Humanitas: Indonesian Psychological Journal
Vol. 23 (1), February 2026, 31-51
ISSN: 2598-6368(online); 1693-7236(print)

Understanding Career Maturity in Adolescents: Examining the Predictive Model of Social Intelligence and Self-Efficacy

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ARTICLE INFO

Article history
Received: 8 May 2025
Revised: 26 December 2026
Accepted: 28 December 2026

Keywords
Adolescents
Career maturity
Predictive model
Social intelligence
Self-efficacy

ABSTRACT

This study aims to examine the predictive roles of social intelligence and self-efficacy in adolescents' career maturity. The participants were 89 adolescents in Makassar City, ranging from secondary to higher education levels, selected through purposive random sampling. Data were collected using standardised measures of social intelligence, self-efficacy, and career maturity. Multiple hierarchical regression analysis using the R programming language was conducted to test the hypothesised model. The results revealed that self-efficacy significantly predicted career maturity, while social intelligence contributed indirectly by enhancing self-efficacy, which in turn supported adolescents' career development. These findings emphasise that strengthening self-belief through mastery experiences and positive reinforcement plays a more crucial role in shaping career maturity, whereas social intelligence facilitates interpersonal understanding and adaptive social interactions that indirectly foster self-efficacy. The study suggests that interventions combining self-efficacy enhancement with social intelligence training could be an effective strategy to support adolescents in achieving their career goals. Although the sample size was relatively modest, a supplementary Monte Carlo simulation demonstrated sufficient statistical power and model sensitivity to support the robustness of these findings.

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Introduction

Senior high school students are in late adolescence, typically ranging in age from 15 to 19 years (Das et al., 2017), a developmental period characterized by increased self-exploration and preparation for future roles. During this stage, adolescents face a critical task of preparing for their future careers, which is essential for a successful transition to adulthood and the labor market (Cheung, 2024; Wang et al., 2022). Similarly, university students, representing the next phase of development from high school, are in a crucial stage of acquiring the competencies needed for employment. Higher education plays a central role in developing skills demanded by the twenty-first-century workplace, such as communication, problem-solving, collaboration, and critical thinking (Damodar et al., 2024; Ni et al., 2023). These findings highlight the importance of promoting career maturity among adolescents in both

ISSN 2598-6368 (online) / ISSN 1693-7236 (print)

secondary and higher education contexts to ensure smoother educational and occupational transitions.

Career maturity refers to an individual's readiness to make age-appropriate and effective career decisions, encompassing both the ability to plan and to pursue long-term career goals (Jianchao et al., 2022; Savickas & Porfeli, 2011). This construct includes attitudinal dimensions (e.g., career planning, exploration) and cognitive dimensions (e.g., decision-making skills, understanding of labor market information). High levels of career maturity are theoretically associated with adaptive decision-making, greater confidence in career choices, and stronger goal commitment, whereas low career maturity can lead to indecision, anxiety, and difficulty adapting to career-related challenges (Damodar et al., 2024; Ni et al., 2023). Within Super's theory of vocational development, career maturity represents a developmental achievement that reflects one's ability to respond effectively to career-related tasks at different life stages (Cheung, 2024). Understanding these dynamics is therefore critical for designing interventions that foster both social and personal competencies to enhance adolescents' career readiness.

According to Super's developmental stages, the career development process for adolescents aged 15–24 falls within the exploration stage, in which individuals begin to consider multiple occupational alternatives without making permanent commitments. This stage involves exploratory behaviors that promote self-awareness, the identification of work values and interests, and an understanding of vocational abilities and opportunities (Godoi et al., 2024; Savickas & Porfeli, 2011). However, not all adolescents or university students exhibit the same level of confidence in making career decisions. Many report feelings of uncertainty and low career decision-making self-efficacy (Pang et al., 2021; Ulas & Yildirim, 2019), suggesting the need to examine factors that contribute to career maturity.

National data from the Central Statistics Agency (BPS) show that the number of unemployed university graduates in Indonesia reached 7,86 million out of a total workforce of 147,71 million (Frisnoiry et al., 2024). This high level of graduate unemployment undermines the quality of human resources, reduces global competitiveness, and hinders economic growth. Moreover, limited employability among graduates is associated with broader social challenges, including underemployment, labor mobility pressures, and dissatisfaction during the school-to-work transition, where psychological competencies play a critical role (Chen et al., 2025). Enhancing adolescents' career maturity—particularly through psychological and social factors—may therefore contribute to improving career readiness and reducing graduate unemployment.

Among these factors, self-efficacy plays a pivotal role. Self-efficacy refers to an individual's belief in their capacity to organize and execute the actions required to achieve specific goals (Bandura, 1997). It influences how people think, feel, and behave when facing challenges. Empirical evidence has consistently shown that students with higher self-efficacy display more proactive career behaviors, such as career exploration, goal setting, and decision-making (Bubić et al., 2015; Chang et al., 2024). In contrast, low self-efficacy often results in career indecision and avoidance behaviors (Liu et al., 2023; Rahim et al., 2021). Studies further demonstrate that self-efficacy contributes significantly to career maturity by fostering confidence and perseverance in career planning (Hamzah et al., 2021; Liu et al., 2023).

Another psychological factor that supports career development is social intelligence. Social intelligence refers to the ability to understand and manage oneself and others in social contexts (Ivashkevych & Yatsjuryk, 2019; Smutchak et al., 2024). Empirical research conceptualizes social intelligence as a set of socio-cognitive competencies related to interpersonal understanding, social awareness, and adaptive behavior, which play an important role in self-regulation and effective social functioning (Kurmanova et al., 2024). These skills enable adolescents to communicate effectively, resolve interpersonal conflicts, and adapt to different social environments—all of which are essential in career decision-making and transition processes (Kodama, 2021; Smutchak et al., 2024).

Research suggests that adolescents with higher levels of social intelligence tend to exhibit greater career maturity because they are better able to engage in constructive social interactions and obtain information relevant to career planning (Aydogmus, 2019; Liu et al., 2014). However, empirical studies examining the simultaneous influence of social intelligence and self-efficacy on career maturity—particularly among adolescents in educational settings—remain scarce. Most prior research has been conducted in industrial or workplace contexts. Nevertheless, the understanding of how these psychological and social factors jointly contribute to adolescents' career development remains limited.

