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Task Motivation Task Specific Emotions and Written Performance among Chinese EFL Learners in an Education 5.0 Context

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Abstract

Education 5.0 calls for learner-centred, adaptive, and evidence-informed approaches that connect technological innovation with learners' cognitive, motivational, and emotional needs. Within EFL writing, however, the extent to which task motivation and task-specific emotions translate into immediate written performance remains unclear, particularly in technology-mediated educational environments. This study examines the relationships among intrinsic and extrinsic task motivation, task-specific enjoyment and anxiety, and written performance among 117 non-English-major Chinese university learners. Participants completed a timed argumentative writing task and responded to adapted measures of task motivation and task-specific emotions. Writing performance was operationalised through complexity and accuracy in the final structural model; fluency was not retained in the model because the necessary data were unavailable. PLS-SEM with 3,000 bootstrap resamples was used to assess the measurement and structural models. The results showed that intrinsic motivation, extrinsic motivation, task enjoyment, and task anxiety did not significantly predict writing complexity or accuracy. Task motivation was positively associated with task-specific emotion, but task-specific emotion did not significantly predict written performance, and the proposed indirect effects were nonsignificant. These findings suggest that motivational and emotional variables should not be treated as sufficient stand-alone explanations of immediate writing quality. Instead, **Education 5.0-oriented EFL writing policy** should connect affective support with technology-enhanced writing processes, writing self-regulation, feedback, digital literacy, and teacher guidance. The study therefore contributes an evidence-informed basis for rethinking EFL writing policy as a coordinated cognitive, affective, pedagogical, and technological process rather than as a narrow focus on final textual output.

1. Introduction

Education 5.0 provides a useful policy lens for reconsidering what educational systems should prioritise in an era characterised by rapid technological change, personalised learning, and increasing expectations for learner agency. Recent work conceptualises Education 5.0 not simply as the adoption of new technologies but as a broader transformation of educational purposes, learning relationships, and institutional practices. Garwe's account of Heritage-based Education 5.0, for example, emphasises learner participation, creativity, problem solving, contextual responsiveness, and the co-construction of knowledge rather than a purely technology-driven model [16]. For EFL education, this orientation suggests that writing policy should attend simultaneously to linguistic development, learner agency, psychological conditions, digital participation, and responsible use of emerging technologies.

Writing is particularly relevant to this policy discussion because it requires learners to coordinate lexical retrieval, grammatical encoding, discourse organisation, revision, and sustained attention. Motivation can influence whether learners invest effort in a demanding task, while task-specific emotions may shape attention, cognitive engagement, persistence, and regulation. Recent research continues to show that these relationships are context-sensitive. Abdi Tabari and Goetze found that anxiety and self-efficacy interact with task complexity in L2 written production, while [33, 34] updated control-value theory

emphasises that emotions emerge from control and value appraisals and influence learning through multiple cognitive and motivational mechanisms [1, 33]. Accordingly, the immediate effect of a learner's motivation or emotional state on a single writing product should not be assumed to be linear or deterministic.

The rapid development of technology-enhanced writing environments makes this issue more consequential. AI-supported writing, automated feedback, collaborative online writing, and generative-AI tools increasingly mediate planning, drafting, feedback, revision, and reflection. Recent evidence indicates that technology can support writing motivation and self-regulated learning when it is embedded within purposeful pedagogy rather than treated as an autonomous solution. [30], for instance, found that AI literacy and writing self-efficacy were important resources for L2 writing motivation in AI-mediated contexts. Similarly, recent studies of GenAI-assisted prewriting and AI-supported writing instruction indicate that collaborative use, self-evaluation, and structured pedagogical support can influence learners' confidence, motivation, emotion regulation, and writing outcomes [22, 26, 30].

This technological transition creates a policy question that extends beyond whether a particular digital tool improves a particular writing score: What should evidence-informed EFL writing policy prioritise when technology changes the conditions under which learners plan, compose, receive feedback, and regulate their writing? A policy response should not equate innovation with technology adoption. Technology-enhanced writing environments therefore need to be built around clear pedagogical aims. Their design should protect learner agency and emotional well-being while also addressing digital literacy, feedback quality, and assessment integrity. Research with Chinese tertiary EFL learners shows that engagement with GenAI-mediated feedback is influenced by teacher support as well as learners' motivation and emotions. Digital writing environments are consequently better understood as socio-pedagogical systems than as neutral tools [46].

RQ1. To what extent do intrinsic and extrinsic task motivation predict Chinese EFL learners' written performance, as reflected in writing complexity and accuracy?

RQ2. To what extent do task-specific enjoyment and anxiety predict Chinese EFL learners' written performance, and do task-specific emotions help explain the relationship between task motivation and written performance?

2. Literature Review

2.1 Education 5.0 and the policy context of EFL writing

In this study, Education 5.0 serves as a forward-looking policy perspective rather than an additional construct in the empirical model. Recent work in this area gives particular attention to learner agency, creativity, problem solving, responsiveness to context, and the responsibility of educational institutions to connect learning with wider social needs [16]. Applied to EFL writing, these principles call for policies that attend to the writing process rather than concentrating mainly on grammar scores or final products.

Learners need support as they generate ideas, compose, respond to feedback, revise, and gradually take ownership of their writing. Policy must also consider how technology enters this process. Digital tools can widen access to feedback, collaboration, and personalized assistance, but they become educationally useful only when they fit the learning goals, draw on teacher expertise, respond to learners' needs, and operate within appropriate ethical safeguards. Thus, Education 5.0 is used here as a framing concept for interpreting how evidence about motivation, emotion, writing processes, and technology can inform future EFL writing policy rather than as a variable directly tested in the present model.

2.2 Technology-enhanced writing environments and learner agency

Technology-enhanced writing environments increasingly include automated feedback, collaborative platforms, and generative-AI systems that can intervene at different stages of the writing process. Recent research suggests that these environments can support writing development when learners remain cognitively and communicatively active. In a study of GenAI-assisted collaborative prewriting, [26, 27] found that collaboration improved the quality of outlines and encouraged more effective prompting, although gains in overall task motivation were not statistically significant. [22] likewise reported that AI-supported writing combined with structured self-evaluation was associated with improvements in emotion regulation, motivation, self-competence, and writing achievement. These findings are relevant to Education 5.0 because they position technology as a scaffold for human learning rather than a substitute for learner decision making. At the same time, technology-mediated writing can create new risks, including overreliance, reduced ownership, unequal access, and blurred boundaries between assistance and authorship. Evidence from Chinese tertiary EFL learners shows that teacher support, motivation, and emotions remain important even when writing feedback is mediated by ChatGPT [46]. Consequently, evidence-informed EFL writing policy should specify not only which technologies may be used but also how they should be integrated with teacher guidance, self-regulation, assessment, feedback, and responsible learner agency.

2.3 Task motivation and cognitive engagement

Motivation helps learners engage with tasks that demand sustained intellectual effort. Self-determination theory differentiates relatively autonomous motivation from motivation driven largely by external regulation. More recent research also treats motivation as fluid and responsive to context [2, 37]. In writing, motivated learners may begin a task more readily and persist for longer, although effort by itself cannot ensure linguistic accuracy or complexity. Studies of AI-mediated EFL writing point to a similar pattern which writing motivation develops alongside resources such as teacher affective support, AI literacy, and writing self-efficacy [30]. Motivation should therefore be examined within the wider conditions of learning, not as a separate force that determines performance on its own.

2.4 Task-specific emotions and written performance

Task-specific emotions are the feelings learners experience while carrying out a particular activity. Control-value theory explains these emotions partly through learners' judgements about how much

control they have and how much the task matters to them. Those emotions may then influence attention, cognitive processing, motivation, and performance [33]. Enjoyment can sustain engagement and allow more flexible thinking, whereas anxiety may draw cognitive resources away from the task. Neither effect, however, is inevitable. Research on L2 writing shows that anxiety and self-efficacy interact with task complexity, and the pattern differs across writing outcomes [1]. Studies published in 2026 add another layer to this account: writing emotions appear to develop in relation to self-regulated learning and learner mindsets, while enjoyment and boredom may mediate links between future-oriented motivational selves and writing achievement [10, 29]. Such evidence supports the study of task-specific emotions, but it also cautions against assuming that one emotional state will determine the quality of a single text.

2.5 Writing performance and the CAF framework

Complexity, accuracy, and fluency (CAF) provide useful ways of describing observable features of L2 production. Complexity captures the range and sophistication of the language used, accuracy reflects the extent to which production is free from error, and fluency concerns the amount or rate of output. Psychological variables may account for only a modest share of differences in written performance, however. Task complexity, language proficiency, self-efficacy, strategic knowledge, and the surrounding context also matter [1]. The final structural model in this study included complexity and accuracy. Fluency was omitted because the necessary data were unavailable. This limitation needs to remain explicit when the results are interpreted, since the study did not test the full CAF framework.

2.6 Integrating motivation, emotion, technology, and policy

The literature points towards an account of EFL writing in which motivation and task-specific emotions operate within particular instructional and technological settings. Education 5.0 supplies a policy rationale for this view by encouraging writing education that is learner-centered, digitally informed, responsive to the future, and sensitive to learners' psychological experiences. Technology can support feedback, scaffolding, collaboration, and self-regulation, although its contribution depends on the design of the task, the guidance provided by teachers, and the agency exercised by learners. The present study examines a useful limit to the explanatory reach of motivation and emotion. Both may matter in theory without producing measurable direct effects on the immediate features of one written text. This possibility reflects current evidence that writing emerges from the interaction of cognitive, affective, technological, and instructional conditions rather than from any single predictor.

3. Research Methodology

3.1 Participants

The participants were 117 undergraduate students at a Chinese university, none of whom was majoring in English. All were intermediate-level EFL learners and had studied English in formal classrooms for at least six years. They were recruited from an initial sampling frame of 375 non-English-major students.

