional e-training. Findings show that Effort Expectancy and the refined Facilitating Conditions (Continuous Availability and Time Flexibility) are the strongest predictors of adoption, while GWE enhances the EE–BI relationship and SP strengthens the SI–BI link.
The research contributes theoretically by integrating socio-emotional constructs into a predominantly technology-focused model, offering a more holistic understanding of MOOC adoption. Practically, it provides guidance for MOOC designers to incorporate collaborative elements and for HR professionals to consider social competencies when designing e-training strategies.
While limited by participant diversity and scope, the study underscores that successful professional MOOC adoption depends on both technological ease of use and the social dynamics within learning environments. Future work should examine additional social and cultural variables across broader contexts to refine strategies for sustainable, engaging professional e-learning.

References

1. Aday, L. A. (2006). Designing and conducting health surveys: A comprehensive guide (3rd ed.). Jossey-Bass.
2. Agresti, A., & Finlay, B. (2009). Statistical methods for the social sciences (4th ed.). Pearson Prentice Hall.
3. 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
4. Al-Rahmi, W. M., et al. (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
5. 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
6. 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.
7. Ang, K. L. M., Ge, F. L., & Seng, K. P. (2020). Big educational data analytics: Survey, architecture and challenges. IEEE Access, 8, 116392–116414.
8. Apperly, I., 2012. What is "theory of mind"? Concepts, cognitive processes and individual differences. Quarterly Journal of Experimental Psychology, 65(5), pp. 825-839.
9. Babiker, M. et al., 2014. Health care professional development: Working as a team to improve patient care. SUDANESE JOURNAL OF PEDIATRICS, pp. 9-16.
10. Baron-Cohen, S. (1997). Mindblindness: An essay on autism and theory of mind. MIT Press.
11. Brace, I. (2004). Questionnaire design: How to plan, structure and write survey material for effective market research. Kogan Page.
12. Castaño-Muñoz, J., Kalz, M., Kreijns, K., & Punie, Y. (2018). Who is tak-ing MOOCs for teachers' professional development on the use of ICT? A cross-sectional study from Spain. Technology, Pedagogy and Education, 27(5), 607-624.
13. Chattopadhyay, S. (2014). 11 Differences between a MOOC and an Online Course. Retrieved February 2, 2021, from http://idreflections.blogspot.com/2014/06/11-differences-between-mooc-and-online.html
14. 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/
15. 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
16. 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.
17. Ekblaw, R., 2016. Effective Use Of Group Projects In Online Learning. Contemporary Issues in Education Research , 9(3), pp. 121-128.
18. 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
19. Engel, D., Woolley, J. L., Chabris, C. & Malone, T., 2014. Engel D, Woolley AW, Jing LX, Chabris CF, Malone TW (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), pp. 1-16.

20. 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
21. 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
22. Hall, J.A., & , F.J. (Eds.). (2001). Interpersonal Sensitivity: Theory and Measurement (1st ed.). Psychology Press.
23. 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
24. Heyes, C., 2014. Submentalizing: I Am Not Really Reading Your Mind. Perspectives on Psychological Science, 9(2), pp. 131-143.
25. 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
26. Ingram, H. (2000). Linking teamwork with performance. Journal of Team Performance Management, 2(4), 5-10.
27. 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
28. Larson, J. (2010). In Search of Synergy in Small Group Performance. New York: Psychology Press.
29. Liu, M., Kang, J., & McKelroy, E. (2015). Examining learners' perspective of taking a MOOC: reasons, excitement, and perception of useful-ness. Educational Media International, 52(2), 129-146.
30. 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
31. Makary, M. & Daniel, M., 2016. Medical error—the third leading cause of death in the US. [Online] Available at: https://www.bmj.com/content/353/bmj.i2139.full
32. Mayo, A. & Woolley, A., 2016. Teamwork in Health Care: Maximizing Collective Intelligence via Inclusive Collaboration and Open Communication. AMA Journal of Ethics, pp. 933-940.
33. McAuley, A., Stewart, B., Siemens, G. & Cormier, D., 2010. MOOC Model for Digital Practice. Charlottetown: University of Prince Edward.
34. McCluskey, M. (2020). Taking a MOOC during COVID-19: What to know, U.S. News and world report. https://www.usnews.com/higher-education/online-education/articles/taking-a-mooc-during-coronavirus-pandemic-what-to-know.
35. 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. https://ijoc.org/index.php/ijoc/article/view/2316
36. 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/
37. Mulik, S., Srivastava, M., & Yajnik, N. (2018). Extending UTAUT model to examine MOOC adoption. NMIMS Management Review, 36(2), 26-44.
38. Nordin, N., Norman, H., & Embi, M. A. (2015). Technology acceptance of massive open online courses in Malaysia. Malaysian Journal of Dis-tance Education, 17(2).

39. Observatory of Educational Innovation. (2020). MOOCs and their contribution to lifelong learning. Observatory of Educational Innovation. https://observatory.tec.mx/edu-bits-2/mooc-courses-and-their-contribution-to-lifelong-learning
40. Onah, D. F., Sinclair, J., & Boyatt, R. (2014). Dropout rates of massive open online courses: behavioural patterns. EDULEARN14 proceedings, 1, 5825-5834.
41. Ossiannilsson, E. (2021). MOOCs for lifelong learning, equity, and liberation. In Proceedings of the EdMedia + Innovate Learning 2021 Conference. ResearchGate. https://www.researchgate.net/publication/354127436
42. Pallant, J. (2007). SPSS survival manual: A step by step guide to data analysis using SPSS for Windows (3rd ed.). Open University Press.
43. 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
44. Research and Markets. (2025, May 5). 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. 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
45. Richards, D. & Pryce, J., 2006. EI: Well-being and performance. Competency emotional intelligence, Volume 13, pp. 41-45.
46. Rollins, A., 2018. elearningindustry.com. [Online] Available at: https://elearningindustry.com/whats-a-mooc-history-principles-characteristics [Accessed 2 February 2021].
47. Salovey, P., & Mayer, J. (1990). Emotional Intelligence. Imagination, Cognition, and Personality, 9, 185-211.
48. Siemens, G., 2004. Connectivism: A Learning Theory for the Digital Age. [Online] Available at: http://www.elearnspace.org/Articles/connectivism.htm
49. 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
50. Tourangeau, R., Rips, L. J., & Rasinski, K. (2000). The psychology of survey response. Cambridge University Press. https://doi.org/10.1017/CBO9780511819322
51. Venkatesh, V., Morris, M., Davis, G. & Davis, F., 2003. User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), pp. 425-478.
52. 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
53. Yuan, L., & Powell, S. (2013). MOOCs and Open Education: Implications for Higher Education. JISC CETIS. Retrieved from http://publications.cetis.org.uk/2013/667
54. 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.