Despite growing attention to adolescents' career development, several research gaps remain unaddressed. Empirically, most existing studies have examined either self-efficacy or social intelligence in isolation, without integrating both variables into a single predictive model of career maturity (e.g., Aydogmus, 2019; Hamzah et al., 2021). This leaves unclear how interpersonal competencies interact with personal beliefs to shape adolescents' readiness for career decision-making. Theoretically, previous studies have emphasized cognitive or motivational aspects of career maturity but have not sufficiently incorporated social-cognitive mechanisms that may explain how social understanding enhances self-efficacy and, consequently, career readiness (Bandura, 1997; Savickas & Porfeli, 2011). Methodologically, much of the prior research has relied on correlational approaches or structural equation modeling without testing the hierarchical contributions of predictors using robust inferential procedures such as multiple hierarchical regression or simulation-based power analysis. In terms of population, most prior evidence has been derived from Western or industrial samples, limiting generalizability to adolescents within collectivist and developing cultural contexts such as Indonesia.

Addressing these gaps, the novelty of the present study lies in developing and testing a predictive model that integrates social intelligence and self-efficacy to explain career maturity among adolescents in both secondary and higher education levels. The study's state of the art contribution is the combination of advanced statistical validation using the R programming language and a supplementary Monte Carlo simulation to confirm model sensitivity and power—an analytical rigor rarely employed in this domain. The urgency of this investigation is reinforced by the increasing youth unemployment rate and the mismatch between educational attainment and workforce readiness in Indonesia (Frisnoiry et al., 2024), underscoring the need for empirically validated psychological models that inform effective career guidance and intervention strategies. Therefore, this study aims to examine the predictive roles of social intelligence and self-efficacy in shaping adolescents' career maturity across secondary and higher education levels.

Method

Research Design

This study employed a quantitative cross-sectional design to examine the predictive roles of social intelligence and self-efficacy in explaining career maturity among adolescents. The cross-sectional approach was selected because it allows data to be collected at a single point in time to identify patterns and associations among variables efficiently. This design is suitable for understanding how individual differences in psychological factors contribute to career maturity without requiring longitudinal observation, thus providing an empirical snapshot of adolescents' developmental readiness in career decision-making.

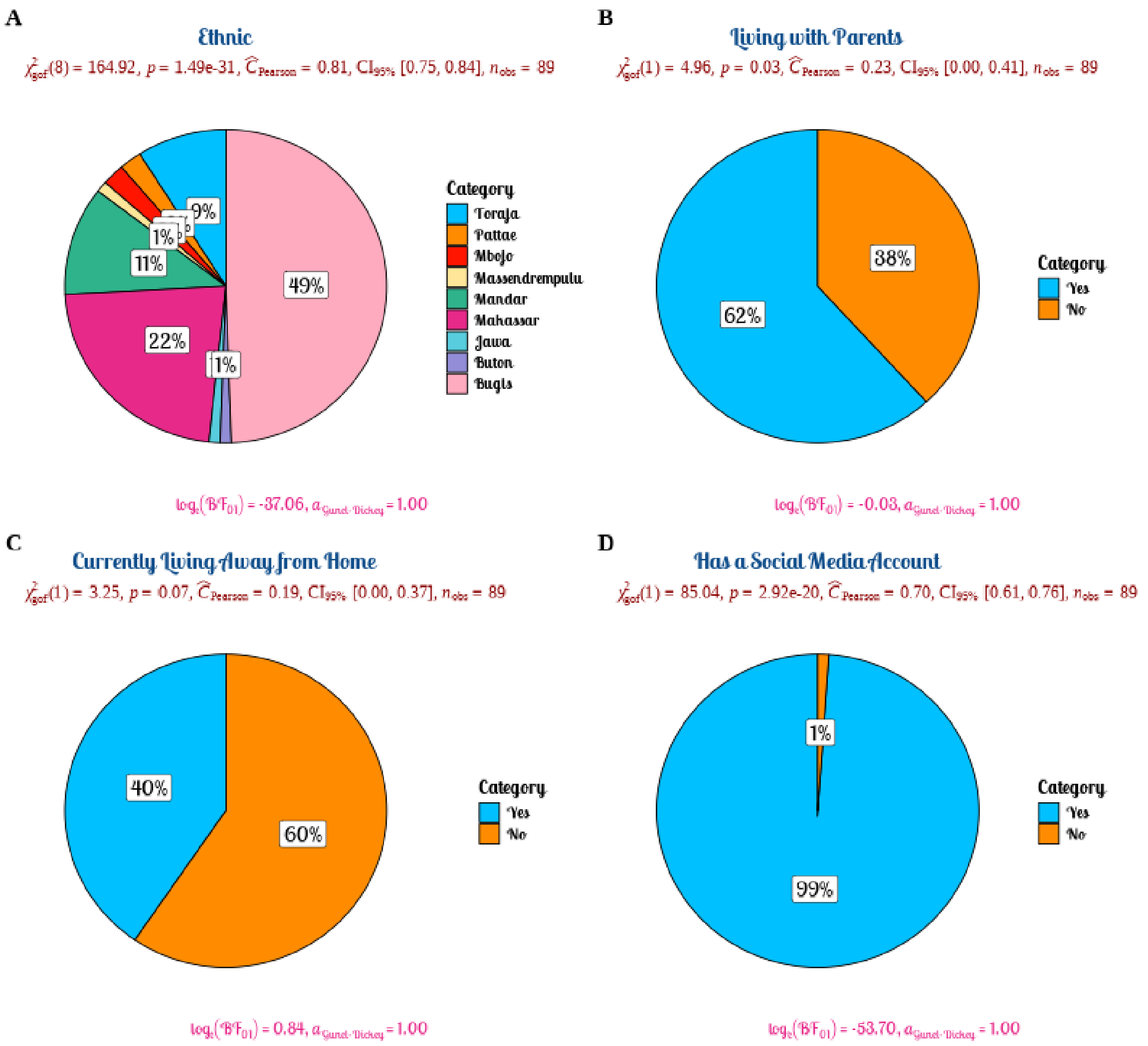
Participants

During the study design phase, no previous research employing similar measurement instruments was identified; therefore, an a priori power analysis was not conducted. Instead, after participant recruitment was completed, a sensitivity power analysis was performed using

ISSN 2598-6368 (online) / ISSN 1693-7236 (print)

the *pwrss* package (Bulus, 2023). Based on calculations with an effect size of $f^2 = 0.15$ ($k = 2$, $\alpha = 0.05$, $\beta = 0.20$, and power = 0.80; Faul et al., 2009), the minimum sample size required to detect this effect was 58 participants. A total of 89 adolescents participated in this study, recruited through a convenience sampling technique. Participants' mean age was 18.58 years ($SD = 3.14$), ranging from 12 to 23 years. The majority of participants were undergraduate students (62%, $n = 56$) and identified as Bugis ethnicity (49%, $n = 44$). Most participants lived with their parents (62%, $n = 55$), were not currently living away from home (60%, $n = 53$), and nearly all reported having social media accounts (99%, $n = 88$), as illustrated in Figure 1.