Figure 2. A conceptual SEM model

3.2. Hypotheses Development

3.2.1. Motivation and Written Task Performance

Learners' motivational orientations can influence how much mental effort they devote to a demanding task. Self-determination theory suggests that intrinsic motivation may encourage sustained involvement and persistence, qualities that can support performance during cognitively complex work. In contrast, extrinsic motivation may produce weaker or less consistent effects on performance outcomes. In second language writing tasks, higher engagement may lead to greater linguistic elaboration, increased production volume, and more careful monitoring of linguistic accuracy. Based on this theoretical reasoning, the following hypotheses are proposed.

H1a

Intrinsic motivational orientation positively predicts writing complexity.

H1b

Intrinsic motivational orientation positively predicts writing accuracy.

H1c

Intrinsic motivational orientation positively predicts writing fluency.

H2a

Extrinsic motivational orientation predicts writing complexity.

H2b

Extrinsic motivational orientation predicts writing accuracy.

H2c

Extrinsic motivational orientation predicts writing fluency.

3.2.2. Task-specific emotions and Written Task Performance

The effectiveness of emotions elicited during task performance can impact cognition. Following control-value theory [33], positive achievement emotions in reaction to the task (e. g. enjoyment of the writing process) expand cognition and promote flexible cognition, while negative achievements emotions (like anxiety) can narrow cognition and disrupt working memory. With SLA writing, it is hypothesized that enjoyment would promote production and creativity, while anxiety would impede the use of linguistic

monitoring mechanisms and fluency. Empirical evidence nevertheless suggests that these relationships may change with task complexity and may account for only small amounts of variance in written production [1]. Based on this reasoning, the following hypotheses were proposed:

H3a: task-specific enjoyment positively predicts writing complexity.

H3b: task-specific enjoyment positively predicts writing accuracy.

H3c: task-specific enjoyment positively predicts writing fluency.

H4a: task-specific anxiety negatively predicts writing complexity.

H4b: task-specific anxiety negatively predicts writing accuracy.

H4c: task-specific anxiety negatively predicts writing fluency.

3.2.3. Optional Mediation Hypothesis (Recommended for SEM Papers)

Because your model suggests that motivation may influence emotions, which then influence performance, a mediation hypothesis strengthens the theoretical model.

H5a: Emotion mediates task-specific enjoyment →performance relationship

H5b: Emotion mediates task-specific anxiety →performance relationship

H5c: Task-specific emotions (enjoyment and anxiety) mediate the relationship between motivational orientations and written task performance.

Final Hypothesis Structure (SEM Model)

Total hypotheses in the model:

H1a: Intrinsic motivation → writing complexity

H1b: Intrinsic motivation → writing accuracy

H1c: Intrinsic motivation → writing fluency

H2a: Extrinsic motivation ⟶ writing complexity

H2b: Extrinsic motivation → writing accuracy

H2c: Extrinsic motivation → writing fluency

H3a: Enjoyment → writing complexity

H3b: Enjoyment → writing accuracy

H3c: Enjoyment → writing fluency

H4a: Anxiety → writing complexity

H4b: Anxiety → writing accuracy

H4c: Anxiety → writing fluency

H5a: Emotion mediates task-specific enjoyment →performance relationship

H5b: Emotion mediates task-specific anxiety →performance relationship

H5c: Task-specific emotions ◊ Task-specific emotions ◊ written performance.

Total = 15 structural paths, which is typical for SEM studies in psychology journals.

Table 1
Hypothesized relationships

Hypothesis	Predictor Variable	Outcome Variable	Expected Direction	Theoretical Basis
H1a	Intrinsic Motivation	Writing Complexity	Positive	Self-determination theory
H1b	Intrinsic Motivation	Writing Accuracy	Positive	Self-determination theory
H1c	Intrinsic Motivation	Writing Fluency	Positive	Self-determination theory
H2a	Extrinsic Motivation	Writing Complexity	Positive / Weak	Motivational orientation research
H2b	Extrinsic Motivation	Writing Accuracy	Positive / Weak	Motivational orientation research
H2c	Extrinsic Motivation	Writing Fluency	Positive / Weak	Motivational orientation research
H3a	Enjoyment	Writing Complexity	Positive	Control-value theory of achievement emotions
H3b	Enjoyment	Writing Accuracy	Positive	Control-value theory
H3c	Enjoyment	Writing Fluency	Positive	Control-value theory
H4a	Anxiety	Writing Complexity	Negative	Cognitive interference theory
H4b	Anxiety	Writing Accuracy	Negative	Cognitive interference theory
H4c	Anxiety	Writing Fluency	Negative	Cognitive interference theory
H5a	Intrinsic Motivation	Enjoyment	Positive	Motivation-emotion linkage
H5b	Intrinsic Motivation	Anxiety	Negative	Motivation-emotion linkage

Table 1 summarizes the hypothesized relationships among motivational factors, task-specific emotions, and dimensions of written performance. Intrinsic motivation and enjoyment were expected to positively predict writing complexity, accuracy, and fluency, whereas anxiety was expected to negatively predict these outcomes. Comparatively weaker positive effects were hypothesized for extrinsic motivation. In addition, intrinsic motivation was expected to be positively associated with enjoyment and negatively associated with anxiety. Overall, the conceptual model proposes that intrinsic motivation and enjoyment

facilitate writing performance, whereas anxiety impairs it, with intrinsic motivation positively related to enjoyment and negatively related to anxiety.

3.2 Instruments

3.2.1. Motivation questionnaire

Intrinsic and extrinsic motivational orientations were measured using adapted items from established motivation scales based on self-determination theory.

3.2.2. Emotion questionnaire

Task-specific enjoyment and anxiety were measured immediately after the writing task using a short emotion scale adapted from previous foreign language emotion research.

3.2.3. Writing task

Participants completed a timed argumentative writing task lasting 30 minutes. The task required learners to express their opinion on a social topic and provide supporting arguments.

3.2.4. Writing performance measures

Writing performance was analysed using the CAF framework:

Complexity

Mean length of T-unit and clause density

Accuracy

Error-free T-units ratio

Fluency

Total number of words produced

3.2 Data collection procedure

3.3 *Data analysis*

Data were analysed using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4.0. The analysis followed a two-stage logic: assessment of the measurement model and assessment of the structural model. The measurement model was examined using indicator loadings, internal consistency, convergent validity, and discriminant validity. The structural model was assessed using variance inflation factors (VIF), path coefficients (β), bootstrap t statistics and p values, coefficients of determination (R^2), and effect sizes (f^2). A bootstrapping procedure with 3,000 resamples was used to evaluate the stability and statistical significance of the estimated paths. Because the study focuses on

latent motivational and emotional constructs and their relationships with writing-performance dimensions, PLS-SEM was used to estimate the measurement and structural relationships simultaneously.

4. Findings

4.1 Descriptive statistics

PLS-SEM was conducted using SmartPLS 4.0 to examine relationships among task motivation, task-specific emotions, and written-performance indicators. The initial sampling frame comprised 375 non-English-major learners from approximately 16 schools at Linyi University. The final analytic sample consisted of 117 learners because of access and data-collection constraints. A chi-square goodness-of-fit comparison indicated no statistically significant difference between the sample and the larger population in gender distribution, χ^2 (1) = 3.701, p = 0.054, φ = 0.178. This result provides limited evidence that the sample differed from the target population in gender composition, but it should not be interpreted as establishing full population representativeness.

Table 2
Gender distribution of participants

Gender	Population (N = 375)	Population Proportion (%)	Sample (n = 117)	Sample Proportion (%)	Expected Sample	(O − E) ²/E
Female	225	60.0	60	51.3	70.2	1.925
Male	150	40.0	57	48.7	46.8	1.776
Total	375	100	117	100	117.0	3.701

Table 2 compares the gender distribution of the 117 participants with that of the target population of 375 individuals. Females constituted 60.0% of the population but represented 51.3% of the sample, whereas males accounted for 40.0% of the population and 48.7% of the sample. Based on the population proportions, the expected frequencies were 70.2 females and 46.8 males, compared with the observed frequencies of 60 and 57, respectively. The chi-square goodness-of-fit test yielded χ^2 (1) = 3.701, p = 0.054, indicating that the difference between the observed sample distribution and the expected population distribution was not statistically significant at the 0.05 level. Thus, although the sample contained a slightly higher proportion of males and a lower proportion of females than expected, the gender distribution did not differ significantly from that of the target population.

4.2 Assessment of measurement model

In the second phase of the study, the measurement model (Fig. 2) was tested and different parameters were examined to assess its reliability and validity. Researchers used composite reliability as a demonstration of internal consistency, item reliability, and average variance extracted (AVE) to test

convergent validity. Further, the researchers carried out a discriminant validity analysis by using cross Loadings and Fornell-Larcker criteria in the same way as was done by [17]. Per the values given in Table 3, each variable had a composite reliability (CR) which ranged between 0. 788 and 0. 911 and due to this, thus, the threshold of 0. 7 has been fulfilled. This can also be considered as confirmation that the items measuring the constructs were not only consistent internally but more reliable. Factor loadings, CR, and AVE are three parameters which can be used to assess the overall performance of a measurement tool. The higher the factor loadings, the more reliable and valid the construct becomes. This is how [11, 17] interpreted the score. This can be seen from Table 5 that all component factor loadings were above the minimum cut-off value of 0. 5, which is in keeping with what is recommended by Hair et al.

In addition, the task-motivation construct recorded an AVE of .65. while the AVE values for the remaining constructs ranged from 0.674 to 0.725. Although task motivation had the lowest value, its AVE was still well above the recommended minimum of 0.50 for establishing convergent validity [17, 21].Therefore, all constructs explained an acceptable proportion of the variance in their respective indicators. Discriminant validity was subsequently assessed using the Fornell–Larcker criterion. As shown in Table 6, the square root of each construct's AVE was greater than its correlations with the other constructs, suggesting that the constructs were sufficiently distinct from one another. Taken together, these results support the convergent and discriminant validity of the measurement model and are consistent with the recommended assessment procedures outlined by ([17 35, 36]). When considered alongside satisfactory reliability coefficients, the findings also indicate that the measures used in this study were reliable.

