

RESEARCH ARTICLE

AI-Mediated Emotional Framework in Collaborative Learning: Examining the Influence of Group Emotional Climate on Collaboration Outcomes

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ABSTRACT

This study aims to examine the influence of Group Emotional Climate on Collaboration Outcomes in AI-mediated collaborative learning environments. Although artificial intelligence is increasingly becoming part of higher education learning systems, the emotional and socio-regulatory process of collaborative learning is still not fully explained. Due to this reason, the present study develops an AI-mediated emotional framework by examining Co-Regulation and Mutual Support and Shared Motivation as mediating mechanisms, while AI Readiness is tested as both a direct predictor and moderating factor. A quantitative cross-sectional survey design was applied, and data were collected from 319 respondents with collaborative learning experience. The proposed model was tested through Partial Least Squares Structural Equation Modelling using SmartPLS. The findings show that Group Emotional Climate has a significant positive influence on Collaboration Outcomes, Co-Regulation and Mutual Support, and Shared Motivation. The result also confirms that Co-Regulation and Mutual Support significantly improves Collaboration Outcomes and mediates the relationship between Group Emotional Climate and Collaboration Outcomes. However, Shared Motivation does not significantly influence Collaboration Outcomes and does not mediate the relationship. AI Readiness also shows no significant direct influence on Collaboration Outcomes and does not moderate the relationship between Group Emotional Climate and Collaboration Outcomes. From the above findings, it can be understood that emotional climate improves collaboration mainly when it is converted into active co-regulation and mutual support. Therefore, collaboration in AI-mediated learning environments depends more on emotional regulation and mutual assistance than on shared motivation or general AI readiness alone.

1.0 INTRODUCTION

1.1 Background of the Study

The higher education sector is now experiencing a significant transformation because artificial intelligence is becoming connected with teaching, learning, administration and student support in a more systematic way. Recent review evidence shows that AI in education is no longer limited to technical experimentation. Rather, it has become a broad educational force that influences how learners receive content, how teachers support learning and how institutions organise academic processes. Fu et al. (2024), through a scoping meta-review and bibliometric analysis of 126 review articles, identified teaching, learning and administration as three major areas where AI is becoming embedded in educational contexts. This indicates that AI is now operating across the full higher education system.

In the case of student learning, AI also has a strong connection with self-regulated learning. Lan and Zhou (2025) found that AI-empowered systems can support the major phases of self-regulated learning, including forethought, performance and self-reflection. Therefore, AI can help learners plan, monitor and evaluate their own academic progress. Similarly, Msambwa et al. (2025) showed that AI tools can enhance personalised learning, communication, motivation and collaborative learning environments in higher education. From these findings, it can be understood that AI does not only deliver information. It also shapes the learning environment. Patrick et al. (2025) further argued that AI can support higher-order thinking, although uncritical dependence on AI remains a concern. Therefore, AI in higher education needs to be understood as both an opportunity and a controlled academic challenge. This makes AI central to contemporary university learning design.

The current development of artificial intelligence in higher education also changes the relationship between human learners and technological systems. Traditionally, technology was mainly understood as a supporting tool for information access and task completion. However, recent literature suggests that AI can be positioned as a collaborator in the learning process. Atchley et al. (2024) argued that AI should not be viewed only as a threat to higher education. Rather, it can work as a critical collaborator when it is used through metacognitive awareness and proper educational judgement. This argument is important because it moves the discussion from replacement toward collaboration.

In online collaborative learning, the effectiveness of technology also depends on human and platform-related factors. Chan and Ng (2024), through a PLS-SEM study of online collaborative tool users, found that perceived usefulness, social presence and platform interactivity are important for collaborative learning effectiveness and continuance intention. This means that students do not collaborate effectively only because a platform is available. Rather, the platform must support interaction, usefulness and social connection. In a similar way, Msambwa et al. (2024) showed that AI tools can support personalised self-assessment, communication, motivation and collaborative learning environments. Therefore, human-AI collaboration in higher education should be understood as a relationship nexus where technological support, learner motivation and social interaction work together and learner confidence over time.

Collaborative learning is often discussed as a cognitive and social learning process. However, recent studies show that collaboration is also strongly emotional and socio-regulatory. In group learning situations, students do not only exchange information or complete shared tasks. They also manage emotions, respond to

interpersonal tension and develop collective forms of support. Huang et al. (2024) showed that socio-emotional interaction and cognitive engagement have a bidirectional relationship in problem-based collaborative learning, where co-regulation helps to connect emotional interaction with learning engagement. This indicates that emotion is not a secondary issue in collaboration. Rather, it is part of the learning mechanism itself.

The importance of emotional climate is also confirmed in higher education collaborative learning experiences. Ippolito and Kingsbury (2024) found that a positive social and emotional climate significantly predicts collaborative engagement, satisfaction and perceived learning. Similarly, Tan and Jung (2024) showed that emotional presence, including interest, curiosity, regulation, expression management and emotional awareness, develops throughout collaboration and shapes learning outcomes. These findings suggest that group emotions are dynamic and they influence how learners participate in shared learning.

Wang, Wang, Li, et al. (2024) also found that positive emotional interaction can predict learning engagement directly and indirectly through reduced loneliness. This is important in online learning because emotional disconnection can weaken participation. Moreover, Törmänen et al. (2025) demonstrated that group-level emotional dynamics and regulation move together across collaborative episodes and influence productive group outcomes. From the above literature, it can be said that collaborative learning outcomes cannot be explained only through cognition, task structure or technology. The emotional climate of the group is also a foundational condition for effective collaboration. It also determines whether students remain active during difficult group moments.

As artificial intelligence becomes more integrated into education, a new research

direction is developing around AI-mediated emotional support, affective computing and emotional analytics. Ngo et al. (2024) demonstrated that AI-based facial expression recognition can be used to detect emotional regulation patterns in synchronous online collaborative learning. This indicates that AI may help identify emotional states that are usually difficult for teachers to observe in digital environments.

The emotional role of AI is also visible in language and personalised learning contexts. Yang and Zhao (2024) found that AI tools can create different emotional responses among EFL students and that students use several regulation strategies when interacting with AI. Therefore, AI can support learning, but it can also create emotional uncertainty. Yuvaraj et al. (2025), in a systematic review of affective computing in education, mapped emotion-recognition modalities, models and intervention designs, showing that this field is expanding. Zheng et al. (2025) showed that AI-enabled personalised learning can improve engagement and learning outcomes through adaptive emotional and cognitive scaffolding. Similarly, Shingjergji et al. (2026) highlighted the importance of affective state detection, ethical concerns and design implications in online higher education. Therefore, AI-mediated emotional support is becoming a future direction for collaborative learning research.

1.2 Problem Statement

From the above literature, it can be understood that artificial intelligence is becoming important in higher education, collaborative learning is strongly influenced by emotional climate and AI-mediated emotional support is emerging as a new educational direction. However, a research gap is present. Previous studies have examined AI in education, self-regulated learning, collaborative learning, emotional climate and affective computing. Yet, these streams are often discussed separately. Due to this reason, the relationship between group

emotional climate and collaboration outcomes in an AI-mediated learning context is not fully explained.

1.3 Research Gap

Existing research shows that emotional climate can influence collaboration and that AI can support learning environments. However, limited attention has been given to whether students' readiness to accept AI changes the strength of the relationship between group emotional climate and collaboration outcomes. In other words, AI readiness may work as an important boundary condition, but this issue is clearly underexplored.

1.4 Research Aim and Objectives

Therefore, this study aims to examine how Group Emotional Climate influences Collaboration Outcomes through Co-Regulation and Mutual Support and Shared Motivation, while testing the direct and moderating role of AI Readiness.

1.5 Research Contribution

This study contributes by developing an AI-mediated emotional framework that connects emotional climate, socio-regulation, motivation and collaboration outcomes within one structural model.