Figure 1
Socio-Demographic Characteristics of Participants



Instruments

All instruments were originally developed in English and subsequently translated into Bahasa Indonesia by two independent bilingual researchers. Following the International Test Commission (ITC, 2018) guidelines, a systematic translation and cultural adaptation process was implemented to ensure conceptual equivalence and cultural appropriateness for Indonesian adolescents. To further confirm content validity, Aiken's V index (Aiken, 1985) was employed. Three subject-matter experts evaluated the relevance of each item, and all items achieved Aiken's V values above 0.92, indicating strong content validity. Each scale was administered using a 5-point Likert format (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, to 5 = Strongly Agree). Furthermore, the psychometric properties of all instruments were empirically evaluated (Furr, 2022) in accordance with the Standards for Educational and Psychological Testing (AERA, APA, & NCME, 2014) using confirmatory factor analysis (CFA) with the maximum likelihood mean-adjusted (MLM) estimator. Conventional model fit indices were applied to evaluate the empirical models (see Kline, 2023; Wang & Wang, 2020). Internal consistency reliability was assessed using McDonald's omega coefficient (Viladrich et al., 2017) and Cronbach's alpha (Taber, 2018). The analysis was conducted on a pilot-testing sample of 89 adolescents from Makassar City, Indonesia.

Social Intelligence was measured using the original 25-item social intelligence scale for adolescents, developed by Jamil (2017) based on Albrecht's theoretical framework (Albrecht, 2009). Following confirmatory factor analysis (CFA), a final set of 14 items was retained, forming a five-correlated factor model that demonstrated good fit to the data (S-Bχ^2 = 73.90, df = 67, p = 0.26; RMSEA = 0.03 [0.00–0.07], p-close = 0.72; SRMR = 0.07; CFI = 0.95; TLI = 0.93). All retained items were psychometrically valid, as indicated by positive and statistically significant factor loadings (λ = 0.47–0.84, $p < 0.05$). The scale also exhibited adequate internal consistency (α = 0.81; ω = 0.82), with item-total correlations ranging from 0.21 to 0.66.

Self-efficacy was measured using the original 24-item of self-efficacy scale developed by Siregar (2018) based on Bandura's theory (Bandura, 1997). Following confirmatory factor analysis (CFA), a final set of 9 items was retained, forming a second-order model that demonstrated good fit to the data (S-Bχ^2 = 26.30, df = 24, p = 0.34; RMSEA = 0.03 [0.00–0.09], p-close = 0.63; SRMR = 0.05; CFI = 0.99; TLI = 0.99), with positive and statistically significant factor loadings (λ = 0.33–0.87, $p < 0.05$), indicating that all retained items were valid. The scale also showed adequate internal consistency (α = 0.87; ω = 0.88), with item-total correlations ranging from 0.32 to 0.72.

Career maturity was measured using the original 54-item career maturity scale developed by Novianti (2012), based on Sciarra's theory (Sciarra, 2004). Following confirmatory factor analysis (CFA), a final set of 20 items was retained, forming a second-order model that demonstrated good fit to the data (S-Bχ^2 = 187, df = 166, p = 0.13; RMSEA = 0.04 [0.00–0.06], p-close = 0.81; SRMR = 0.07; CFI = 0.96; TLI = 0.95). All retained items showed positive and statistically significant factor loadings (λ = 0.41–0.81, $p < 0.05$), indicating that all final items were valid. The scale also exhibited adequate internal consistency (α = 0.92; ω = 0.92), with item-total correlations ranging from 0.37 to 0.73.

Data Analysis

Descriptive and Correlation Analysis. This study began with a descriptive analysis to illustrate the characteristics of the participants and the main study variables. Subsequently, statistical assumptions were examined, including tests of normality and multicollinearity (Appelbaum et al., 2018; Dancey & Reidy, 2020). Following Dormann et al. (2013), we considered a correlation threshold of $|r| \geq 0.70$ as an indicator of when collinearity might begin to distort estimates and predictions. This criterion was applied to screen bivariate correlations among predictors for potential multicollinearity in the multiple regression analysis. In addition, multicollinearity diagnostics in regression referred to the Variance Inflation Factor (VIF; Field, 2024). Finally, Pearson correlation analysis was conducted to determine whether there were significant relationships among the variables (Dancey & Reidy, 2020).

Hierarchical Multiple Regression Analysis. Subsequently, hierarchical multiple regression analysis was performed to examine the predictive effects of social intelligence and self-efficacy on career maturity and to test the research hypotheses. In Step 1**,** social intelligence was entered as the first independent variable. In Step 2, self-efficacy was added as a second independent variable to assess its unique contribution while controlling for social intelligence. To ensure stable and interpretable results, separate Ordinary Least Squares (OLS) regression models were estimated for each step.

Sensitivity Analyses. To assess the robustness of the estimated associations to potential omitted variable bias, three complementary sensitivity analyses were performed using the same sample (N = 89) and the fully adjusted regression model predicting career maturity from social intelligence and self-efficacy.

Coefficient Stability Analysis. The first analysis employed the coefficient stability approach based on the framework proposed by Oster (2019) and extended by Okamoto dan Oshio (2025). This method compares a "short" model (career maturity ~ social intelligence) with a "long" model (career maturity ~ social intelligence + self-efficacy) to evaluate the potential influence of unobserved confounders on the estimated coefficient. Two key statistics were computed: (i) δ_{zero}, representing the degree of selection on unobservables (relative to observables) required to reduce the focal coefficient to zero, and (ii) $\beta^*(\delta = 1)$, the coefficient estimate under equal selection on observed and unobserved factors. The benchmark value $R_{max} = 1.3 \times R^2_{long}$ was adopted to reflect the maximum plausible model fit achievable if unobservables were included. Larger δ_{zero} values indicate that stronger unobserved selection would be necessary to nullify the observed effect, implying greater robustness. Conversely, smaller δ_{zero} values ($\delta < 1$) suggest high susceptibility to omitted variable bias. The adjusted coefficient $\beta^*(\delta = 1)$ provides insight into the potential attenuation of the observed association when moderate unobserved confounding is assumed.

Partial R²-Based Sensitivity Analysis. The second analysis utilized the partial R^2-based sensitivity framework developed by Cinelli & Hazlett (2020). This method quantifies the minimum strength of an unobserved confounder—expressed as its partial R^2 with both the exposure and the outcome—required to (a) fully explain away the observed point estimate (robustness value, RV, $q = 1$), and (b) render the effect statistically indistinguishable from zero at a two-tailed $\alpha = 0.05$. Analyses were conducted in R (version 4.4.3) using the *sensemakr* package (Cinelli et al., 2024). The output includes both numerical robustness statistics and contour plots visualizing how varying confounding strengths affect the estimated coefficient. Smaller robustness values (RV < 0.05) indicate that even weak unobserved confounders could overturn the observed effect, while higher values suggest greater resilience to omitted variable bias. No external benchmark confounders were specified, as the focus was to evaluate the intrinsic sensitivity of the model itself.