Table 3
Measurement model reliability and convergent validity

Construct		Items	Loading	Cronbach Alpha	CR	AVE
Task Motivation	TM			0.89	0.888	0.725
Intrinsic motivation	IM1	• I completed this writing task because I found the essay interesting/ □□□□□□□□□□ □□□□□□□□□□□□ □□	0.795			
	IM2	• I completed this writing task because I found it enjoyable/ □□ □□□□□□□□□□□□□□□□□	0.873			
	IM3	• I completed this writing task because I enjoyed doing it/ □□□□□ □□□□□□, □□□□□□□□□□□□□□□□	0.884			
	ER			0.598	0.817	0.694
Extrinsic motivation	ER1	While writing this essay, I felt like time was passing very slowly / □□□□□□□□□, □□□□□□□□□□□□□□□□ □				
	ER2	• If I had a choice, I would not write this essay/ □□□□□□, □□□□□□□□□	0.938			
	ER3	• I completed this writing task because I found it enjoyable/ □□ □□□□□□□□□□□□□□□□□	0.714			
Task Specific Emotion	TSE			0.877	0.911	0.674
Enjoyment	TE1	• I enjoyed doing the writing task just now/ □□□□□□□□□□□□, □□□□□	0.814			
	TE2	• I felt a strong sense of accomplishment while writing this essay/ □□□□□□□□□□□□□□□□□□□□	0.891			
	TE3	• I experienced a sense of enjoyment while writing this essay/ □□□□□□□□□□□□, □□□□□□	0.887			
	TE4	• While writing this essay, I was completely immersed in the task/ □□□□□□□, □□□□□□□□□□□□	0.812			
	TE5	• I completed this writing task smoothly/ □□□□□□□□□□□□□□□	0.812			
Anxiety	TA1	While writing, I felt anxious because I was unable to				

Construct		Items	Loading	Cronbach Alpha	CR	AVE
		express my ideas clearly/ □□□□□, □□□□□□□□□□□□□□□□□□				
	TA2	I felt nervous while doing the writing task just now/ □□□□□□□□□□□, □□□□□				
	TA3	• While doing the writing task, I was constantly worried about making mistakes/ □□□□□□□□□□□, □□□□□□	0.928			
	TA4	• While doing the writing task, I felt frustrated because I could not think of how to express my ideas/ □□□□□□□□□□□, □□□□□□□□□□□□□□□	0.948			
	TA5	While doing the writing task, I was worried about getting a low score, and my heart was pounding/ □□□□□□□□□□□, □□□□□□□□□□□□□□				
Written Performance				0.462	0.788	0.650
Accuracy	AC	• Percentage of error-free T-units, Errors per 100 words	1,000			
Complexity	LE	• Lexical density, Lexical diversity, Lexical sophistication	1,000			
Fluency	FL	Words produced per minute	-			

Table 3 reports the measurement properties of task motivation, task-specific emotion, and written performance. The intrinsic-motivation items loaded strongly and consistently, with values ranging from 0.795 to 0.884. The construct also achieved satisfactory internal consistency and convergent validity (alpha = 0.809, CR = 0.888, AVE = 0.725). Extrinsic motivation met the criteria for composite reliability and convergent validity (CR = 0.817, AVE = 0.694), although its lower Cronbach's alpha (alpha = 0.598) calls for a more cautious interpretation of internal consistency.

Task-specific emotion also showed relatively strong construct-level reliability and convergent-validity indices (α = 0.877, CR = 0.911, AVE = 0.674). Written Performance likewise produced acceptable reported values for composite reliability (CR = 0.788) and average variance extracted (AVE = 0.650), but its Cronbach's alpha was comparatively low (alpha = 0.462). The dimensional structure of this construct therefore needs closer examination. Overall, the measurement evidence is more convincing for the motivation and emotion measures than for Written Performance. Conclusions about measurement quality should remain provisional until the missing item loadings and the inconsistencies between several displayed loadings and construct-level statistics have been resolved.

Table 4
Likert scale's value

Likert scale's value							
Scale Value	1	2	3	4	5	6	7
Response Option	Strongly Disagree	Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Agree	Strongly Agree

A seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree) was used to measure learners' task-specific motivation and emotions. This format is theoretically appropriate because motivation, enjoyment, and anxiety represent graded psychological constructs that may vary in intensity rather than occurring as binary states. The use of a seven-point response format is also consistent with recent EFL and L2 research measuring motivational and affective variables ([1, 4, 42, 48]). The wider response range therefore enabled greater differentiation in participants' motivational and emotional responses while retaining a neutral midpoint.

4.3 Reflective indicator loadings

The reflective indicator loadings across the four major components (with a total of 20 sub-variables) were determined through a PLS-SEM process. Almost every item in the variables satisfied the loading criterion (> 0. 708) that was suggested in the procedure [17]. However, five loadings (ER1 TA1 TA2 TA5 FL) were below the threshold of 0. 708 indicating the items with the least loading to be dropped from the model due to their low loadings. Overall, all of the rest of the items showed loading values that were above 0. 7 or at least very close to that number, and are considered a benchmark in literature [11, 17]).

4.4 Internal consistency reliability

Furthermore, internal consistency reliability was assessed to determine how consistently the items within each construct measured the same underlying concept. Following the recommendations of [17], both Cronbach's alpha (CA) and composite reliability (CR) were reported. Cronbach's alpha estimates item consistency under the assumption that all items contribute equally to a construct, whereas composite reliability accounts for differences in their outer loadings. Values of 0.70 or above are generally considered acceptable for both measures [17]. As presented in Table 3, CA values ranged from 0.462 to 0.809, while CR values ranged from 0.788 to 0.911. All constructs therefore met the recommended threshold for composite reliability. However, because at least one CA value fell below 0.7. the internal consistency of that construct should be interpreted cautiously and examined further rather than described as uniformly acceptable.

4.5 Convergent and discriminant terms validity

Following the recommendation by [15], this current research has employed an analytical model of convergent and discriminant validity checkers. Convergent validity can be measured through the correlation between items having the same dimension and it also identifies the average variance

extraction (AVE). [17] the recommended value should be above 0. 50. indicating that fifty per cent or more of the variance in a variable item is extracted. That is, if it reveals an item with high convergent validity [17]. Task Motivation (0. 725), Task Specific Emotion (0. 674), and Written Performance (0. 650) are among three constructs that were obtained with AVE scores above 0. 500. It is advised that each item has outer loadings > 0. 70 for convergent validity [17]) thereby all constructs are verified through this method.

Table 5
Variance inflation factors

AC	VIF
	1,099
LE	1,099
ER2	1,222
ER3	1,222
IM1	1,487
IM2	2,083
IM3	2,177
TA3	2,386
TA4	2,386
TE1	2,085
TE2	3,225
TE3	3,050
TE4	1,978
TE5	1,446

The measurement-model assessment is presented in Table 3. Retained indicator loadings were generally above 0.7. and the reported composite reliability (0.788–0.911) and AVE (0.650–0.725) values exceeded commonly applied criteria for composite reliability and convergent validity. However, Cronbach's alpha was below 0.70 for Extrinsic Motivation (α = .598) and Written Performance (α = 0.462), indicating that internal consistency was not uniformly supported across the measures.

Collinearity diagnostics are presented in Table 5. The VIF values fell between 1.099 and 3.225. TE2 (3.225) and TE3 (3.050) were slightly above the conservative cut-off of 3, although every value remained below 5.

On another note, discriminant validity was assessed to determine whether the constructs in the model represented empirically distinct concepts. [17]. describe discriminant validity as the extent to which a construct differs from other constructs within a structural model. In the present study, it was evaluated using three complementary procedures, namely; the Fornell–Larcker criterion, indicator cross-loadings, and the heterotrait–monotrait ratio of correlations (HTMT). For the Fornell–Larcker assessment, the square root of the average variance extracted (AVE) for each construct was compared with its correlations with the other constructs.

As reported in Table 3, the square root of the AVE for each construct exceeded its correlations with the remaining constructs. The results therefore satisfied the Fornell–Larcker criterion. The cross-loading analysis provided further support for discriminant validity. More specifically, each indicator loaded more strongly on its intended construct than on any other construct in the model. The bold values presented in Table 3 illustrate this pattern, indicating that the constructs were adequately differentiated.

Furthermore, discriminant validity was also examined using the HTMT criterion. Values above the recommended threshold of 0.90 may indicate that two constructs are not sufficiently distinct [17, 21, 38]). As shown in Table 5 in Appendix S1, all HTMT values were below 0.90. Taken together, the Fornell–Larcker, cross-loading, and HTMT results provide support for the discriminant validity of the measurement model.

4.6 Model of structure

The first step in structural model development was the collinearity study and next the path coefficients (β), t and p values were utilized to show the links of structural variables. Hair et al. [17] stated, among other indices, R (the coefficient of determination) and effect size (f) were all considered and discussed at the structural level.

4.6.1 Collinearity

The idea is that collinearity should be used to find out and determine the set of predictors. VIF (variance inflation factor) greater than 5 indicates that predictor variables are collinear. On the contrary, it means that collinearity cannot be considered a significant issue if VIF is lower than 5 [17, 38].

[17] point out that when VIF is > 5 it would be a problem; when it is between 3 and 5 problems do not arise usually, but when it is less than 3 collinearity is negligible. In this study, Written Performance Intention has two predictors: AC and LE (VIF = 1. 099). The six predictors (ER2 ER3 IM1, IM2 and IM3) of Task Motivation Intention (VIF = 1. 222, 1. 222, 1. 487, 2. 083, and 2. 177) have VIF less than 7. Task-Specific Emotion Intention is explained by eight variables (TA3 TA4 TE1, TE2, TE3, 4 and 5) (VIF = 2. 386, 2. 386, 2. 085, 3. 225, 3. 05. 1. 978 1. 446). Plainly all of the VIF values are much less than 5 (Table 3). Due to this, the main conclusion is that collinearity is not a matter of concern here since all VIF values are way below five. [17].