2.0 LITERATURE REVIEW

2.1 Theoretical Foundation

The theoretical foundation of this study is developed through the integration of Group Affective Tone and Social Interdependence Theory. Group Affective Tone explains that the emotional condition of a group can be developed when the affective experiences of individual members become shared within the group environment. George (1990) argued that personality and group interaction

can create a collective emotional tone, and this collective tone can influence prosocial behaviour and group performance. In the context of collaborative learning, this theory becomes important because students do not complete group tasks only as isolated individuals. Rather, they operate within a shared emotional environment where comfort, encouragement, emotional understanding and group-level positivity may influence the way members interact with one another.

At the same time, Social Interdependence Theory provides the collaborative logic of the present study. Johnson and Johnson (2009) explained that positive interdependence develops promotive interaction, shared regulation and stronger achievement. This means that when students understand that their individual success is connected with the success of other members, they become more likely to support, encourage and regulate one another during the learning process. Therefore, collaboration outcomes are not produced only through the completion of academic tasks. Rather, they are produced through mutual emotional support, shared responsibility, coordinated participation and the ability of group members to work together during challenging learning situations.

In this particular study, Group Emotional Climate is treated as the emotional foundation of collaborative learning, while Collaboration Outcomes represent the final group-level learning result. Co-Regulation and Mutual Support and Shared Motivation are used to explain how positive emotional climate may be transformed into effective collaboration. From the above theoretical foundation, it can be understood that positive group emotion creates the relational condition for collaboration, while social interdependence explains why group members convert this emotional condition into support, motivation and learning achievement. This theoretical position is also suitable for AI-mediated collaborative learning because technology may support

interaction, but it cannot fully replace the emotional and interdependent nature of group learning. Therefore, the present study develops a relationship framework between group affect, co-regulation, shared motivation and collaboration outcomes, where emotional climate is considered as a central explanatory factor rather than only a background condition.

2.2 Group Emotional Climate

Group Emotional Climate is used as the main independent variable of this study because it explains the emotional base through which collaborative group functioning is developed. In collaborative learning, students do not only exchange knowledge or divide academic responsibilities among themselves. They also experience emotional comfort, encouragement, interpersonal support and affective understanding within the group. Ippolito and Kingsbury (2024) found that a positive social and emotional climate significantly predicts collaborative learning engagement, satisfaction and perceived learning. From this finding, it can be understood that emotional climate works as an important condition that supports both the process and the experience of collaboration.

The importance of emotional climate is also connected with the concept of emotional presence. Tan and Jung (2024) showed that emotional presence includes interest, curiosity, regulation, expression management and awareness, and these elements develop throughout the collaborative learning process. This indicates that group emotion is not fixed at the beginning of collaboration. Rather, it changes through interaction and influences how students continue to participate in shared learning. Similarly, Vega-Ramírez et al. (2024) found that cooperative learning improves classroom emotional climate, and this emotional climate further supports motivation, enjoyment and prosocial behaviour. Therefore, emotional

climate can work as a bridge between the structure of cooperation and the outcome of group learning.

Recent empirical studies also show that emotional interaction is closely connected with engagement, cohesion and group regulation. Wang, Wang, Li, et al. (2024) found that positive emotional interaction predicts learning engagement directly and also indirectly through reduced loneliness. Yoon et al. (2024) showed that team building strengthens emotional ties, group efficacy and group cohesion in a virtual learning environment. Zeng et al. (2024), through a PLS-SEM approach, also found that perceived climate and peer-group interaction influence emotional outcomes. Moreover, Törmänen et al. (2025) demonstrated that group emotion and regulation move together across collaborative episodes and shape productive learning processes. From the above literature, it can be said that Group Emotional Climate is not only an affective background of collaboration. Rather, it is a structural emotional condition that shapes how members support, motivate and coordinate with one another during collaborative learning. Due to this reason, this study positions Group Emotional Climate as the starting point of the proposed model.

2.3 Collaboration Outcomes

Collaboration Outcomes represent the dependent variable of this study. In the context of collaborative learning, outcomes are not limited to final academic marks or task completion. Rather, they include effective teamwork, successful discussion, productive learning experience, improved understanding and the achievement of group objectives. He et al. (2024), through a person-centred analysis of 9,398 Chinese students, found that different personal-collaborative motivation profiles are associated with collaborative problem-solving performance. This indicates that collaboration outcomes

are influenced by how students participate motivationally and socially within the group.

Collaborative learning outcomes also depend on valid engagement and interaction processes. Xu et al. (2024) developed and validated a student engagement measure for collaborative learning by including behavioural, cognitive and emotional dimensions. This is important because collaboration becomes effective when learners are behaviourally active, cognitively involved and emotionally connected. Similarly, Xu and Lou (2024) found that socially shared regulation of learning and academic emotions change across collaborative project phases and jointly predict group product performance. Therefore, collaboration outcomes are not developed in a single moment. Rather, they are produced through a continuous process of interaction, regulation and emotional adjustment.

In computer-supported collaborative learning, Sun et al. (2025) found that interaction quality, transactive memory and cognitive engagement are connected with learning performance during and after the pandemic. This shows that collaboration outcomes depend on how effectively members interact, remember shared responsibilities and remain cognitively engaged with the task. From the above studies, it can be understood that Collaboration Outcomes are multidimensional in nature. They do not only reflect whether the group completed the task. Rather, they reflect whether the collaborative process became effective, productive and educationally meaningful.

2.4 Co-Regulation and Mutual Support

Co-Regulation and Mutual Support is used in this study as one of the main mediating variables between Group Emotional Climate and Collaboration Outcomes. In collaborative

learning, students do not only manage their own understanding or motivation. Rather, they also help one another to remain emotionally stable, motivated and engaged during the task. Huang et al. (2024) showed that socio-emotional interaction and cognitive engagement have a bidirectional relationship in problem-based collaborative learning, and this relationship is supported through co-regulation. From this finding, it can be understood that co-regulation works as an important mechanism through which emotional interaction can be transformed into cognitive and collaborative engagement.

The importance of co-regulation is also visible in team coordination. Kazemitabar et al. (2024) found that socially shared emotion regulation is connected with team coordination mechanisms in hackathon-based collaboration. This indicates that when group members regulate emotions together, they are also more able to coordinate their actions, responses and task-related responsibilities. Similarly, Sharma et al. (2024), through a systematic review, showed that adaptive digital learning environments can support self-regulation and socially shared regulation in collaborative settings. Therefore, regulation is not only an individual learning skill. It also becomes a group-level process in digital and collaborative learning environments.

In the context of language and writing collaboration, Stell and Iwashita (2024) found that regulated learning strategies in co-regulatory processes change according to task complexity and partner familiarity. This means that mutual support is dynamic and depends on the condition of the group. Vega-Ramírez et al. (2024) also showed that cooperative learning improves emotional climate, and this emotional climate mediates the effect on motivation, enjoyment and prosocial behaviour. Therefore, emotional climate may influence collaboration outcomes through the development of supportive and co-regulatory behaviour.

Recent literature further confirms that socio-emotional interaction and regulation are closely connected. Ahola et al. (2025) argued that socio-emotional interaction and regulation are intertwined in collaborative learning. Channa et al. (2025) also showed that participatory roles are related to regulation strategies when groups face socio-cognitive and socio-emotional challenges. Moreover, Kok (2025) highlighted that socially shared regulation includes cognitive, metacognitive, behavioural, motivational and emotional dimensions. Liu and Ding (2025) found that negative emotions in online collaborative learning can be managed through regulation strategies such as suppression, reappraisal and co-regulation. Zhang and Teng (2025) also showed that co-regulated learning strategies interact with self-regulation to support collaborative learning achievement. From the above literature, it can be said that Co-Regulation and Mutual Support is a central mechanism in collaborative learning. It explains how a positive emotional climate can move beyond general group feeling and become actual support, coordination and effective collaboration.