Monte Carlo Simulation-Based Sensitivity Analysis. The third analysis implemented a Monte Carlo simulation to assess the stability and accuracy of the regression coefficients across repeated random sampling from the empirical data, while also strengthening the overall validity of the predictive model (Daud et al., 2024, 2025; Nurhidaya et al., 2025). This procedure was particularly important given the modest sample size (N < 100), allowing the robustness of the model to be evaluated under large-scale simulated population assumptions. A synthetic population of N = 1,000,000 observations was generated, and 2,000 iterations were conducted. In each iteration, a random sample of 200 observations was drawn, and the regression model predicting career maturity from social intelligence and self-efficacy was re-estimated. The simulation produced two key metrics: (i) root mean square error (RMSE), reflecting estimation accuracy, and (ii) bias, representing the average deviation between simulated and empirical estimates. Accordingly, this simulation-based sensitivity analysis was applied to evaluate the stability and reliability of the regression model derived from the empirical data, providing a complementary assessment of its statistical robustness and predictive validity.

Power Analyses. To further assess the adequacy of the sample size and the ability of the model to detect true effects, a Monte Carlo simulation was conducted to evaluate statistical power, following established guidelines from previous studies (Donnelly et al., 2022; Muthen & Muthen, 1998-2019). The procedure adopted the model population approach set to theoretical values (Theoretical Simulation – Generalized/Idealized) with moderate effects ($\beta \approx 0.4–0.5$; Cohen, 1988). The simulated population ranged from $N = 50$ to 2,500 with 10,000 replications per condition, and analyses were performed using Mplus version 8.3 (Muthen & Muthen, 1998-2019). Simulation outcomes were evaluated using the criteria of power > 0.80 (Cohen, 1988) and Mean Squared Error (MSE; Muthén & Muthén, 2002).

Statistical Methods. All statistical tests were conducted using a two-tailed criterion, with the significance level set at $\alpha = 0.05$ to account for the modest sample size ($N = 89$). This decision is consistent with previous observations that the interpretation of p-values is influenced by sample size (Bakan, 1966; Nunnally, 1960). Statistical analyses and visualizations were conducted using the R programming language (version 4.4.3; R Core Team, 2025) through RStudio (version 2024.12.1+563; RStudio Team, 2025). Several library packages were utilized, including *readxl* (Wickham, Bryan, et al., 2023) for importing Excel datasets, *jmv* (Selker et al., 2023) for descriptive and inferential analyses, *lmtest* (Hothorn et al., 2022) for supporting regression testing, and *ggplot2* (Wickham, Chang, et al., 2023) for data visualization. Additional packages were also employed, and further details can be obtained upon request from the authors.

Procedures

Prior to data collection, informed consent was obtained from all participants. They were clearly informed about the study's objectives, voluntary participation, confidentiality of responses, and their right to withdraw at any time without penalty. After providing consent, participants completed a standardized online questionnaire assessing social intelligence, self-efficacy, and career maturity. The survey began with sociodemographic items, followed by the main scales, and the overall completion time was approximately 30 minutes.

Results

Table 1

Statistical Information and Relationship between Main Variables

Variable	Mean	Std. Deviation	Skewness	Kurtosis	1	2	3
1. Social Intelligence	53.58	7.69	-1.23	2.91	–		
2. Self-Efficacy	36.31	5.16	-0.15	-0.89	0.21*	–	
3. Career Maturity	76.04	12.43	-0.13	-0.07	0.15	0.73***	–

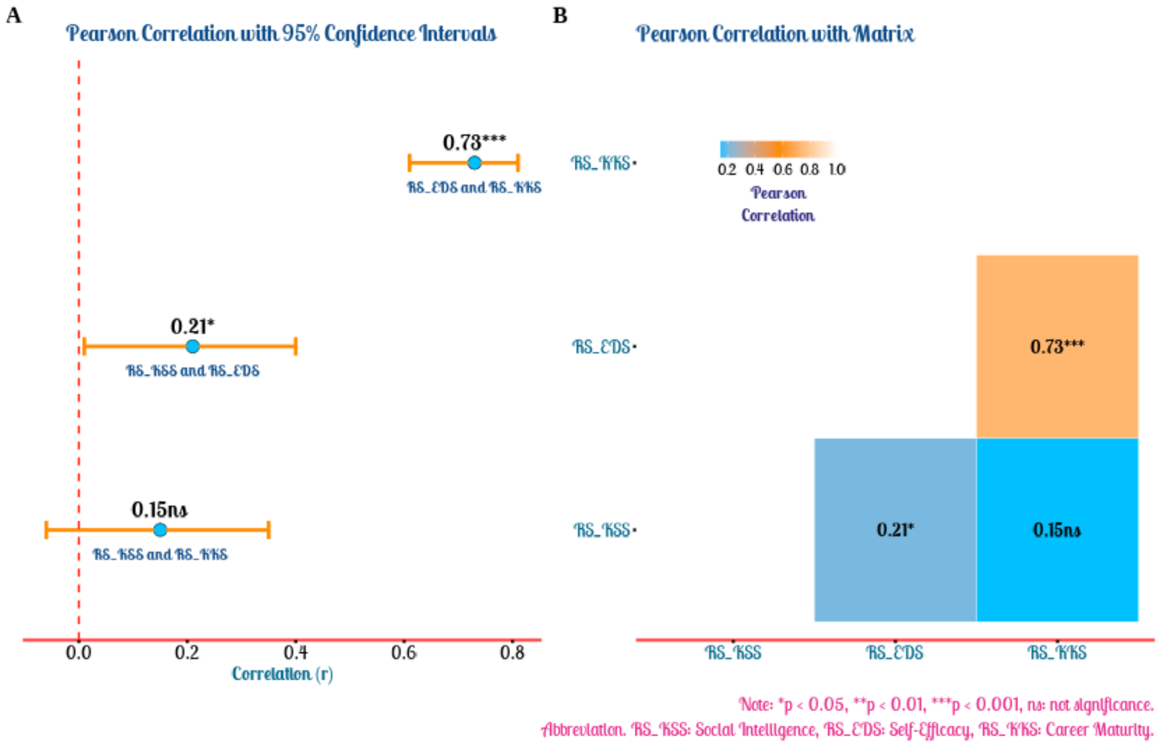
Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Descriptive Statistics and Correlation

The results presented in Table 1 indicate that the skewness values for all variables fall within the acceptable range of −2 to 2, and the kurtosis values range from −7 to 7 (Gallo-Giunzioni et al., 2025; Kim, 2013; Morris & O'Kello, 2025; Privado et al., 2024). Therefore, it can be concluded that the data are normally distributed. In addition, the results of the assumption check show that the VIF values for all predictor variables are below 10, which means there is no multicollinearity problem (Field, 2024). Thus, the data has met the assumptions required for further predictive model testing. Descriptive statistics and Pearson correlation results between the main variables are also presented in Table 1.