4.6.2 Structural model relationship

A bootstrapping procedure using 3,000 resamples was conducted to estimate the significance of the structural paths. The strongest substantively relevant relationship was between task motivation and task-specific emotion (β = 0.719, t = 16.281, p < 0.001). Task motivation was also negatively associated with extrinsic motivation (β = −.429, t = 4.888, p < 0.001) and significantly associated with intrinsic motivation (β = 1.000, t = 590.010, p < .001), although these higher-order measurement relationships should not be interpreted as substantive causal effects. Task-specific emotion was negatively associated with task anxiety (β = −0.220, t = 2.480, p = 0.013), but it did not significantly predict written performance (β = 0.073, t = 0.683, p = 0.495). The reported indirect effects on writing outcomes were also nonsignificant. The table labels for nonsignificant paths and higher-order statistics were reconciled where the reported p values clearly required correction; remaining higher-order statistics should be checked against the final SmartPLS output.

4.6.3 Coefficient of determination (R2)

Concerning the coefficient of determination, R Square (R2) was used in this study not only to compare the models' explanatory power but also the degree of prediction they offer [17]. It quantifies the amount of variation in the response variable that can be explained or predicted by the independent variables. The coefficient of determination (R2) indicates how much variance in an endogenous construct is explained by the model. Its value generally ranges from 0 to 1, with higher values reflecting greater explanatory power. [17] suggest that (R2) values of approximately 0.75, 0.5. and 0.25 may be interpreted as substantial, moderate, and weak, respectively. As shown in Table 6, the model demonstrated weak explanatory power for emotional regulation (ER), imagination (IM), technology acceptance (TA), and written performance. By contrast, accuracy, complexity, and task-specific emotion showed moderate levels of explained variance. Task-specific emotion recorded the highest (R2) value at 0.668, indicating that the model accounted for 66.8% of the variance in this construct. Under the stated thresholds, this represents moderate but not substantial with explanatory power.

Table 6
Coefficients of determination

Accuracy	**R-square**	**Deliberation**
	0.668	**moderate**
Complexity	0.655	moderate
ER	0.184	weak
IM	1,000	Verify model specification
TA	0.049	weak
TE	1,000	Verify model specification
Task Specific Emotion	0.517	moderate
Written Performance	0.005	weak

As shown in Table 6, the reported model explained 66.8% of the variance in accuracy (R^2 = .668), 65.5% in complexity (R^2 =0 .655), and 51.7% in task-specific emotion (R^2 = 0.517). The explained variance was lower for extrinsic motivation (R^2 = .184), task anxiety (R^2 = 0.049), and written performance (R^2 = 0.005). The R^2 values of 1.000 reported for intrinsic motivation and task enjoyment should be verified against the final SmartPLS model because such values may reflect the specification of higher-order constructs rather than meaningful explanatory power. Accordingly, these values are not interpreted as evidence that the model fully explains intrinsic motivation or enjoyment.

4.6.4 Effect sizes (f^2) for structural model relationships

The effect sizes (f) are indicators of how strongly a driver variable or the factor variable affects the dependent variable F2 compares how R2 is affected when a variable is excluded from the model. This is executed, thus, the real impact of the regressor on the target could be found through using the cutoffs for effect sizes (e. g. small: 0.02. moderate: 0.15. large: 0. 350) [17]. Table 7 presents the f effect sizes the results of f-based effect size analysis indicates that ER IM TA, and TE were of little consequence in accuracy and complexity (f = 0.00. 0.019). Apart from that, Task Motivation turned out having a moderate effect about Emotional Regulation (f = 0.225) and This way practically contributing to explaining ER.

Table 7
f² effect sizes

ER -> Accuracy	***Effect size (f²)***	**Effect-size magnitude**
	0.000	**Negligible**
ER -> Complexity	0.000	Negligible
IM -> Accuracy	0.001	Negligible
IM -> Complexity	0.001	Negligible
TA -> Accuracy	0.000	Negligible
TA -> Complexity	0.000	Negligible
TE -> Accuracy	0.019	Negligible
TE -> Complexity	0.019	Negligible
Task Motivation -> ER	0.225	Medium
Task Motivation -> IM	0.054	Small
Task Motivation -> Task Specific Emotion	10.70	Large
Task Specific Emotion -> TA	0.051	Negligible
Task Specific Emotion -> TE	0.374	Large
Task Specific Emotion -> Written Performance	0.05	Negligible
Written Performance -> Accuracy	1.851	Large
Written Performance -> Complexity	1.810	Large

Table 7 presents the f^2 effect sizes for the relationships examined in the structural model. Task motivation showed a large effect on task-specific emotion (f^2 = 1.070), whereas the effect of task-specific emotion on written performance was negligible (f^2 = 0.005). The direct effects of extrinsic motivation, intrinsic motivation, task anxiety, and task enjoyment on accuracy and complexity were also negligible, with f^2 values ranging from 0.000 to 0.019. Several large values associated with relationships between the higher-order constructs and their dimensions were observed; however, these relationships were treated as higher-order measurement relations rather than as substantive structural effects.

Final Hypothesis Structure (SEM Model)

Total hypotheses in the model:

H1a: Intrinsic motivation → writing complexity

H1b: Intrinsic motivation → writing accuracy

H1c: Intrinsic motivation → writing fluency

H2a: Extrinsic motivation → writing complexity

H2b: Extrinsic motivation → writing accuracy

H2c: Extrinsic motivation → writing fluency

H3a: Enjoyment → writing complexity

H3b: Enjoyment → writing accuracy

H3c: Enjoyment → writing fluency

H4a: Anxiety → writing complexity

H4b: Anxiety → writing accuracy

H4c: Anxiety → writing fluency

H5a: Emotion mediates task-specific enjoyment →performance relationship

H5b: Emotion mediates task-specific anxiety →performance relationship

H5c: Task-specific emotions ◊ Task-specific emotions ◊ written performance

Table 8
Structural-model path coefficients

Hypotheses	Path	*β*	SD *[δ]*	T statistics (|O/STDEV|)	*P* values	Justification
H1:	Intrinsic motivation (IM) to writing complexity (LE)	0.027	0.080	0.332	0.740	Not significant
	Intrinsic motivation (IM) to writing accuracy (Ac)	-0.026	0.078	0.332	0.740	Not significant
H2:	ER -> Ac	-0.002	0.062	00.027	0.979	Not significant
	ER -> LE	0.002	0.064	00.026	0.979	Not significant
H3:	TE -> Ac	0.119	0.085	1,397	0.163	Not significant
	TE -> Le	-0.121	0.088	1,368	0.171	Not significant
H4:	TA -> Ac	-0.010	0.061	0.171	0.864	Not significant
	TA -> Le	0.011	0.063	0.170	0.865	Not significant
	TM -> ER	-0.429	0.088	4,888	0.000	Significant
	TM -> IM	1,000	0.000	590.010	0.000	Significant
	TM -> TSE	0.719	0.044	16,281	0.000	Significant
	TSE -> TA	-0.220	0.089	2,480	0.013	Significant
	TSE -> TE	1,000	0.000	18821,637	0.000	Significant
	TSE -> WP	0.073	0.106	0.683	0.495	Not significant
	WP -> Ac	0.803	0.028	28,529	0.000	Significant
	WP -> Le	0.810	0.049	16,582	0.000	Significant
H5:	TM -> TSE -> W -> Ac	0.042	0.062	0.676	0.499	Not Significant
	TM -> TSE -> WP -> Le	0.042	0.062	0.677	0.498	Not Significant

As shown in Table 8, intrinsic motivation did not significantly predict writing complexity (β = 0.027, *t* = 0.332, *p* = 0.740) or accuracy (β = −0.026, *t* = 0.332, *p* = 0.740). Similarly, extrinsic motivation was

unrelated to accuracy (β = −0.002, *t* = 0.027, *p* = 0.979) and complexity (β = 0.002, *t* = 0.026, *p* = 0.979). Task enjoyment also showed no significant association with accuracy (β = 0.119, *t* = 1.397, *p* = 0.163) or complexity (β = −0.121, *t* = 1.368, *p* = 0.171), while task anxiety was not significantly related to either accuracy (β = −0.01. *t* = 0.171, *p* = 0.864) or complexity (β = 0.011, *t* = 0.17. *p* = 0.865). At the higher-order level, task motivation was positively associated with task-specific emotion (β = 0.719, *t* = 16.281, *p* < 0.001), whereas task-specific emotion did not significantly predict written performance (β = 0.073, *t* = 0.683, *p* = 0.495). The indirect effects of task motivation on accuracy (β = 0.042, *p* = 0.499) and complexity (β = 0.042, *p* = 0.498) through task-specific emotion and written performance were also nonsignificant. Overall, the hypothesized direct and indirect effects of motivation and task-specific emotions on writing accuracy and complexity were not supported.

5. Discussion

5.1 Intrinsic motivation and written performance

The results provide no evidence that intrinsic motivation significantly predicted writing complexity (β = 0.027, t = 0.332, p = 0.740) or accuracy (β = −0.026, t = 0.332, p = 0.740). Although intrinsic task motivation is theoretically relevant to engagement, it was not associated with measurable differences in the immediate linguistic features assessed here. One possible explanation is that motivation works through engagement, strategic behaviors, self-regulation, or emotional experience before any change becomes visible in the quality of a written text. The finding is compatible with contemporary views of motivation as context-sensitive and embedded within broader cognitive and instructional systems [2]. It also accords with the possibility that motivation affects writing indirectly through engagement, strategy use, self-regulation, or emotional processes rather than through an immediate change in objective textual quality. Abdi Tabari and Goetze similarly demonstrate that affective and self-efficacy variables interact with task conditions in L2 written production, suggesting that psychological effects cannot be separated from the characteristics of the writing task [1].

From an Education 5.0 perspective, this finding cautions against policy approaches that assume increasing learner motivation alone will produce better writing. Future-oriented writing policy should instead create environments in which motivation is supported by explicit strategy instruction, feedback, opportunities for revision, and technology-mediated scaffolding. Recent AI-mediated writing research likewise indicates that motivation is intertwined with writing self-efficacy and AI literacy rather than operating independently [30].