2.5 Shared Motivation

Shared Motivation is another mediating variable of this study because collaborative learning requires collective enthusiasm, common commitment and shared willingness to achieve group goals. In a collaborative learning environment, students may have individual motivation, but the success of group learning also depends on whether members develop a common motivational direction. He et al. (2024), through a person-centred analysis of 9,398 Chinese students, found that personal-collaborative motivation profiles are associated with collaborative problem-solving performance. This indicates that motivation in collaboration is not only individual in nature. Rather, it is also connected with how learners participate with others inside a group.

The relationship between socially regulated learning and motivation is also important in online collaborative settings. Wang, Wang, Huang, et al. (2024) found that different latent profiles of online socially regulated learning predict collaborative learning motivation, including intrinsic, extrinsic and social motivation. From this finding, it can be understood that shared motivation is developed within the regulatory structure of the group. When learners regulate their effort, emotion and participation together, they may become more collectively motivated to complete the learning task.

Longitudinal studies also show that motivation and emotional regulation develop together across time. Zhang and Gao (2024) found that enjoyment and group-level emotion regulation co-evolve and jointly predict sustained engagement in online collaborative English learning. Similarly, Zhang et al. (2024) showed that collective emotion regulation strategies are positively related with sustained group enjoyment and writing performance. These findings indicate that shared motivation is not created only at the beginning of group work. Rather, it is maintained through emotional regulation, enjoyment and repeated interaction.

The role of peers is also important in developing group motivation. Järvenoja et al. (2025) found that peer influence on situational motivation is embedded in socially shared regulation processes and becomes stronger when motivation regulation appears with cognitive regulation. Liu and Ye (2025) also found that socially shared regulation mediates the relationship between group cooperation and online self-regulated learning through perceived task value. Therefore, Shared Motivation can be understood as a collective motivational condition that may explain how emotional climate supports collaboration outcomes. In this study, Shared Motivation is positioned as a possible pathway through which Group

Emotional Climate may influence Collaboration Outcomes.

2.6 AI Readiness and AI-Mediated Emotional Support

AI Readiness is included in this study as both a direct predictor and a moderating factor in AI-mediated collaborative learning. As artificial intelligence becomes more connected with online and higher education environments, students' willingness to accept AI support becomes important. In the context of collaborative learning, AI is not only used for content delivery or assessment. Rather, it is increasingly connected with emotional support, group interaction, regulation and collaborative engagement. Ngo et al. (2024) demonstrated that facial expression recognition can be used to examine emotional regulation in synchronous online collaborative learning. This indicates that AI can support teachers and learners by identifying emotional patterns that may not be easily visible in digital settings.

The emotional role of AI is also complex. Yang and Zhao (2024) found that AI tools can create different emotional experiences among EFL students and that learners use different emotional regulation strategies when using AI. Therefore, AI may support learning, but it may also create uncertainty, discomfort or emotional tension if learners are not ready to use it. This makes AI Readiness an important factor in understanding AI-mediated collaborative environments.

Recent studies also show that human-AI collaboration is becoming more socio-emotional in nature. Dang et al. (2025) examined human-AI collaborative learning in mixed reality and showed that cognitive and socio-emotional interaction patterns develop between learners and embodied generative AI agents. Edwards et al. (2025) also developed an AI agent that can detect socially shared regulation trigger events and support group-

level metacognitive awareness. Similarly, Kim et al. (2025) explained that AI agents can detect and scaffold different phases of socially shared regulation, including task understanding, planning, enactment, adaptation and evaluation.

Generative AI can also change the structure of group interaction. Feng et al. (2025) showed that the integration of a generative AI chatbot restructures participation and shifts the social climate of collaborative problem-solving groups. Zheng et al. (2025) found that AI-enabled personalised learning can improve engagement and outcomes through emotional and cognitive scaffolding. Kim et al. (2026) also showed that generative AI-assisted collaborative argumentation shapes participation and epistemic engagement depending on how AI is integrated. From the above literature, it can be understood that AI Readiness may influence Collaboration Outcomes directly and may also change how Group Emotional Climate affects collaboration. Therefore, this study positions AI Readiness as a direct and moderating factor in the proposed AI-mediated emotional framework.

2.7 Hypothesis Development and Conceptual Framework

Based on the above theoretical and literature review, this study develops a conceptual framework that connects Group Emotional Climate, Co-Regulation and Mutual Support, Shared Motivation, AI Readiness and Collaboration Outcomes. In the context of this study, Group Emotional Climate is considered as the starting point of

the model because the emotional condition of the group can influence how learners interact, support one another and remain engaged during collaborative tasks. A positive emotional climate may create comfort,

encouragement and emotional safety among group members. Therefore, it can directly improve the quality of collaboration and the achievement of group learning objectives.

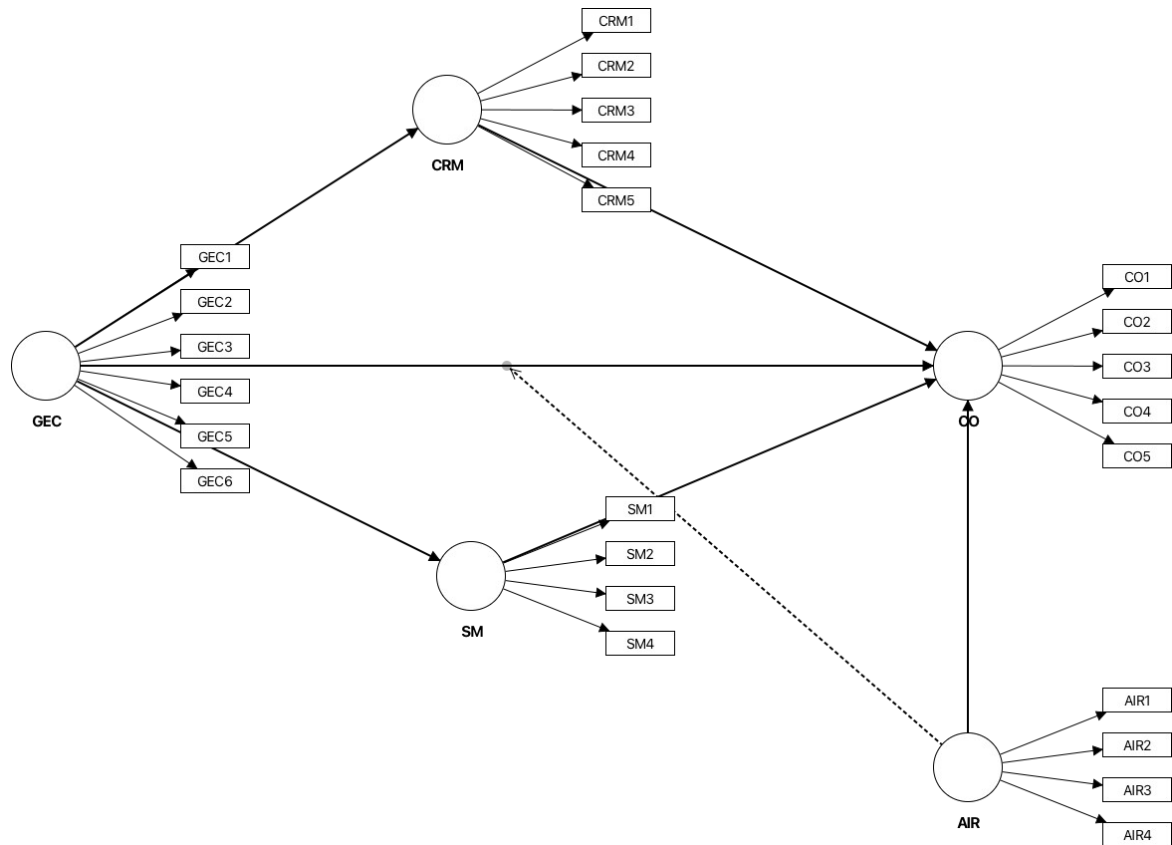


Figure 1: Conceptual Framework

H1: Group Emotional Climate (GEC) has a significant positive influence on Collaboration Outcomes (CO).