Figure 2

Confidence Interval Plot and Correlation Matrix Between Variables



In addition, Table 1 shows that social intelligence is positively and significantly correlated with self-efficacy ($r = 0.21$, $p = 0.043$), but not significantly correlated with career maturity ($r = 0.15$, $p = 0.149$). In contrast, self-efficacy shows a strong and significant positive correlation with career maturity ($r = 0.73$, $p < 0.001$). This finding indicates that adolescents with higher levels of self-efficacy tend to have better career maturity (Figure 2). Although social intelligence is positively correlated with the other two variables, the relationship is relatively weaker, especially with career maturity. Overall, these results emphasize the important role of self-efficacy in supporting adolescent career development, while social intelligence may play an indirect role through increasing self-efficacy.

Hierarchical Regression and Model Comparison

After testing the assumptions and correlations, a multiple hierarchical regression analysis was conducted. The results of the analysis in Table 2 show a comparison between the two regression models predicting the dependent variable. Model I explains 2% of the variance in the dependent variable ($R^2 = 0.02$), with an adjusted R^2 of 0.01. The Bayesian Information Criterion (BIC) for Model I is 711.46, and the overall model test shows no significant effect

($F_{(1, 87)} = 2.11$, $p = 0.149$), indicating that the predictor variables in Model I do not contribute significantly to explaining the variance in the dependent variable. In contrast, Model II includes additional predictors, which increases the explained variance to 53% ($R^2 = 0.53$), with an adjusted R^2 of 0.52. The BIC for Model II is 650.81, which is lower than that of Model I, indicating a better model fit. The overall model test showed a significant effect ($F_{(2, 86)} = 48.56$, $p < 0.001$), which confirms that the predictors in Model II jointly explain a significant proportion of the variance in the dependent variable.

Table 2.
Assessment of Fit Across Regression Models

Model	R^2	Adj. R^2	BIC	Overall Model Test				Model Comparison				p
				F	$df1$	$df2$	p	ΔR^2	F	$df1$	$df2$	
Model I	0.02	0.01	711.46	2.12	1	87	0.149	–	–	–	–	–
Model II	0.53	0.52	650.81	48.56	2	86	< 0.001	0.51	92.78	1	86	< 0.001

Note: R^2: R-Square, Adj.R^2: Adjusted R-Square, BIC: Bayesian Information Criterion. ΔR^2: Model II (Model II – Model I).

In addition, the model comparison analysis (ΔR^2) showed that the addition of the second predictor to Model II resulted in an increase in explained variance of 51% ($\Delta R^2 = 0.51$, $F_{(1, 86)} = 92.78$, $p < 0.001$), indicating that the additional predictor significantly improved the model. Therefore, this finding suggests that although Model I did not make a significant contribution, Model II offered a much better fit by explaining more variance in the dependent variable. The lower BIC in Model II also indicates that this model is more efficient. Thus, Model II is a better choice to explain the dependent variable.

Table 3.
Results of Multiple Hierarchical Regression Analysis

Regression Model	B(SE)	β	t	p	95% CI
Model I					
Intercept	62.70(9.27)	–	6.77	< 0.001	44.28–81.12
Social Intelligence	0.25(0.17)	0.15	1.45	0.149	-0.09–0.59
RMSE	12.21	–	–	–	–
Model II					
Intercept	12.46(8.31)	–	1.50	0.137	-4.05–28.96
Social Intelligence	-0.004(0.12)	-0.003	-0.03	0.973	-0.25–0.24
Self-Efficacy	1.76(0.18)	0.73	9.63	< 0.001	1.39–2.12
RMSE	8.47	–	–	–	–

Note: B: Unstandardized Estimate, β: Standardized Estimate, 95% CI: Confidence Interval, RMSE: Root Mean Square Error.

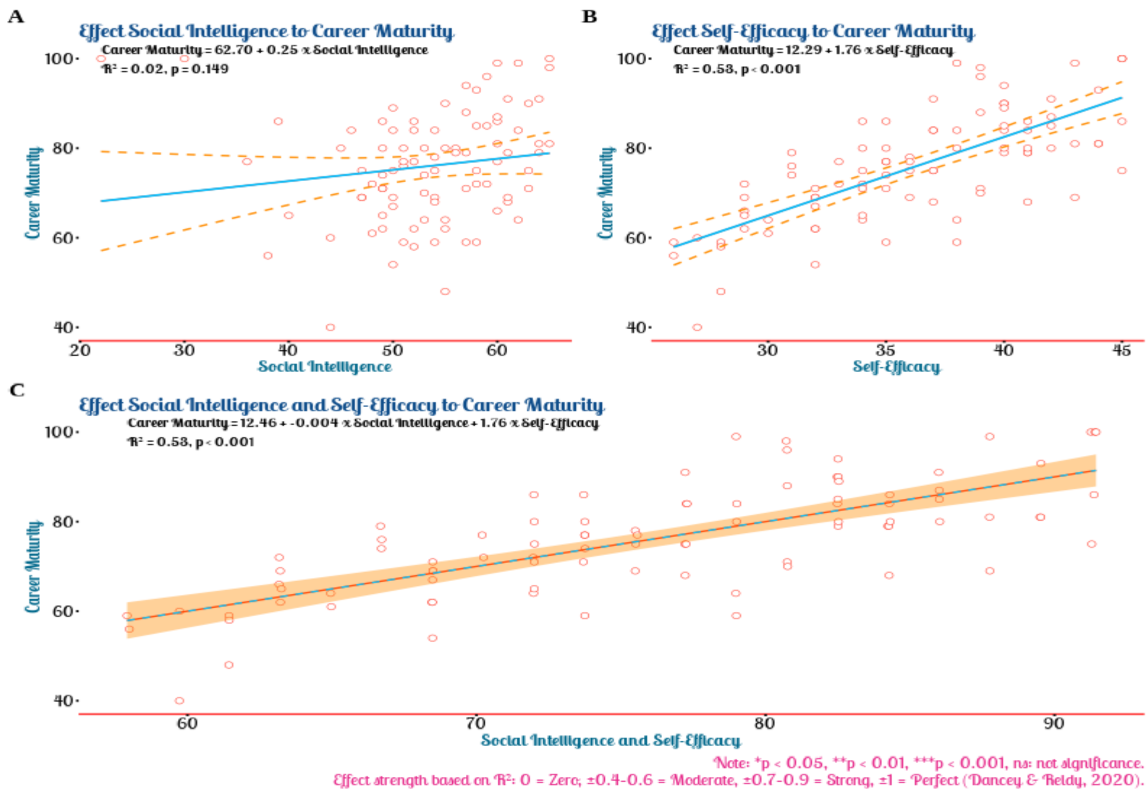
After obtaining the regression model that is most able to explain the empirical data, the effect test and robustness check of the model are presented in Table 3. The results of the hierarchical regression analysis (Table 3) show that Model I only considers the effect of social intelligence on the career maturity variable (Figure 3). The regression results reveal that social intelligence has a positive effect on career maturity, although it is not significant ($B = 0.25$, $p = 0.149$). This result indicates that each one-unit increase in social intelligence is associated with a 0.25 unit increase in career maturity, but this effect was not statistically significant. The 95% confidence interval for this effect ranges from -0.09 to 0.59, indicating an uncertain estimate. The intercept value of 62.70 ($p < 0.001$) indicates that when the social intelligence value is zero, the predicted value for career maturity is 62.70. Meanwhile, the RMSE value of 12.21 indicates the average error rate in the model prediction.