Methodological differences may further explain why the present results diverge from some earlier studies. Much of the existing literature has examined overall language achievement or relied on learners' self-reported writing ability. By contrast, this study used objective, task-based measures of writing accuracy and complexity. The findings therefore do not necessarily challenge motivational theory. Instead, they suggest that intrinsic motivation alone offers only a partial explanation of immediate EFL writing performance. High-quality writing is more likely to emerge from the combined influence of

motivation, achievement emotions, cognitive engagement, linguistic competence, and contextual support. Future research should consequently examine possible mediation and moderation mechanisms involving writing self-efficacy, self-regulated learning, and instructional feedback.

5.2 Extrinsic motivation and written performance

Contrary to the predictions made in H2a and H2b, extrinsic motivation was not significantly associated with either writing accuracy (β = 0.002, p = 0.979) or vocabulary richness (β = 0.002, p = 0.979). H2c could not be tested because the data required to estimate writing fluency were unavailable. Extrinsic motivation was unrelated to writing accuracy (beta = -0.002, t = 0.027, p = 0.979) and complexity (beta = 0.002, t = 0.026, p = 0.979); the final model did not test the path to fluency. With coefficients so close to zero, external incentives accounted for virtually none of the variation in the two observed writing outcomes. This result should not be read as evidence that extrinsic motivation is harmful. It indicates instead that an external reason for completing the task, such as a grade or certificate, was not enough to produce an immediate improvement in linguistic quality when proficiency, strategic knowledge, and task conditions were unchanged. Self-determination theory offers a useful explanation. External demands are more likely to sustain engagement when learners internalize them and connect them with goals and values they personally endorse [37].

External incentives may prompt learners to participate, but completing a task does not necessarily engage the lexical, grammatical, and organizational processes needed for effective writing. These processes are more likely to develop when learners also feel competent, have some autonomy, and see value in the learning opportunity. Control-value theory likewise suggests that motivational appraisals can shape achievement through emotion, cognitive engagement, and self-regulation. Shao et al. [8], for example, found that achievement emotions mediated the relationship between motivational appraisals and foreign-language achievement. Emotion may therefore be one route through which motivation influences performance, even when motivation has no direct effect of its own and the conditions remain unchanged.

This distinction matters for EFL writing policy in technology-enhanced settings. Digital platforms and AI tools can speed up parts of the writing process and provide immediate feedback, yet greater tool use or more completed tasks should not be mistaken for deeper learning. Research on GenAI-supported collaborative prewriting found improvements in aspects of the writing process without a statistically significant change in overall task motivation [26]. Policies governing such tools should therefore require opportunities for learner choice, reflection, revision, and responsible use alongside access to the technology itself.

A nonsignificant direct relationship does not make extrinsic motivation irrelevant to EFL writing. Writing places several demands on learners at the same time, including retrieving words, planning sentences, organizing ideas across a text, and monitoring what they have written. A learner may therefore be strongly motivated by grades or other external outcomes yet remain unable to produce an accurate and lexically sophisticated text without sufficient language knowledge and effective writing strategies. [8]

similarly argue that extrinsic motivation may contribute more effectively to language learning when it is accompanied by autonomy, perceived competence, and meaningful engagement. Motivation is also dynamic: it develops through learners' interactions with their environment and through their perceptions of task value, control, and available learning opportunities [31].

The absence of a direct effect also reinforces the importance of teacher mediation. In AI-mediated EFL writing, teacher support, motivation, and emotional experiences remain connected to learners' engagement with feedback [46]. An Education 5.0 approach should therefore position teachers as designers and interpreters of technology-enhanced writing experiences rather than as passive users of automated tools.

Moreover, differences in measurement may help explain why these findings depart from some previous research. The difference between the present findings and earlier research may partly reflect how performance was measured. Many previous studies have examined general language achievement or asked learners to rate their own ability. This study instead used direct measures of vocabulary richness and grammatical accuracy from a completed text. These indicators show what learners produced on a specific task and are closely tied to the lexical and grammatical knowledge they brought to it. They offer a direct view of performance, but a single text cannot represent how the same learners would write across different topics, genres, or settings.

The present study results also need to be interpreted within the limits of the measurement design and the task. The analysis drew on a single timed writing task and did not include planning, revision, uptake of feedback, or development across an extended period. The nonsignificant direct effects observed here should therefore not be extended to every form of writing motivation or to longer-term growth in writing.

On balance, extrinsic motivation by itself explained little of the difference in learners' EFL writing performance. What learners produced was likely shaped by a combination of motivational orientation, achievement emotions, autonomy, language competence, self-regulation, instructional support, and features of the task. Further studies could test how writing self-efficacy, emotional experience, feedback quality, and autonomy-supportive teaching alter or carry the influence of extrinsic motivation. This would help establish the circumstances in which external motives contribute to EFL writing development.

5.3 Task enjoyment and written performance

Task enjoyment was not significantly associated with writing complexity ($\beta = -0.121$, $t = 1.368$, $p = 0.171$) or accuracy ($\beta = 0.119$, $t = 1.397$, $p = 0.163$), and the enjoyment–fluency relationship was not tested in the final model. These results indicate that experiencing a writing task as enjoyable did not, by itself, produce measurable improvements in the immediate linguistic features examined. This does not invalidate the broader role of positive emotion. [33] updated control-value theory emphasises that achievement emotions operate through multiple interacting cognitive and motivational mechanisms rather than through a universal direct effect on performance.

For one thing the finding does clash with what we expected from positive psychology and control-value theory (CVT) since they both have it that positive feelings result in cognitive engagement effort creativity, academic performance etc. [33]. However, looks like the impact of enjoyment on writing performance is a matter of indirect influence rather than of a very direct effect. The main idea here is that CVT describes an enjoyable situation that stimulates learning as an engagement in cognitive processes and self-regulated learning besides an effective combination of different learning strategies that ultimately impact the success but not the immediate improvement in the performance. Because of this, it is conceivable that the learners writing with a sense of pleasure probably put greater effort into their writing and stayed engaged longer but the actual level of good writing was still determined by whether they had the knowledge of grammar, vocabulary use, strategic knowledge, and the cognitive resources to do lexical retrieval, syntactic planning, discourse organisation, and self-monitoring effectively, and largely. This distinction is consistent with [25], whose learners perceived a sustained online discussion environment as supporting participation, confidence, and linguistic development; [25]; their study examined a collaborative learning context rather than the immediate predictive effect of enjoyment on CAF measures.

One explanation is that enjoyment may facilitate engagement or persistence without immediately changing the linguistic resources available for a single writing product. Recent 2026 evidence similarly shows that writing enjoyment can function as a mediator within broader motivational systems, rather than necessarily acting as a simple direct predictor of writing achievement [10, 29]. The present null effect may therefore reflect the short-term and task-specific nature of the assessment rather than the absence of any educational value of enjoyment.

Our result differs from and also adds to previous research. Based on one of the cited studies, Dewaele and Li [12] showed the positive effect of language learning enjoyment on learner engagement motivation resilience, and overall language achievement has been well established in the literature. Another meta-analysis [8] also supported the positive relationship between enjoyment and language learners' outcomes, regardless of the learning context. Though, in both of these studies, authors mainly focused on general outcome measures, classroom engagement, or long-term achievements, instead of writing complexity and accuracy as objective writing indicators. This means that the present results agree Mainly with the new directions of the control-value theory, which highlights that achievement emotions affect performance mainly through the mediator of cognitive engagement and self-regulated learning not through direct performance improvement [33], Likewise, [40].

Task characteristics may also matter. Topic familiarity, task complexity, time pressure, proficiency, and assessment conditions can constrain the extent to which positive affect is converted into observable textual gains [1] findings on task complexity, anxiety, and self-efficacy reinforce this contextual interpretation. Technology-enhanced writing environments can change these task conditions by supporting planning, delivering feedback, and creating opportunities to revise. Such support still requires deliberate pedagogical design; its presence alone does not guarantee better writing.

5.4 Task-specific anxiety and written performance

Task-specific anxiety did not significantly predict writing complexity (β = 0.011, t = 0.170, p = 0.865) or accuracy (β = −0.010, t = 0.171, p = 0.864), and the anxiety–fluency relationship was not tested. The nonsignificant results indicate that anxiety did not directly account for the objective writing outcomes measured in this study. Anxiety should therefore be interpreted in relation to the conditions under which it occurs rather than treated as an inhibitor with the same effect in every situation. This reading is consistent with current control-value theory, which links emotional effects to perceived control and value, task demands, available cognitive resources, and learners' ability to regulate their responses [33]. Abdi Tabari and Goetze similarly show that the relationship between anxiety and L2 written production changes across task conditions [1].

The nonsignificant mediation paths suggest that enjoyment and anxiety were not the main processes through which motivational orientations influenced writing achievement in this sample. As the present study did not confirm the results of the previous researches in which emotions were shown to explain the relation of motivation and language accomplishment [40] it still seems acceptable from a theoretical viewpoint that both Control-Value Theory and Self-Determination Theory see motivation as mainly leading to achievement via several interdependent processes - autonomous engagement, self-regulation, strategic learning and cognitive engagement rather than only emotions [2, 37, 33]. That means, the absence of the path from emotion to achievement does not imply that emotion is unimportant but indicates that the researchers have probably missed some variables like writing self-efficacy, metacognitive regulation, strategy use, or task effort etc). Additionally, methodological factors may have played a role in the current study’s results being different from those of previous studies. Whereas much of the past literatures have looked at language learning achievement in general or simply self-reported competence and grades, this study was based on the use of two objective linguistic features, vocabulary variety and grammatical accuracy, obtained in the same writing task. These features are so strictly tied up with a learner’s current state of language skills that temporary motivational or emotional fluctuation hardly ever affects them. Besides, by not including writing speed and only taking into account two indicators of writing the study could have resulted in poor construct reliability and weak structural paths.