H2: Group Emotional Climate (GEC) has a significant positive influence on Co-Regulation and Mutual Support (CRM).

H3: Co-Regulation and Mutual Support (CRM) has a significant positive influence on Collaboration Outcomes (CO).

H4: Group Emotional Climate (GEC) has a significant positive influence on Shared Motivation (SM).

H5: Shared Motivation (SM) has a significant positive influence on Collaboration Outcomes (CO).

H6: Co-Regulation and Mutual Support (CRM) mediates the relationship between Group Emotional Climate (GEC) and Collaboration Outcomes (CO).

H7: Shared Motivation (SM) mediates the relationship between Group Emotional Climate (GEC) and Collaboration Outcomes (CO).

H8: AI Readiness (AIR) has a significant positive influence on Collaboration Outcomes (CO).

H9: AI Readiness (AIR) moderates the relationship between Group Emotional Climate (GEC) and Collaboration Outcomes (CO).

3.1 Research Design and Paradigm

This study is conducted by following the positivist research paradigm, where a quantitative and cross-sectional survey design is used to examine the structural relationship among the selected variables.

The positivist paradigm is suitable for this study because it allows the researcher to test predefined hypotheses through measurable data and statistical analysis. According to Saunders et al. (2023), quantitative research is appropriate when the study aims to examine relationships among variables through numerical evidence. In the context of this study, the relationship between Group Emotional Climate, Co-Regulation and Mutual Support, Shared Motivation, AI Readiness and Collaboration Outcomes requires empirical testing. Therefore, a cross-sectional survey design is applied because data were collected from respondents at one specific point of time only.

3.2 Population and Sampling

The target population of this study includes students who have experience in collaborative learning activities in higher education. This population is suitable because the study examines emotional climate, shared support, motivation and collaboration outcomes in group-based learning contexts. A non-probability purposive sampling technique was applied because respondents needed to have relevant experience with collaborative academic tasks. Saunders et al. (2023) explained that purposive sampling is appropriate when respondents are selected based on their ability to provide information related to the research problem. After data screening, 319 valid responses were used for the final analysis. This sample size is considered suitable for PLS-SEM analysis.

3.3 Data Collection Procedure

Primary data were collected through a structured questionnaire survey. The questionnaire was designed by using measurement items related to Group Emotional Climate, Co-Regulation and Mutual Support, Shared Motivation,

Collaboration Outcomes and AI Readiness. Before participating in the survey, respondents were informed about the academic purpose of the study. Participation was voluntary, and respondents were allowed to decide whether they wanted to take part in the study. The questionnaire was also kept anonymous so that respondents could provide their answers without fear of personal identification. According to Saunders et al. (2023), ethical data collection requires informed consent, confidentiality and voluntary participation. Therefore, these ethical principles were followed during the data collection process carefully.

3.4 Measures and Instrumentation

All constructs of this study were measured through multi-item scales. Group Emotional Climate was measured through six items that captured positive emotional atmosphere, emotional support, mutual understanding, encouragement and emotional comfort within the group. Co-Regulation and Mutual Support was measured through five items that focused on motivation support, emotional support, stress management and emotional balance. Shared Motivation was measured through four items that examined common motivation, collective commitment, shared enthusiasm and similar levels of contribution. Collaboration Outcomes was measured through five items that reflected effective collaboration, successful teamwork, improved discussion, productivity and objective achievement. AI Readiness was measured through four items that assessed openness toward AI support, perceived usefulness of AI tools, trust in AI recommendations and AI-mediated emotional support. These items were appropriate because they directly reflected the conceptual model and the collaborative learning context of the study. Therefore, the instrument was able to capture both emotional and technological dimensions of collaborative learning.

3.5 PLS-SEM Justification

Partial Least Squares Structural Equation Modelling was used as the main data analysis technique in this study. PLS-SEM is suitable because the proposed model includes multiple direct relationships, mediating relationships and one moderating relationship. Hair et al. (2022) explained that PLS-SEM is appropriate for prediction-oriented studies and for examining complex structural models with latent variables. In education research, Hair and Alamer (2022) also argued that PLS-SEM is useful when researchers examine behavioural, perceptual and learning-related constructs through survey data. Therefore, this method is suitable for testing the AI-mediated emotional framework developed in this study.

SmartPLS was used to conduct the analysis because it provides a systematic approach for assessing both the measurement model and structural model. Sarstedt et al. (2022) noted that proper PLS-SEM reporting should include reliability, validity, predictive power and structural path significance. Becker et al. (2023) also provided guidance for testing mediation and moderation in applied PLS-SEM research. Due to this reason, PLS-SEM was considered appropriate for examining how Group Emotional Climate influences Collaboration Outcomes through Co-Regulation and Mutual Support and Shared Motivation, while also testing AI Readiness as a direct and moderating factor in the model.

3.6 Assessment Procedure

The data analysis followed a two-stage assessment procedure. In the first stage, the measurement model was evaluated by using outer loadings, Cronbach's alpha, composite reliability, Average Variance Extracted and HTMT ratios. These tests were used to

examine indicator reliability, internal consistency reliability, convergent validity and discriminant validity. Henseler et al. (2015) suggested that HTMT is a strong criterion for assessing discriminant validity in variance-based SEM. In the second stage, the structural model was assessed through path coefficients, t-statistics, p-values, R-square, effect size, mediation and moderation analysis. Hair et al. (2022) and Becker et al. (2023) explained that this sequence is necessary for interpreting PLS-SEM results properly. Therefore, hypotheses were tested only after confirming the quality of the measurement model. This procedure also helped to ensure that the interpretation of structural relationships was based on reliable and valid constructs.

4. RESULTS AND ANALYSIS

4.1 Demographic Profile of the Respondents

Before conducting the PLS-SEM analysis, the demographic profile of the respondents was examined to understand the basic characteristics of the sample. A total of 319 valid responses were used for the final analysis, and no missing values were found in the demographic variables. This indicates that the dataset was complete and suitable for further analysis. The demographic profile included gender, age group, study level, field of study, year level, group project experience, university type and AI tool use frequency. These variables were coded numerically in the dataset, and therefore the table presents

the descriptive information based on the coded demographic values.

Table 4.1 presents the demographic profile of the respondents. The mean value for Gender was 1.614 with a median value of 2.000, which indicates that the respondents were distributed across the coded gender categories. Age_Group had a mean value of 1.991 and a median value of 2.000, showing that most respondents were located around the second age category. Study_Level had a mean value of 1.386 and a median value of 1.000, which indicates that respondents were mostly concentrated in the first coded study-level category. Field_of_Study had a mean value of 2.834 and a standard deviation of 1.598, which shows that the respondents came from several academic fields.

Table 4.1:
Demographic Profile of the Respondents

Characteristic	Missing	Mean	Median	Observed Minimum	Observed Maximum	Standard Deviation
Gender	0	1.614	2.000	1.000	3.000	0.591
Age Group	0	1.991	2.000	1.000	5.000	1.000
Study Level	0	1.386	1.000	1.000	3.000	0.586
Field of Study	0	2.834	3.000	1.000	6.000	1.598
Year Level	0	2.583	2.000	1.000	5.000	1.177
Group Project Experience	0	2.558	3.000	1.000	4.000	0.977
University Type	0	1.285	1.000	1.000	2.000	0.452
AI Tool Use Frequency	0	2.683	3.000	1.000	5.000	1.107
Total Valid Responses	0	319	319	319	319	0.000

Source: Prepared by author.

From the above table, it can be understood that the sample had complete demographic information because all variables showed zero missing values. The observed minimum and maximum values were also within the expected coding range for all demographic variables. This indicates that there were no out-of-range demographic responses in the dataset. The standard deviation values show that there was variation in age group, field of study, year level, group project experience and AI tool use frequency. Therefore, the respondents were considered suitable for

examining AI-mediated collaborative learning, Group Emotional Climate, Co-Regulation and Mutual Support, Shared Motivation, AI Readiness and Collaboration Outcomes. After confirming the demographic profile of the respondents, the analysis proceeds to the measurement model assessment.