ISSN 2598-6368 (online) / ISSN 1693-7236 (print)

When the self-efficacy variable is included in the analysis in Model II, the regression results show an increase in the explanation of the career maturity variable. However, social intelligence remains an insignificant predictor (B = -0.004, p = 0.973) so that Hypothesis 1 is rejected. Meanwhile, self-efficacy has a positive and significant effect on career maturity, with a value of (B = 1.76, p < 0.001), which supports Hypothesis II in this study. The 95% confidence interval for this variable ranges from 1.39 to 2.12, indicating that higher self-efficacy is correlated with increased career maturity. With the addition of this predictor, the intercept value in Model II decreases to 12.46 (p = 0.137), reflecting a change in the model. Another increase is seen in the decrease in the RMSE value to 8.47, indicating that Model II has a lower prediction error rate than Model I.

Figure 3

Visualizing the Regression Model with Scatterplot



Model Robustness

Overall, the results from the coefficient stability approach, partial R^2 assessment, and Monte Carlo simulation converge to a consistent conclusion. Social intelligence contributes minimally and unreliably to predicting career maturity, whereas self-efficacy demonstrates a strong, stable, and meaningful effect. The coefficient stability analysis highlights that controlling for self-efficacy nearly eliminates the predictive power of social intelligence, while partial R^2 results confirm that even very small unobserved confounders could nullify its already negligible effect. Monte Carlo simulations further support these findings, indicating that the observed patterns are unlikely to be driven by random variation. Collectively, these sensitivity checks underscore that self-efficacy is the primary robust predictor of career maturity, and any apparent association with social intelligence is statistically fragile and practically negligible.

Coefficient Stability Model

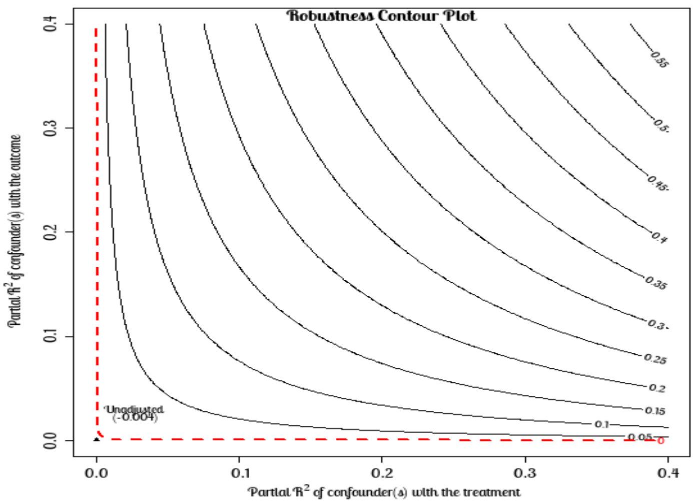
The coefficient stability approach showed that the addition of self-efficacy in the extended model substantially altered the association between social intelligence and career maturity. In the short model (career maturity ~ social intelligence), the R^2 value was 0.02, with a regression coefficient of 0.25 for social intelligence. However, after controlling for self-efficacy in the long model (career maturity ~ social intelligence + self-efficacy), the R^2 increased to 0.53, and the coefficient for social intelligence dropped to −0.004. The estimated δ_{zero} value of 19.32 indicates that the degree of selection on unobservables would need to be roughly 19 times stronger than that on observables to reduce the observed coefficient to zero. This suggests that the small observed effect of social intelligence is unlikely to be meaningfully influenced by omitted variable bias, given its already near-zero magnitude. The adjusted coefficient $\beta^*(\delta = 1) = 0.07$ further confirms that even when assuming equal selection on observed and unobserved factors, the estimated effect remains weak and statistically negligible. Together, these results imply that the predictive contribution of social intelligence to career maturity is minimal and statistically unstable, whereas the inclusion of self-efficacy substantially improves model fit ($\Delta R^2 = 0.51$) and predictive validity.

Partial R² Robustness

Results from the partial R^2–based robustness assessment are consistent with the coefficient stability findings. For the effect of social intelligence on career maturity (controlling for self-efficacy), the unadjusted coefficient was −0.004 (SE = 0.12, $t = -0.03$), confirming the absence of a statistically significant effect. The robustness value (RV, $q = 1$) was 0.004, indicating that an unobserved confounder explaining approximately 0.4% of the residual variance in both the predictor and the outcome would be sufficient to completely eliminate the observed effect. Similarly, the robustness value at $\alpha = 0.05$ was 0.00, suggesting that even very weak confounding could render the association non-significant. The contour plot (see Figure 4) visually illustrates these results: the near-horizontal contour lines and the proximity of the "unadjusted" estimate (indicated by the black triangle) to the origin demonstrate that the model's sensitivity is extremely high—meaning even small confounding effects could fully explain away the already negligible association. These findings indicate that, after controlling for self-efficacy, the effect of social intelligence on career maturity is negligible and statistically unstable.

Figure 4.

Robustness Contour Plot of Social Intelligence Effect on Career Maturity



ISSN 2598-6368 (online) / ISSN 1693-7236 (print)

Monte Carlo Simulation

Then, to evaluate the robustness of the regression model, a sensitivity analysis was conducted using simulated data. The results are presented in Table 4. In Model I, the average simulated coefficient for social intelligence is 0.25 (S.SE = 0.003), with a fairly narrow 90% percentile interval (PI), ranging from 0.01 to 0.49. Although the effect is positive, the effect is still small and not statistically significant, which is consistent with the initial (empirical) regression model analysis. In addition, the simulated RMSE for Model I is 1.74 (S.SE = 0.002), although lower than the RMSE observed in the empirical model (12.21), this reflects the reduction in variance due to the control of simulated disturbances and cannot be directly interpreted as a better model fit. It is important to note that the consistency in the magnitude and direction of the effects seen in the simulations suggests that social intelligence does not have a significant impact on career maturity and its effect is small.