The result is also relevant to technology-enhanced writing policy because digital environments can both reduce and intensify anxiety. Immediate feedback and opportunities for revision may reduce uncertainty, whereas unfamiliar tools, surveillance, algorithmic evaluation, or fear of incorrect AI use may introduce new forms of anxiety. Recent research on AI-mediated writing confirms that learners’ affective responses remain important even when feedback is technologically delivered [46]. Policy should therefore require clear guidance, psychological safety, transparent assessment practices, and teacher support when digital writing technologies are introduced.

The absence of significant anxiety effects should not be interpreted as evidence that emotional support is unnecessary. Instead, it indicates that anxiety alone was insufficient to explain the immediate writing outcomes in this sample. Future models should examine anxiety together with writing self-efficacy, metacognitive regulation, strategy use, task effort, and proficiency, preferably across multiple writing tasks and over time.

Despite Hypotheses H5a-b, bootstrapped indirect effects did not differ from zero. This lack of significant indirect effects implies that task-specific emotions did not explain the link from motivational orientations to EFL writing performance. The two indirect paths involving intrinsic motivation to EFL writing accuracy (through task emotions) (β = 0.042, t = 0. 676, p = 0.499) and the one path involving EFL writing performance (β = 0.042, t = 0.673, p = 0.498) were negligible. This outcome seems to indicate that neither motivation-based fun nor anxiety could act as the connecting factor between motivation and writing complexity or accuracy levels. These observations contradict the predictions of CVT but they do not go against the theory's main assumption that motivational states largely impact the achievement mainly via the intermediary of cognitively based engagement/ learning activities / achievement-emotions and less directly via the pathway of, e. g. direct influence [33]. Rather, these findings suggest that in this particular situation the emotional processes alone could not sufficiently support the objective writing performance. One possible reason for this is that writing an essay in the learners' second language involves, in great measure, linguistic skills, knowledge of strategy use, as well as cognitive resources like the retrieval of vocabulary items, the grammatical encoding of words, the organisation of discourse, and the revision of the writing. Thus, short-lived emotions like fun and anxiety might not have any major impact on the immediate assessment of lexical complexity and grammatical accuracy.

5.5 The mediating role of task-specific emotions

The proposed indirect effects were nonsignificant. The indirect paths involving task motivation, task-specific emotion, and writing outcomes were not different from zero (β = 0.042, p = 0.499/.498). Thus, the present evidence does not support the claim that enjoyment or anxiety mediated the relationship between task motivation and the writing outcomes examined. These results refine rather than simply reject control-value and self-determination perspectives: motivational and emotional processes may be important without constituting sufficient mechanisms for explaining immediate objective writing quality.

A plausible explanation is that objective writing performance depends strongly on linguistic knowledge, cognitive resources, strategic competence, and self-regulation. Short-lived emotional states may influence engagement while leaving insufficient time to alter the underlying linguistic resources expressed in a single timed essay. Recent research increasingly supports models in which writing motivation and emotion interact with self-efficacy, self-regulated learning, teacher support, and technology-mediated processes rather than operating as isolated predictors [10, 26, 29, 30].

This finding has a direct policy implication for Education 5.0. Evidence-informed EFL writing policy should avoid a simple chain such as technology ◊ motivation ◊ emotion ◊ better writing. A more defensible model is technology-enhanced environment ◊ pedagogical design and teacher mediation ◊ learner agency and self-regulation ◊ motivation and emotional experience ◊ writing development. The present study provides empirical evidence for cautioning against overly linear accounts of this process.

5.6 Implications for evidence-informed EFL writing policy in Education 5.0

Finally, policy should be evidence-informed and iterative. Rather than prescribing a single technology or a universal model of AI-supported writing, institutions should monitor learning outcomes, learner experiences, equity, digital access, teacher workload, academic integrity, and unintended affective consequences. This approach positions Education 5.0 as a framework for responsible educational transformation: technology is valuable when it strengthens human learning, learner agency, and equitable educational opportunity.

A second policy priority is affective and motivational design. The present null findings show that motivation and emotion should not be treated as guaranteed predictors of immediate writing quality, but they remain relevant conditions of participation and learning. Writing curricula should therefore combine motivational support with explicit instruction in planning, drafting, revision, self-regulation, feedback use, and linguistic development. Technology should amplify these processes rather than replace them. Evidence from AI-supported self-evaluation and computer-peer-feedback environments suggests that structured digital support can contribute to motivation, emotion regulation, and writing engagement when integrated with pedagogy [3, 22].

The combined evidence from the present study and recent technology-enhanced writing research supports a policy shift from technology adoption to technology-pedagogy alignment. In Education 5.0, digital writing tools should be selected and implemented according to clearly defined learning purposes: supporting idea generation, planning, feedback, revision, self-evaluation, collaboration, or reflection. Policies should specify the learner's responsibility for final textual decisions, require transparent disclosure where appropriate, and protect opportunities for learners to demonstrate independent writing competence. These principles are consistent with recent evidence that AI literacy, writing self-efficacy, teacher affective support, and learner motivation jointly shape engagement in AI-mediated writing [30, 46].

Table 9
Hypothesis-testing summary

Hypothesis	Statistical Results (β, 95% CI, p)	Interpretation	Prior Findings (cite)	Suggested Discussion Wording
H1a (IM to Complexity)	β = 0.027, 95% CI [–0.15. .204], p = 0.740 (ns)	No effect: intrinsic motivation did not increase writing complexity.	Contrasts Gao [who found motivation to lexical complexity. Other studies predict positive effects of intrinsic value.	"Intrinsic motivation was unrelated to complexity (β ≈ 0.03, p > 0.70), indicating no support for H1a. This null effect contradicts some prior findings of motivation boosting complexity."
H1b (IM to Accuracy)	β=–0.026, 95% CI [–0.179, 0.127], p = 0.740 (ns)	No effect: intrinsic motivation did not affect accuracy.	Previous work (e.g., Gao reported motivation → accuracy effects, but some (Li) found none.	"Intrinsic motivation was not significantly associated with accuracy (β≈–0.03, p = 0.740). This lack of association aligns with Li but contrasts with Gao et al. who observed a positive link."
H1c (IM to Fluency)	(Not tested)	Fluency was not analysed due to model; no data.	No available in current model.	"Writing fluency was not included in the final SEM path; thus, H1c cannot be evaluated in this model. Future research should examine whether intrinsic motivation predicts fluency."
H2a (ER to Complexity)	β = 0.002, 95% CI [–0.121, 0.125], p = 0.979 (ns)	No effect: extrinsic motivation did not affect complexity.	Li found extrinsic value predicted performance; our result contrasts that.	"Extrinsic motivation showed no relation to complexity (β ≈ 0.002, p ≈ 0.98). This null finding differs from Li, who reported a modest positive effect of

Hypothesis	Statistical Results (β, 95% CI, p)	Interpretation	Prior Findings (cite)	Suggested Discussion Wording
				extrinsic value on performance."
H2b (ER to Accuracy)	β=−0.002, 95% CI [−0.122, 0.118], p = 0.979 (ns)	No effect: extrinsic motivation did not affect accuracy.	Few prior studies link extrinsic motives to writing accuracy; results vary.	"Extrinsic motivation was unrelated to accuracy (β≈−0.002, p > 0.97), indicating H2b is unsupported. This suggests external incentives alone did not influence writing accuracy in our sample."
H2c (ER to Fluency)	(Not tested)	Fluency path not available.	N/A	"Fluency outcome was omitted in analysis; no test for ER → fluency was performed."
H3a (Enjoyment to Complexity)	β=−.0121, 95% CI [−0.287, 0.045], p = 0.171 (ns)	No effect: enjoyment did not increase complexity.	Meta-analyses find enjoyment *positively* correlates with L2 achievement.	"Task enjoyment did not significantly predict complexity (β≈−0.12, p ≈ 0.17). This null effect contrasts with meta-analytic evidence linking enjoyment to higher L2 achievement."
H3b (Enjoyment to Accuracy)	β = .119, 95% CI [−0.05. 0.288], p = 0.163 (ns)	No effect: enjoyment did not improve accuracy.	Prior studies (Wu and Halim [report positive effects of enjoyment on writing outcomes.	"Enjoyment was not significantly associated with accuracy (β ≈ 0.12, p ≈ 0.16). Despite theories suggesting enjoyment boosts performance, our data show no direct benefit on accuracy."
H3c	(Not tested)	No fluency data.	N/A	"Writing fluency was not analysed for

Hypothesis	Statistical Results (β, 95% CI, p)	Interpretation	Prior Findings (cite)	Suggested Discussion Wording
(Enjoyment to Fluency)				enjoyment effects in this model."
H4a (Anxiety to Complexity)	β=–0.01. 95% CI [–0.10. 0.080], p = 0.864 (ns)	No effect: anxiety did not reduce complexity.	Meta-analyses report anxiety *negatively* correlates with L2 achievement.	"Task anxiety showed no significant effect on complexity (β≈–0.01, p ≈ 0.86). This contradicts findings of a negative link between anxiety and performance."
H4b (Anxiety to Accuracy)	β = 0.011, 95% CI [–0.079, 0.101], p = 0.865 (ns)	No effect: anxiety did not reduce accuracy.	Previous work (e.g., Gao [found anxiety impaired accuracy.	"Anxiety was uncorrelated with accuracy (β ≈ 0.01, p≈.86). Contrary to expectations and past reports, we observed no detrimental effect of anxiety on writing accuracy."
H4c (Anxiety to Fluency)	(Not tested)	No fluency data.	N/A	"Writing fluency was not assessed for anxiety effects in this study."
H5a (IM to Enjoyment to Accuracy)	Indirect β ≈ 0.042, p ≈ 0.499 (ns)	No mediation via enjoyment for accuracy.	Control-value theory suggests enjoyment often mediates motivation–performance, but evidence is limited.	"The indirect path via enjoyment was non-significant (p ≈ 0.50), indicating no mediation. This suggests enjoyment did not carry any effect of intrinsic motivation to accuracy."
H5b (IM to Anxiety to Accuracy)	Indirect β ≈ 0.042, p ≈ 0.498 (ns)	No mediation via anxiety for accuracy.	In Li, anxiety mediated some motivation effects.	"The indirect path via anxiety was non-significant (p ≈ 0.50). Thus, anxiety did not

Hypothesis	Statistical Results (β, 95% CI, p)	Interpretation	Prior Findings (cite)	Suggested Discussion Wording
				mediate the relationship between intrinsic motivation and writing accuracy."
H5a (IM to Enjoyment to Fluency)	(Fluency not modelled)	Not applicable.	–	"We did not model fluency outcomes, so mediation for fluency cannot be assessed."
H5b (IM to Anxiety to Fluency)	(Fluency not modelled)	Not applicable.	–	"Fluency outcomes were not included; mediation to fluency is not evaluated."