4.2 Preliminary Data and Model Overview

The data analysis of this study was conducted through SmartPLS by using 319

valid responses. The model was developed with five main latent constructs, namely Group Emotional Climate (GEC), Co-Regulation and Mutual Support (CRM), Shared Motivation (SM), AI Readiness (AIR) and Collaboration Outcomes (CO). Among these constructs, Group Emotional Climate works as the main independent variable, Collaboration Outcomes works as the dependent variable, Co-Regulation and

Mutual Support and Shared Motivation work as mediating variables, while AI Readiness works as both direct predictor and moderating variable. The bootstrapping procedure was conducted with 5,000 subsamples and two-tailed testing. Therefore, the model was suitable for examining direct effects, mediation effects and moderation effects in one structural framework.

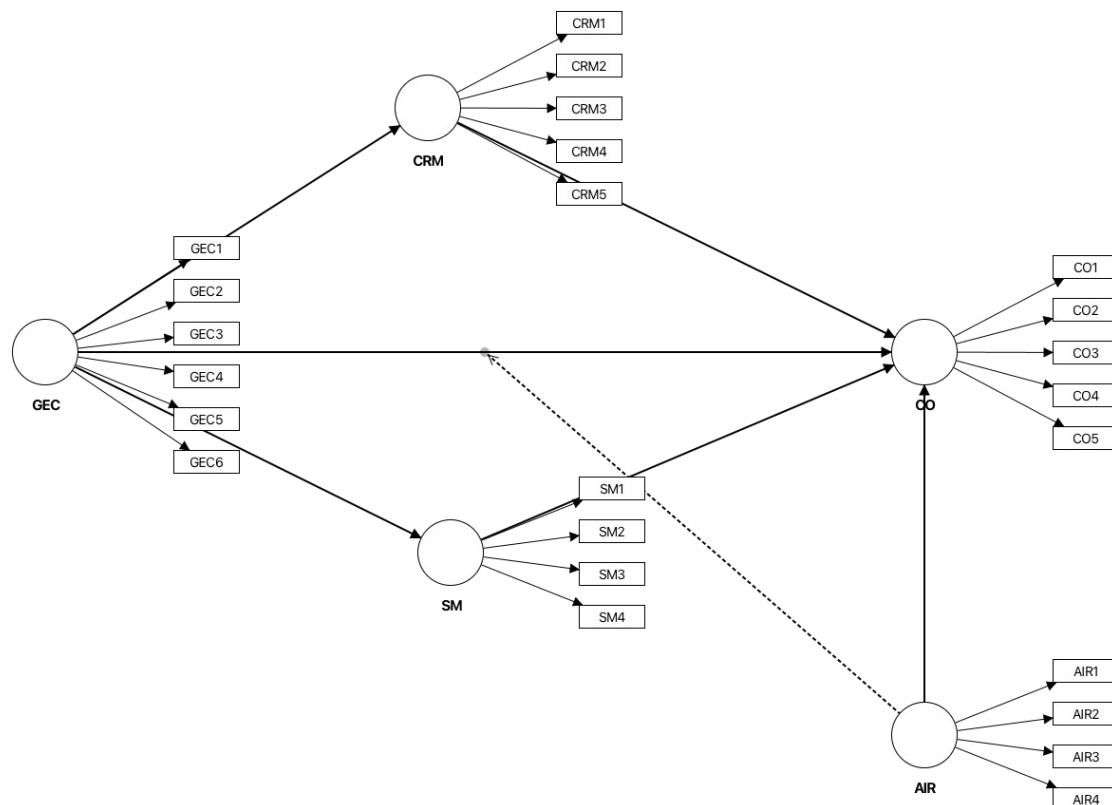


Figure 4.1: PLS-SEM Model Overview

4.3 Measurement Model Assessment Overview

The measurement model was assessed before interpreting the structural relationships. This step was necessary because the validity of the structural model depends on the reliability and validity of the measurement items. In this study, the measurement model was evaluated through outer loadings, internal consistency reliability, convergent validity, discriminant validity and collinearity assessment. Therefore, the analysis first reports indicator

reliability, then Cronbach's alpha, rho_A, composite reliability, Average Variance Extracted, HTMT ratio and VIF values. After confirming these measurement criteria, the structural model was examined.

4.3.1 Outer Loadings and Indicator Reliability

The outer loadings were examined to assess the reliability of each indicator. According to the general PLS-SEM threshold, factor loadings above 0.70 are

considered acceptable. Table 4.1 shows that all measurement items have loading values above the recommended value. The loading values ranged from 0.835 to 0.913. Therefore, no item was removed from the model. From the above findings, it can be said that all indicators contributed strongly to their

respective constructs. AIR3 had the highest loading under AI Readiness with 0.913, while GEC6 had the lowest loading with 0.835, which is still above the required threshold. This confirms that the measurement items have acceptable indicator reliability.

Table 4.1:
Outer Loadings

Construct	Item	Loading
AI Readiness	AIR1	0.908
AI Readiness	AIR2	0.899
AI Readiness	AIR3	0.913
AI Readiness	AIR4	0.851
Collaboration Outcomes	CO1	0.897
Collaboration Outcomes	CO2	0.891
Collaboration Outcomes	CO3	0.871
Collaboration Outcomes	CO4	0.860
Collaboration Outcomes	CO5	0.864
Co-Regulation and Mutual Support	CRM1	0.905
Co-Regulation and Mutual Support	CRM2	0.884
Co-Regulation and Mutual Support	CRM3	0.880
Co-Regulation and Mutual Support	CRM4	0.883
Co-Regulation and Mutual Support	CRM5	0.863
Group Emotional Climate	GEC1	0.887
Group Emotional Climate	GEC2	0.876
Group Emotional Climate	GEC3	0.860
Group Emotional Climate	GEC4	0.861
Group Emotional Climate	GEC5	0.890
Group Emotional Climate	GEC6	0.835
Shared Motivation	SM1	0.895
Shared Motivation	SM2	0.893
Shared Motivation	SM3	0.895
Shared Motivation	SM4	0.877

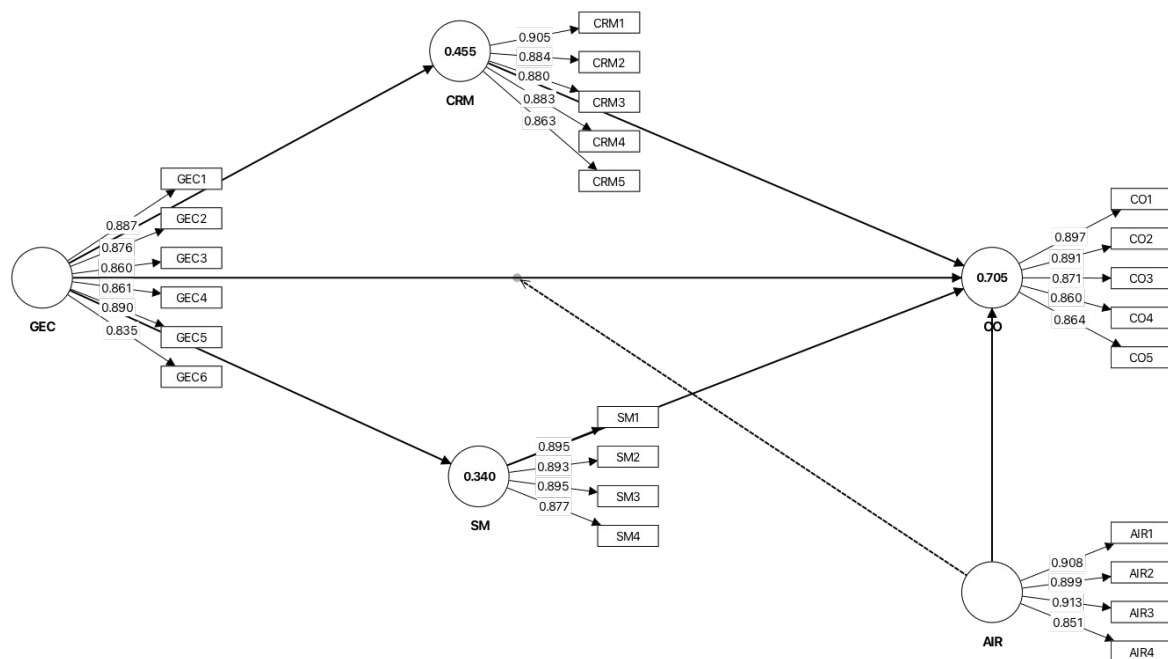


Figure 4.2: Measurement Model Results

4.3.2 Internal Consistency Reliability

Internal consistency reliability was examined through Cronbach's alpha, rho_A and Composite Reliability. Table 4.2 shows that Cronbach's alpha values ranged from