Table 4.

Results of Sensitivity Analysis

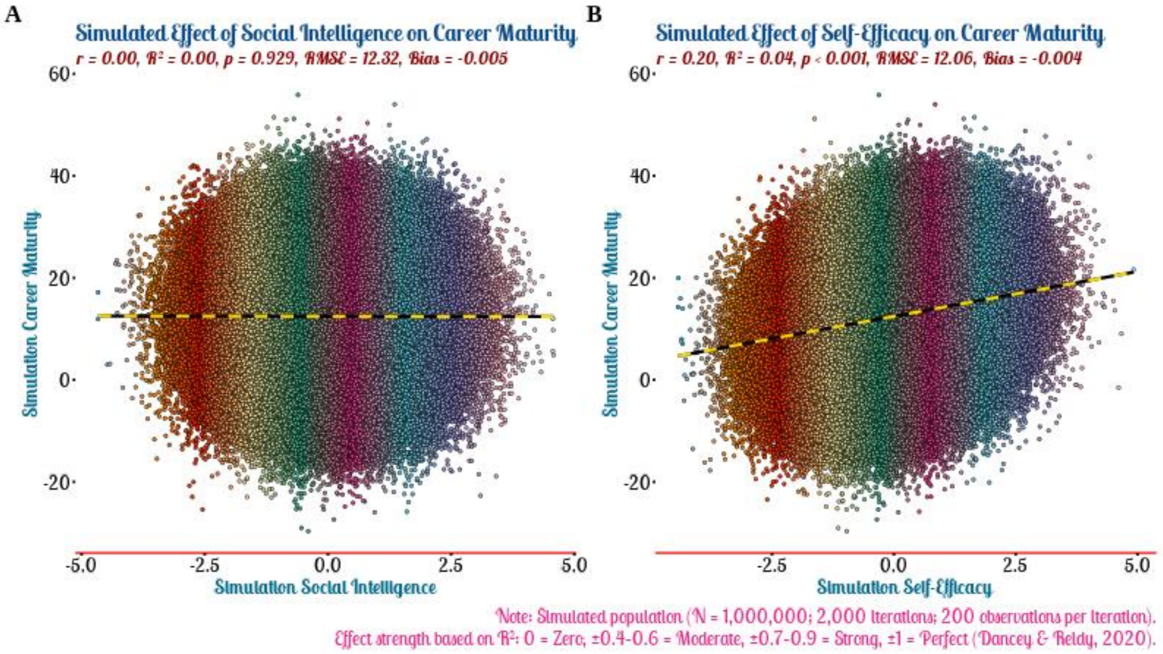
Regression Simulation Model	S.Mean(S.SE)	S.SD	90% PI
Model I			
Intercept	62.71(0.003)	0.12	62.47–62.95
Social Intelligence	0.25(0.003)	0.12	0.01–0.49
RMSE	1.74(0.002)	0.09	1.57–1.91
Model II			
Intercept	12.47(0.014)	0.62	11.25–13.67
Social Intelligence	-0.02(0.014)	0.63	-1.26–1.23
Self-Efficacy	1.76(0.014)	0.61	0.59–2.98
RMSE	8.45(0.009)	0.42	7.61–9.28

Notes: S.Mean: Simulated Mean, S.SE: Simulated Standard Error, S.SD: Simulated Standard Deviation, 90% PI: Percentile Interval, RMSE: Root Mean Square Error.

Meanwhile, in Model II, which includes self-efficacy as an additional predictor, the simulated effect of self-efficacy remains strong and positive (S.Mean = 1.76, 90% PI = 0.59 to 2.98), which strengthens its substantial and stable contribution in predicting career maturity. In contrast, the coefficient for social intelligence becomes slightly negative (S.Mean = -0.02) with a wide 90% percentile interval (-1.26 to 1.23), indicating significant variability and a mean effect close to zero. These findings confirm that social intelligence has no significant effect on career maturity after controlling for self-efficacy. The simulated RMSE in Model II is 8.45 (S.SE = 0.009), which is very close to the empirical RMSE (8.47), indicating the consistency and robustness of the model.

After that, the visual simulation results are also presented to evaluate the strength and direction of the relationship between variables graphically. Figure 5A shows the simulation results of the effect of social intelligence on career maturity in Model I. It can be seen that there is no clear pattern of relationship between the two variables, as indicated by a flat regression line with a correlation value and a coefficient of determination of zero, indicating that social intelligence does not explain the variance of career maturity at all. In addition, the RMSE of the simulation results was recorded at 12.32 and the bias was very small (-0.005), which reflects that the model estimate did not experience systematic errors. However, the very symmetrical and even distribution of data across the horizontal axis indicates that there is no significant linear tendency between social intelligence and career maturity. This is in line with the previous descriptive results, where the average coefficient of the simulation (S.Mean = 0.25; 90% PI = 0.01–0.49) showed a very small and unstable effect even though it had a positive value. Overall, Figure 5A supports the finding that social intelligence is not a significant or substantial predictor of career maturity. The absence of a clear pattern in the visualization, coupled with the low statistical significance and small explained variance, indicates that the effects of social intelligence are weak, inconsistent, and practically negligible, especially when self-efficacy is taken into account as in Model II.

Figure 5.
Visualization of Sensitivity Analysis Using a Scatterplot



In contrast to the results presented in Figure 5B, it can be seen that there is a positive relationship pattern between self-efficacy and career maturity based on simulation data. Although the correlation coefficient (r = 0.20) and determination coefficient (R^2 = 0.04) are relatively small (Dancey & Reidy, 2020). In addition, Figure 5B also shows a statistically significant relationship (p < 0.001) with a consistent and positive trend in the direction of the effect. The slightly sloping regression line illustrates that an increase in self- efficacy tends to be followed by an increase in career maturity, although the effect is visually and numerically small. The RMSE value of 12.06 and a very small bias (-0.004) indicate that the simulation model is quite stable and free from systematic bias. The relatively even data distribution pattern along the self-efficacy range also reflects that the estimated effect is not driven by extreme or outlier influences.