Table 9 summarizes the hypothesis-testing results for the structural model. Intrinsic motivation was not significantly associated with writing complexity (β = 0.027, *t* = 0.332, *p* = 0 .740) or accuracy (β = −0.026, *t* = 0.332, *p* = 0.740). Similarly, extrinsic motivation did not significantly predict complexity (β = 0.002, *t* = 0.026, *p* = 0.979) or accuracy (β = −0.002, *t* = 0.027, *p* = 0.979). Task enjoyment was not significantly related to complexity (β = −.121, *t* = 1.368, *p* = 0.171) or accuracy (β = 0.119, *t* = 1.397, *p* = 0.163). After reconciliation with the path-coefficient output, task anxiety likewise showed no significant association with complexity (β = 0.011, *t* = 0.17. *p* = 0.865) or accuracy (β = −0.01. *t* = 0.171, *p* = 0.864). The corresponding 95% confidence intervals included zero, providing no evidence of significant direct effects on either writing outcome. Thus, H1a–H4b were not supported. The hypotheses concerning writing fluency were not tested because fluency was not included in the final model. The proposed indirect effects reported under H5 were also nonsignificant; however, the specific mediation paths and their bootstrap statistics should be verified against the SmartPLS specific-indirect-effects output before these findings are reported in the final manuscript.

6. Conclusion

This study examined whether intrinsic and extrinsic task motivation and task-specific enjoyment and anxiety predicted the immediate written performance of Chinese EFL learners. Contrary to the original expectations, none of these motivational or emotional variables significantly predicted writing complexity or accuracy in the final structural model, and the proposed indirect effects were nonsignificant. Task motivation was strongly associated with task-specific emotion, but task-specific emotion did not significantly predict written performance. These results indicate that motivation and

emotion should not be treated as sufficient stand-alone explanations of immediate objective writing quality.

The findings contribute to Education 5.0 oriented EFL writing policy by highlighting the need to connect psychological factors with the wider conditions in which writing occurs. Technology-enhanced writing environments can support feedback, collaboration, planning, self-evaluation, and personalized assistance. Recent studies nevertheless show that these benefits depend on how teachers mediate the technology, how well learners understand AI, the agency and self-efficacy learners bring to the task, and the quality of the pedagogical design [22, 26, 30, 46]. Evidence-informed policy should therefore look beyond the adoption of new tools. It should support the writing process as a whole, including learners' motivation, emotional well-being, capacity for self-regulation, digital literacy, and understanding of assessment integrity.

The study also identifies clear limits to its findings. A cross-sectional design, data from one institution, reliance on one timed writing task, and the incomplete treatment of fluency restrict both causal interpretation and generalization. Future work would benefit from following learners over time and examining their performance across several tasks. Models should also include writing self-efficacy and self-regulated learning, and test how motivation and emotion operate alongside AI literacy, teacher support, feedback, and task conditions. The present evidence thus supports a measured revision of EFL writing policy in Education 5.0. Technology is most useful as a pedagogical resource within a human-centered system, while motivation and emotion are better understood as parts of writing development than as independent predictors of textual quality.

Limitations and Future Research

The study has several limitations. Its cross-sectional design does not permit causal conclusions, and participants came from only one institution, limiting the extent to which the findings can be applied to other Chinese EFL populations. Performance was assessed through a single timed task, which may not reflect development over time or differences across genres and task conditions. Fluency was also absent from the final structural model, so the analysis did not cover the complete CAF framework. In addition, the reported statistics for some higher-order constructs, including R-squared values of 1.000, should be checked against the final SmartPLS output before submission. Later studies can address these concerns through longitudinal, multi-task, and multi-site designs that incorporate a wider range of cognitive, affective, and technology-related mechanisms.

Declarations

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Author contributions

W.X. conceived the study, drafted and wrote the manuscript, and prepared the tables and figures. S.J.B. contributed to the review process and was involved in data assessment and analysis. M.J.J. contributed to review and edit the manuscript and provided language proofreading. All authors critically reviewed the manuscript and approved the final version for publication.

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Competing interest

The authors declare no competing financial interests

Ethics approval

This study was reviewed and approved by the School of Languages, Civilisation and Philosophy Research Evaluation Panel, Universiti Utara Malaysia (UUMCAS/SLCP/PD2), which serves as the institutional review body for non-interventional social science research. The study was conducted in accordance with the institutional research ethics and governance procedures of Universiti Utara Malaysia, and all procedures involving human participants followed the relevant ethical guidelines and regulations.

Consent to Participate

We have clarified that the participants were aged 19–21 years and added a statement confirming that all participants provided informed consent electronically before taking part in the study. We have also specified that participation was voluntary and that participants were free to withdraw at any time without penalty. In addition, we have clarified that all procedures involving human participants were conducted in accordance with the relevant institutional guidelines and regulations.

Consent to publish

Not applicable

Declaration of Generative AI and AI-assisted technologies in the writing process

ChatGPT was used solely to assist with language editing. The authors reviewed and revised all AI-assisted text and accept full responsibility for the final manuscript.

Clinical Trial Number

Not applicable

Data availability

The datasets generated and/or analysed during this study are not publicly available due to ethical and privacy considerations. However, they can be obtained from the corresponding author upon reasonable request.