0.913 to 0.935. The rho_A values ranged from 0.913 to 0.950, while Composite Reliability values ranged from 0.938 to 0.948. All these values are higher than the recommended threshold of 0.70. Therefore, it can be said that the constructs have strong internal consistency reliability.

Table 4.2:
Reliability and Convergent Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
AIR	0.917	0.950	0.940	0.798
CO	0.925	0.925	0.943	0.769
CRM	0.929	0.930	0.947	0.780
GEC	0.935	0.936	0.948	0.754
SM	0.913	0.913	0.938	0.792

From the above table, it can be understood that all constructs were measured reliably. Group Emotional Climate showed the highest Cronbach's alpha value of 0.935, while Shared Motivation showed the lowest value of 0.913. However, even the lowest value is much higher than the required minimum level. Therefore, the measurement scales

used in this study are internally consistent and suitable for further analysis.

4.2.3 Convergent Validity

Convergent validity was assessed by using the Average Variance Extracted. The AVE values for all constructs were higher than the recommended value of 0.50. AI Readiness

had an AVE value of 0.798, Collaboration Outcomes had 0.769, Co-Regulation and Mutual Support had 0.780, Group Emotional Climate had 0.754 and Shared Motivation had 0.792. Therefore, each construct explained more than half of the variance of its indicators. From the above findings, it can be said that convergent validity is established for all constructs in the model.

4.2.4 Discriminant Validity

Discriminant validity was assessed by using the HTMT ratio. Table 4.3 shows that all HTMT point estimates were below the conservative threshold of 0.85. This indicates that the constructs are conceptually and empirically distinct. However, the results should be interpreted carefully because the upper confidence interval for CRM and CO reached 0.869, while the upper confidence interval for GEC and CO reached 0.865. Therefore, although the HTMT point estimates support discriminant validity, the relationship between these closely connected constructs should be explained with caution.

Table 4.3:
Discriminant Validity Using HTMT

Relationship	HTMT	2.5%	97.5%
CO ↔ AIR	0.200	0.093	0.318
CRM ↔ AIR	0.206	0.100	0.319
CRM ↔ CO	0.829	0.782	0.869
GEC ↔ AIR	0.204	0.092	0.315
GEC ↔ CO	0.820	0.767	0.865
GEC ↔ CRM	0.722	0.654	0.780
SM ↔ AIR	0.128	0.049	0.244
SM ↔ CO	0.542	0.442	0.626
SM ↔ CRM	0.454	0.342	0.552
SM ↔ GEC	0.631	0.553	0.701

From the above findings, it can be said that the model has acceptable discriminant validity. The higher HTMT values between CRM and CO and between GEC and CO are understandable because these constructs are theoretically related in collaborative learning. However, the point estimates remain below 0.85. Therefore, the constructs can still be treated as separate variables in the structural model.

4.2.5 Collinearity Assessment

Collinearity was assessed through VIF values before testing the structural paths. The inner VIF values ranged from 1.000 to 2.311, which are below the common threshold of 5.00. This indicates that multicollinearity was not a serious issue in the structural model. The highest VIF value was found for GEC → CO with 2.311, followed by CRM → CO with 1.854. These values are acceptable. Therefore, the path coefficients can be interpreted without serious concern about collinearity.

Table 4.4:
Inner Model Collinearity Statistics

Relationship	VIF
AIR → CO	1.049
AIR × GEC → CO	1.002
CRM → CO	1.854
GEC → CO	2.311
GEC → CRM	1.000
GEC → SM	1.000
SM → CO	1.518

4.3 Structural Model Assessment

After confirming the reliability and validity of the measurement model, the structural model was assessed. The structural model was examined through model fit, explanatory power, effect size, direct path coefficients, mediation analysis and moderation analysis. This sequence is important because the relationship among the

constructs can only be interpreted after confirming that the measurement model has acceptable quality. In this study, the structural model explains how Group Emotional Climate influences Collaboration Outcomes directly and indirectly through Co-Regulation and Mutual Support and Shared Motivation. It also examines whether AI Readiness has a direct and moderating role in the model.

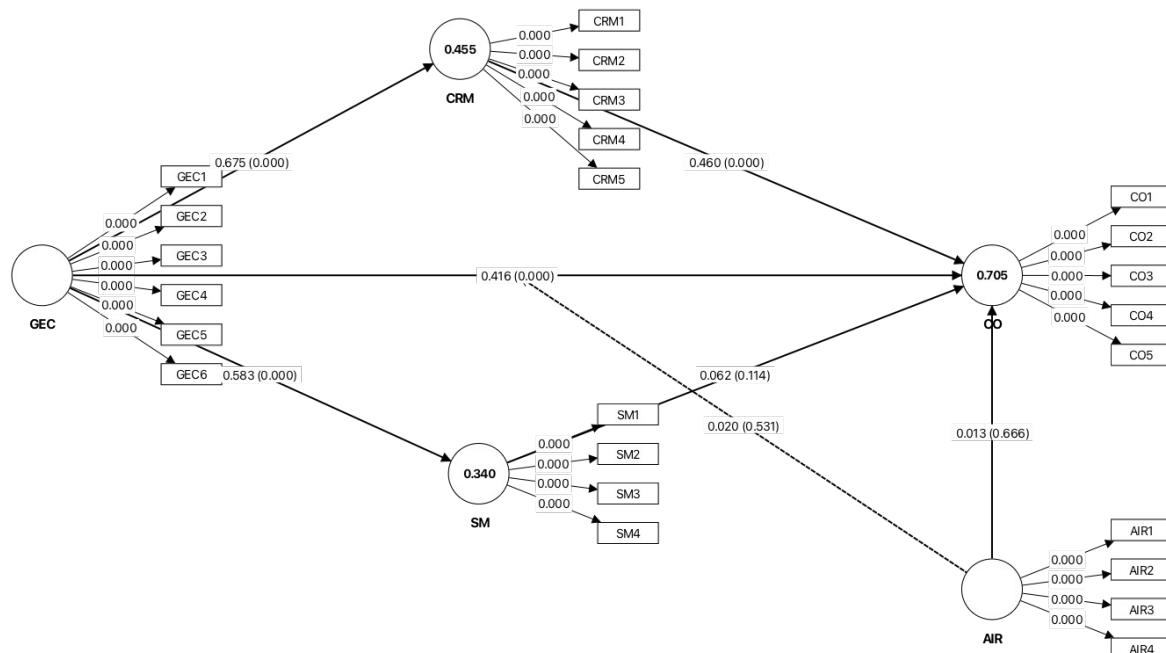


Figure 4.3: Structural Model

4.3.1 Model Fit, R-Square and Effect Size

The model fit was assessed through SRMR, d_ULS and d_G. Table 4.5 shows that the SRMR value for the estimated model was 0.038, which is below the recommended

value of 0.08. Therefore, the model fit can be considered acceptable. The d_ULS value for the estimated model was 0.444, which was lower than the 95% bootstrap value of 0.539. The d_G value was 0.256, which was also lower than the 95% bootstrap value of 0.276.