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Figures

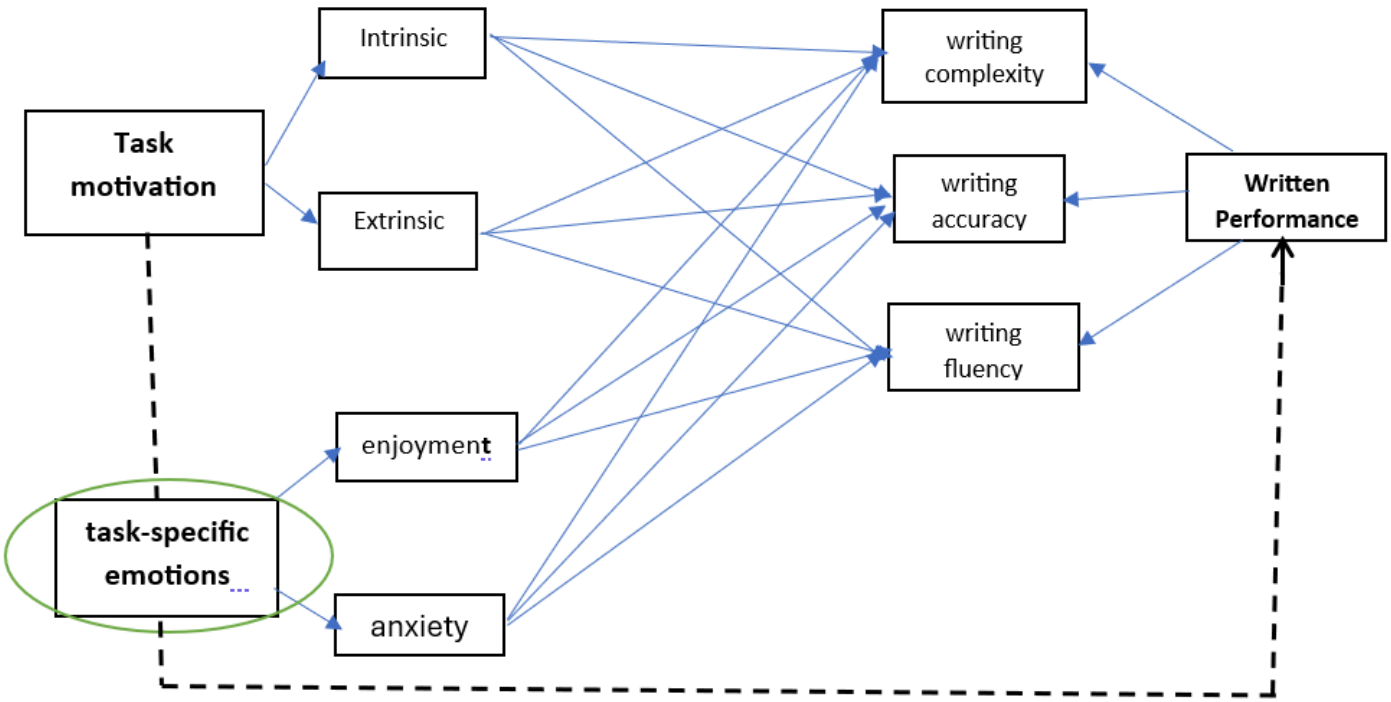

Figure 1

A conceptual SEM model diagram

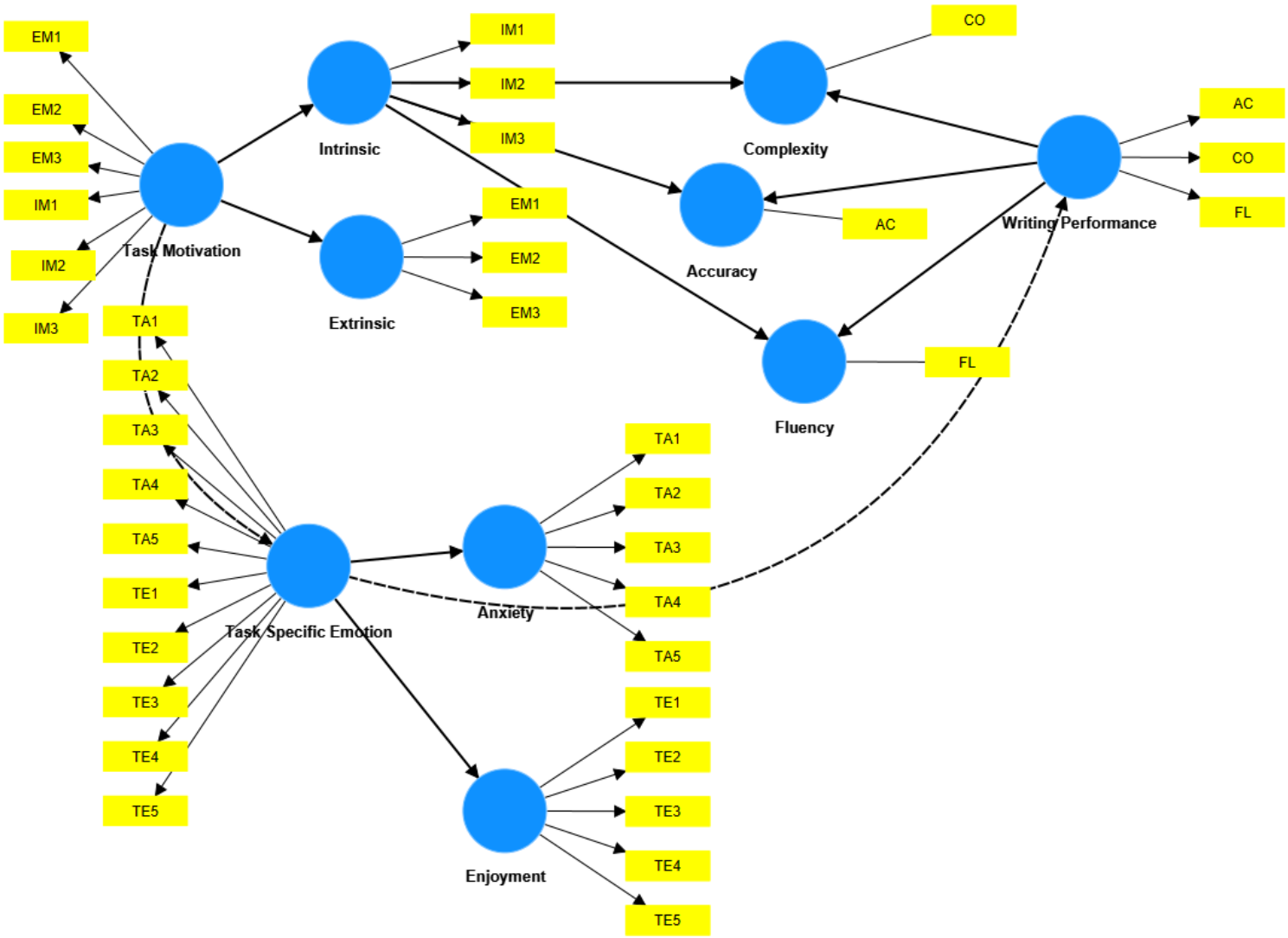

Figure 2

A conceptual SEM model

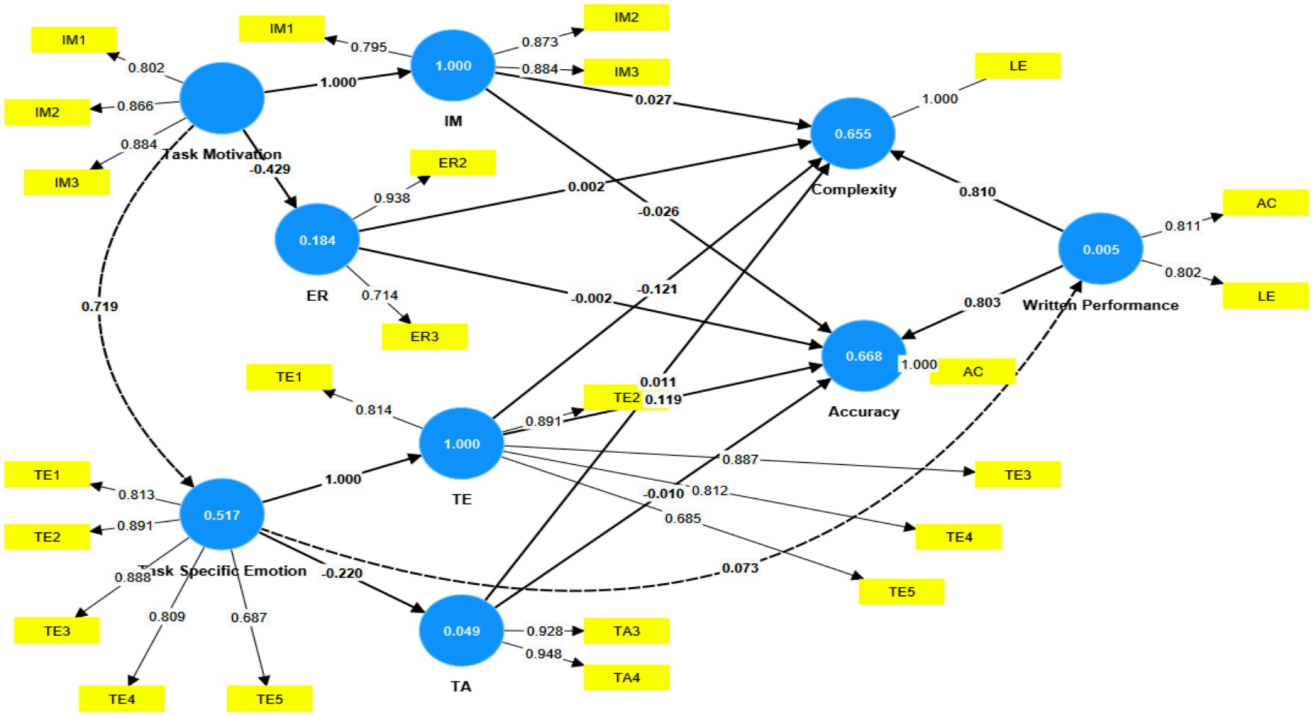

Figure 3

Structural model

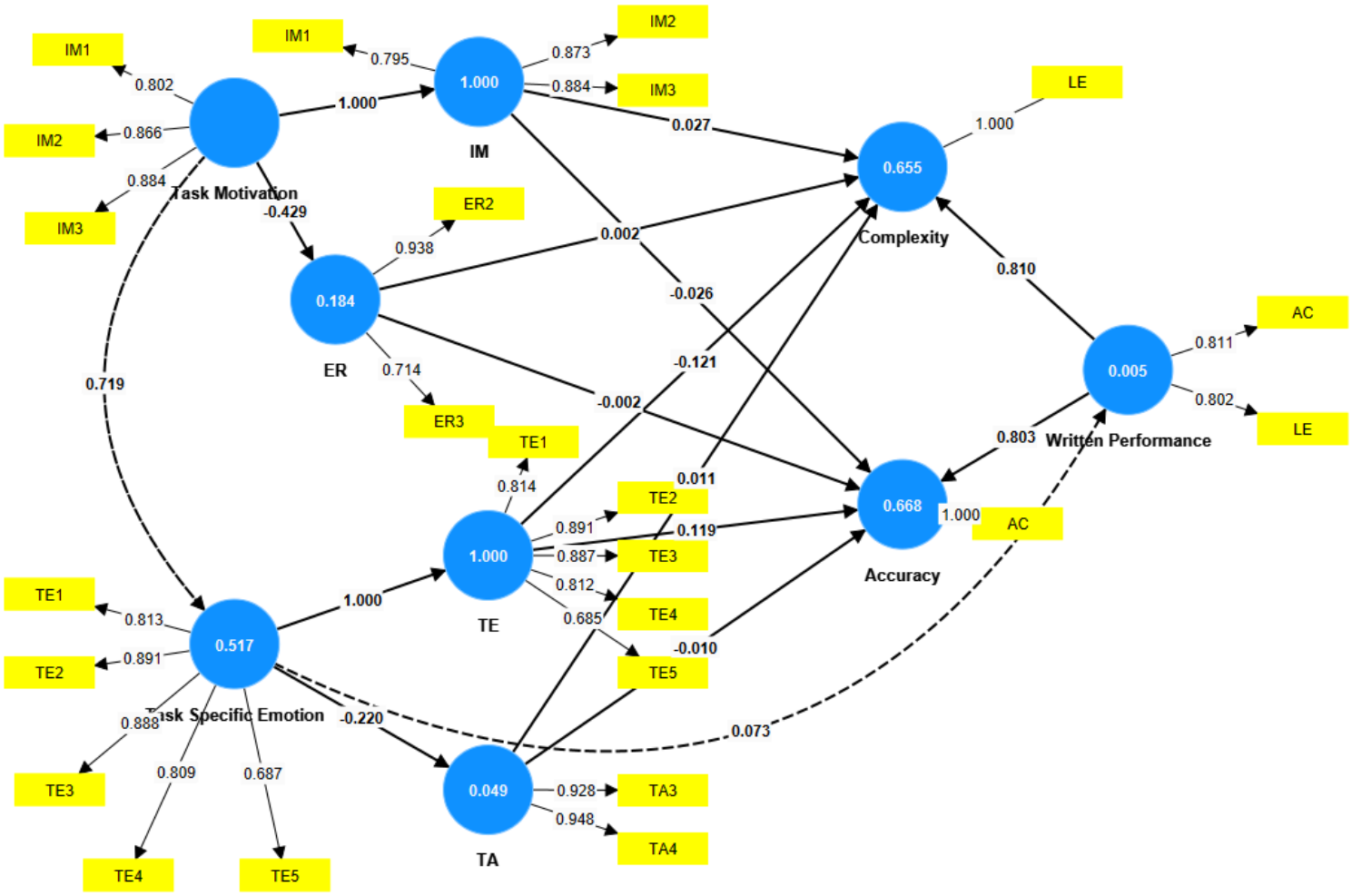

Figure 4

Bootstrapping

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- 1.InstrumentQuesionnaire.doc
- 2.Wangdata117excelsheet.csv
- Dataabbreviation.docx