From this result, it can be said that the model has acceptable overall fit.

Table 4.5:
Model Fit

Model	SRMR	d_ULS	d_G
Saturated Model	0.036	0.385	0.256
Estimated Model	0.038	0.444	0.256

The explanatory power of the model was examined through R-square and adjusted R-square. Table 4.6 shows that Collaboration Outcomes had an R-square value of 0.705 and adjusted R-square value of 0.700. This indicates that the model explains 70.5% of the variance in Collaboration Outcomes. Co-

Regulation and Mutual Support had an R-square value of 0.455, while Shared Motivation had an R-square value of 0.340. Therefore, the model has strong explanatory power for Collaboration Outcomes and moderate explanatory power for the mediating variables.

Table 4.6:
R-Square and Adjusted R-Square

Construct	R-Square	Adjusted R-Square
CO	0.705	0.700
CRM	0.455	0.454
SM	0.340	0.338

The f-square effect size was also examined. The strongest effect was found for GEC → CRM with $f^2 = 0.836$. This shows that Group Emotional Climate has a large effect on Co-Regulation and Mutual Support. GEC → SM also had a large effect with $f^2 =$

0.515. CRM → CO showed a moderate to large effect with $f^2 = 0.387$, while GEC → CO had a moderate effect with $f^2 = 0.253$. However, AIR → CO, AIR × GEC → CO and SM → CO showed very small effects.

Table 4.7:
Effect Size

Relationship	f-square
AIR → CO	0.001
AIR × GEC → CO	0.001
CRM → CO	0.387
GEC → CO	0.253
GEC → CRM	0.836

Relationship	f-square
GEC → SM	0.515
SM → CO	0.008

4.3.2 Direct Hypothesis Testing

The direct hypotheses were tested through bootstrapping with 5,000 subsamples. Table 4.8 presents the path coefficients, t-statistics and p-values. The result shows that Group Emotional Climate has a significant positive influence on Collaboration Outcomes, where $\beta = 0.416$, $t = 8.464$ and $p = 0.000$. Therefore, H1 is supported. This indicates that a positive emotional group environment directly improves collaboration outcomes.

Group Emotional Climate also had a significant positive influence on Co-Regulation and Mutual Support, where $\beta = 0.675$, $t = 22.072$ and $p = 0.000$. Therefore, H2 is supported. This result shows that emotional climate strongly supports mutual regulation and support among group members. Co-Regulation and Mutual Support also had a significant positive effect on Collaboration Outcomes, where $\beta = 0.460$, t

$= 10.668$ and $p = 0.000$. Therefore, H3 is supported.

The result also shows that Group Emotional Climate significantly influences Shared Motivation, where $\beta = 0.583$, $t = 16.098$ and $p = 0.000$. Therefore, H4 is supported. However, Shared Motivation did not have a significant effect on Collaboration Outcomes, where $\beta = 0.062$, $t = 1.582$ and $p = 0.114$. Therefore, H5 is not supported. This indicates that although emotional climate can create shared motivation, shared motivation alone may not be sufficient to produce collaboration outcomes.

AI Readiness also did not have a significant direct effect on Collaboration Outcomes, where $\beta = 0.013$, $t = 0.432$ and $p = 0.666$. Therefore, H8 is not supported. From this result, it can be said that students' general readiness toward AI does not directly improve collaboration outcomes in this model.

Table 4.8:
Direct Hypothesis Testing

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	GEC → CO	0.416	8.464	0.000	Supported
H2	GEC → CRM	0.675	22.072	0.000	Supported
H3	CRM → CO	0.460	10.668	0.000	Supported
H4	GEC → SM	0.583	16.098	0.000	Supported
H5	SM → CO	0.062	1.582	0.114	Not supported
H8	AIR → CO	0.013	0.432	0.666	Not supported

4.3.3 Mediation Analysis

The mediation analysis was conducted by examining the specific indirect effects. Table 4.9 shows that the indirect effect of Group Emotional Climate on Collaboration Outcomes through Co-Regulation and

Mutual Support was significant, where $\beta = 0.311$, $t = 9.524$ and $p = 0.000$. Therefore, H6 is supported. This finding confirms that Co-Regulation and Mutual Support works as a significant mediating mechanism between emotional climate and collaboration outcomes.

However, the indirect effect of Group Emotional Climate on Collaboration Outcomes through Shared Motivation was not significant, where $\beta = 0.036$, $t = 1.574$ and $p = 0.116$. Therefore, H7 is not supported.

From this finding, it can be understood that Shared Motivation does not significantly transmit the effect of Group Emotional Climate on Collaboration Outcomes.

Table 4.9:
Mediation Analysis

Hypothesis	Indirect Relationship	β	t-value	p-value	Decision
H6	GEC $\rightarrow$ CRM $\rightarrow$ CO	0.311	9.524	0.000	Supported
H7	GEC $\rightarrow$ SM $\rightarrow$ CO	0.036	1.574	0.116	Not supported

4.3.4 Moderation Analysis

The moderating effect of AI Readiness was assessed through the interaction term AIR $\times$ GEC $\rightarrow$ CO. The result shows that the moderation effect was not significant, where $\beta = 0.020$, $t = 0.627$ and $p = 0.531$. Therefore, H9 is not supported. This means that AI Readiness does not significantly strengthen

or weaken the relationship between Group Emotional Climate and Collaboration Outcomes. Although the conditional direct effects show that the GEC $\rightarrow$ CO relationship remains positive at low, mean and high levels of AI Readiness, the interaction effect itself is not statistically significant. Therefore, AI Readiness cannot be treated as a meaningful moderator in this model.

Table 4.10:
Moderation Analysis

Hypothesis	Relationship	β	t-value	p-value	Decision
H9	AIR $\times$ GEC $\rightarrow$ CO	0.020	0.627	0.531	Not supported

4.4 Summary of Hypothesis Decisions

Table 4.11 presents the overall hypothesis decisions of the study. From the nine hypotheses, five were supported and four were not supported. The findings show that Group Emotional Climate directly improves

Collaboration Outcomes and also strongly influences both Co-Regulation and Mutual Support and Shared Motivation. However, only Co-Regulation and Mutual Support successfully transfers the effect of Group Emotional Climate into Collaboration Outcomes. Shared Motivation, AI Readiness and the moderating effect of AI Readiness were not statistically significant.

Table 4.11:
Summary of Hypothesis Decisions

Hypothesis	Relationship	Decision
H1	GEC $\rightarrow$ CO	Supported
H2	GEC $\rightarrow$ CRM	Supported
H3	CRM $\rightarrow$ CO	Supported
H4	GEC $\rightarrow$ SM	Supported

Hypothesis	Relationship	Decision
H5	SM → CO	Not supported
H6	GEC → CRM → CO	Supported
H7	GEC → SM → CO	Not supported
H8	AIR → CO	Not supported
H9	AIR × GEC → CO	Not supported

5. Discussion, Implications and Conclusion

5.1 Summary of Major Findings

The findings of this study show that Group Emotional Climate has an important role in explaining Collaboration Outcomes in AI-mediated collaborative learning. The result confirms that Group Emotional Climate directly improves Collaboration Outcomes and also significantly influences Co-Regulation and Mutual Support and Shared Motivation. However, the two mediating pathways do not work in the same way. Co-Regulation and Mutual Support was found as a significant mediating mechanism between Group Emotional Climate and Collaboration Outcomes. However, Shared Motivation did not significantly influence Collaboration Outcomes and did not mediate the relationship between Group Emotional Climate and Collaboration Outcomes. The result also shows that AI Readiness did not have a significant direct effect on Collaboration Outcomes. Moreover, AI Readiness did not moderate the relationship between Group Emotional Climate and Collaboration Outcomes. From these findings, it can be understood that emotional climate becomes useful mainly when it is transformed into active mutual support and co-regulation.

5.2 Group Emotional Climate as the Main Emotional Foundation

A major finding of this study is that Group Emotional Climate works as the main emotional foundation of collaborative learning. The result shows that a positive emotional climate can directly improve Collaboration Outcomes. This finding is consistent with the argument of George (1990), where group affective tone is understood as a shared emotional condition that can influence group behaviour and performance. In the context of this study, students do not only complete tasks through individual effort. Rather, they work within a shared emotional environment where encouragement, emotional comfort and mutual understanding can shape how they interact with one another.

The finding also supports Ippolito and Kingsbury (2024), who showed that social and emotional climate can influence collaborative learning engagement, satisfaction and perceived learning. This means that when students feel emotionally supported in the group, they may become more willing to participate and contribute during collaborative tasks. Tan and Jung (2024) also argued that emotional presence develops throughout collaboration and shapes learning outcomes. Therefore, emotional climate should not be treated as a passive background condition. Rather, it is an active part of the collaborative learning process.

Moreover, the result shows that Group Emotional Climate also improves Collaboration Outcomes indirectly through Co-Regulation and Mutual Support. This is important because Törmänen et al. (2025) found that group emotion and regulation move together during collaborative learning episodes. From this finding, it can be said that emotional climate becomes more powerful when it creates supportive and regulatory behaviour among group members. Therefore, Group Emotional Climate is not only an

emotional variable. It is the starting point of the relationship nexus that connects group affect, support and collaboration outcomes.

5.3 Co-Regulation and Mutual Support as the Strongest Mechanism

The strongest mechanism identified in this study is Co-Regulation and Mutual Support. The result shows that Co-Regulation and Mutual Support has a significant positive influence on Collaboration Outcomes and also significantly mediates the relationship between Group Emotional Climate and Collaboration Outcomes. From this finding, it can be understood that emotional climate does not automatically become collaboration success. Rather, it needs to be converted into active support, shared regulation and mutual assistance during the learning process.

This result is consistent with Huang et al. (2024), who found that socio-emotional interaction and cognitive engagement are connected through co-regulation in problem-based collaborative learning. This means that students may experience positive emotional interaction, but the learning outcome becomes stronger when the group can regulate difficulties, motivation and engagement together. Sharma et al. (2024) also highlighted that collaborative learning in adaptive digital environments requires both self-regulation and socially shared regulation. Therefore, regulation is not only an individual skill. It also becomes a collective learning process.

Kazemitabar et al. (2024) further showed that socially shared emotion regulation is connected with team coordination mechanisms. This supports the present finding because collaboration outcomes depend on how students coordinate their responses and manage group challenges. Ahola et al. (2025) also argued that socio-emotional interaction and regulation are intertwined in collaborative learning.

Similarly, Kok (2025) explained that socially shared regulation includes cognitive, metacognitive, behavioural, motivational and emotional dimensions. Therefore, the result of this study confirms that Co-Regulation and Mutual Support is the real pathway through which a positive emotional group climate becomes productive collaboration. It is not only the presence of positive emotion that matters. Rather, what matters more is whether that emotion becomes supportive and regulatory action.

5.4 The Weak Role of Shared Motivation

One interesting finding of this study is the weak role of Shared Motivation in explaining Collaboration Outcomes. The result shows that Group Emotional Climate has a significant positive influence on Shared Motivation. However, Shared Motivation did not have a significant effect on Collaboration Outcomes. This means that a positive emotional climate can create common enthusiasm and collective commitment, but this shared motivation may not be strong enough to produce effective collaboration by itself.

This finding adds a more careful understanding to the collaborative learning literature. He et al. (2024) showed that personal-collaborative motivation profiles are associated with collaborative problem-solving performance. Wang, Wang, Huang, et al. (2024) also found that socially regulated learning profiles can predict collaborative learning motivation. However, the result of the present study indicates that motivation may need to be supported by stronger regulatory and behavioural mechanisms before it can influence outcomes.

Järvenoja et al. (2025) argued that peer influence on motivation becomes stronger when motivation regulation occurs with cognitive regulation. Liu and Ye (2025) also showed that socially shared regulation and task value are important for online self-regulated learning. Therefore, Shared

Motivation may be useful, but it is not sufficient alone. From this finding, it can be said that collaboration requires more than enthusiasm. It requires organised support, regulation and coordinated action.

5.5 The Non-Significant Role of AI Readiness

Another important finding of this study is that AI Readiness did not significantly influence Collaboration Outcomes and did not moderate the relationship between Group Emotional Climate and Collaboration Outcomes. This result indicates that students' general openness toward AI support does not automatically improve the quality of collaboration. In the context of this study, AI Readiness may reflect a favourable attitude toward AI, but it does not necessarily mean that students are using AI in a meaningful way during group learning.

This finding needs to be interpreted carefully because recent studies show that AI can support emotional and collaborative learning processes. Ngo et al. (2024) showed that AI-based facial expression recognition can help examine emotional regulation in synchronous collaborative learning. Yang and Zhao (2024) found that AI can create both supportive and disruptive emotional experiences. Dang et al. (2025), Edwards et al. (2025) and Kim et al. (2025) also showed that AI can support socio-emotional interaction and socially shared regulation when it is properly designed and integrated.

However, the present result suggests that readiness alone is not enough. Kim et al. (2026) also indicated that the effect of generative AI depends on how it is integrated into collaboration. Therefore, AI Readiness may become useful only when AI tools are actively embedded into group processes.

5.6 Theoretical Contribution

This study contributes to the literature in three important ways. First, it extends

emotional climate research by showing that Group Emotional Climate directly influences Collaboration Outcomes and also works through Co-Regulation and Mutual Support. Second, it contributes to collaborative learning literature by identifying Co-Regulation and Mutual Support as the main mechanism through which emotional climate becomes productive learning behaviour. Third, it contributes to AI-mediated learning literature by showing that AI Readiness does not automatically improve collaboration outcomes and does not significantly moderate the emotional climate-outcome relationship. From this finding, it can be understood that AI-related variables should not be assumed as automatically beneficial. Rather, their role depends on how they are connected with actual collaborative learning processes.

5.7 Practical Implications

The findings provide several practical implications for teachers, universities and AI learning system designers. First, teachers should pay attention to the emotional climate of student groups because positive emotional conditions can support better collaboration outcomes. Second, universities should train students not only to work in groups but also to regulate emotions, manage stress and support one another during collaborative tasks. Third, AI designers should not focus only on technical features or content generation. Rather, AI-supported platforms should include functions that help groups identify emotional difficulties, support coordination and encourage mutual regulation. From the above findings, it can also be understood that AI readiness alone is not enough. Therefore, universities should combine AI literacy with collaborative learning training so that students can use AI tools in a more meaningful and group-oriented way.

5.8 Limitations and Future Research

Although this study provides important findings, some limitations are present. First,

the study used a cross-sectional design, and therefore it cannot explain how group emotional climate and collaboration outcomes change over time. Future studies can use longitudinal research designs to examine the development of emotional climate and co-regulation across different stages of collaboration. Second, the study used self-reported survey data, which may create response bias. Future research can use behavioural data, observation, learning analytics or AI-based interaction records. Third, the study was conducted in a specific higher education context. Therefore, future studies can test the model in different countries, disciplines and learning platforms. Experimental studies can also examine whether actual AI-supported emotional scaffolding changes collaboration outcomes.

5.9 Conclusion

This study examined the AI-mediated emotional framework in collaborative learning by testing the influence of Group Emotional Climate on Collaboration Outcomes. The findings show that emotional climate is important, but its strongest contribution comes through Co-Regulation and Mutual Support. Shared Motivation and AI Readiness were not significant predictors of Collaboration Outcomes. Therefore, this study concludes that effective collaboration depends more on active emotional support and regulation than on motivation or general AI openness alone. In AI-mediated higher education, emotional climate should be supported through meaningful group regulation, not only through technological readiness.

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