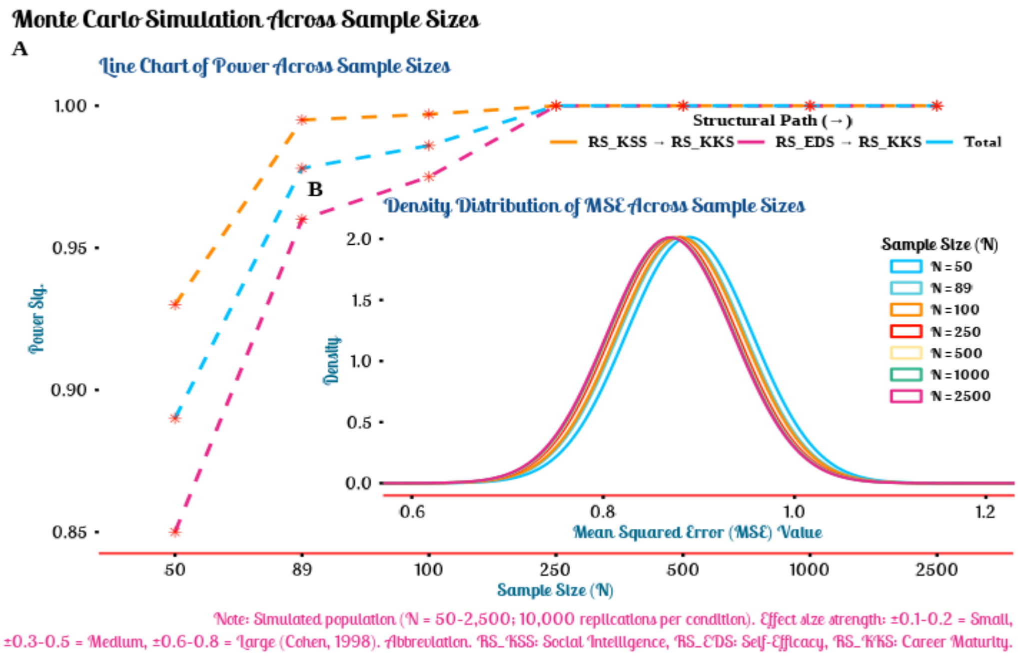
The findings from this plot strengthen the descriptive results of the previous simulation, that self-efficacy shows a positive and relatively stable effect on career maturity. The large mean coefficient of the simulation and the narrow percentile interval (S.Mean = 1.76; 90% PI = 0.59–2.98) indicate that the relationship is not only statistically significant but also practically meaningful in the context of prediction. Thus, the visualization in Figure 4B supports the conclusion that self-efficacy is a stronger and more consistent predictor of career maturity than social intelligence, especially after considering the joint effects in Model II.

Collectively, the simulation results corroborate the analytical findings from coefficient stability and partial R^2. Social intelligence exhibits negligible predictive power for career maturity, whereas self-efficacy consistently demonstrates a positive, stable, and practically meaningful effect.

Power Model Assessment

To further validate the robustness of the regression estimates, a Monte Carlo simulation was conducted across various sample sizes (*N* = 50–2,500) with 10,000 replications per condition (see Figure 6). The line chart (upper panel A) illustrates the statistical power of each path in the regression model, while the density plot (lower panel B) presents the distribution of the MSE across sample sizes. The simulation results show that the power of all regression paths rapidly increases with larger sample sizes and reaches a stable level (power ≈ 1.00) starting around *N* ≈ 89–100. This indicates that at approximately 89 participants, the regression model already achieves adequate statistical power for detecting the true effects. The lower panel further shows that the MSE distribution becomes narrower and more centralized as the sample size increases, suggesting improved estimation precision and reduced sampling variability. Together, these results confirm that the regression model used in this study is both statistically powerful and stable even with moderate sample sizes. Thus, the empirical sample size (*N* ≈ 89) can be considered sufficient to produce reliable parameter estimates and valid inferences.

Figure 6.
Combined Line and Density Plots of Power Across Sample Size



Discussion

The results of this study indicate that social intelligence is positively correlated with both self-efficacy and career maturity. However, the correlation with career maturity is relatively weak, suggesting that while social intelligence contributes to adolescents' career development, its direct influence is not as strong as self-efficacy. High self-efficacy appears to play a more dominant role in supporting career development by motivating adolescents to take initiative, face challenges, and explore various career paths. These behaviors facilitate the acquisition of necessary skills and experiences required for career maturity (Usher & Urdan, 2016; Vaughan-Johnston & Jacobson, 2020).

The nonsignificant effect of social intelligence on career maturity observed in this study aligns with the regression and sensitivity analyses, which showed a weak and unstable contribution after controlling for self-efficacy. This contrasts with previous studies reporting significant roles of social and interpersonal competencies in adolescents' career adaptability and planning. For example, Liu et al. (2014) and Bi & Wang (2023) found that social and interpersonal skills positively predicted career adaptability and planning, while Zhou et al. (2023) demonstrated that career decision-making self-efficacy, influenced by emotional intelligence, significantly contributes to employability outcomes among higher vocational students. Similarly, Hamzah et al. (2021) reported that self-efficacy mediates the relationship between career emotional intelligence and career adaptability, and Pham et al. (2024) highlighted that social support moderates the effect of self-efficacy on career exploration and career choice. These findings suggest that the indirect pathways and contextual factors, such as emotional intelligence and social support, may explain why social intelligence alone did not significantly predict career maturity in the current study (Smutchak et al., 2024).

Although social intelligence did not directly predict career maturity, it was significantly correlated with self-efficacy, suggesting an indirect effect. This supports the theoretical model proposed by Taylor & Betz (1983), which posits that social competencies enhance self-efficacy through positive social reinforcement and successful interpersonal experiences. Therefore, social intelligence remains an important enabler of psychological readiness by enhancing confidence, motivation, and adaptive behaviors in career-related decision-making.

The strong and stable effect of self-efficacy on career maturity in this study underscores the central role of internal belief systems in adolescents' career development. Consistent with Bandura (1997) social cognitive theory, self-efficacy functions as a motivational mechanism that directs individuals to explore, persist, and succeed in goal-directed activities. Adolescents with higher self-efficacy demonstrate more mature career decision-making, better planning, and stronger goal commitment (Usher & Urdan, 2016; Vaughan-Johnston & Jacobson, 2020). Successful experiences enhance self-efficacy, whereas repeated failures without adequate support can undermine confidence and negatively impact career maturity (Uchida et al., 2018). Observing successful peers or role models, encouragement from parents, teachers, and peers, as well as positive emotional states, further strengthen self-efficacy and promote career readiness.

In addition, this study's findings highlight the importance of considering both direct and indirect pathways in career development models. Social intelligence may not exert a strong direct effect on career maturity but operates indirectly through self-efficacy, suggesting that interventions aiming to improve career readiness should target the development of both social competencies and self-efficacy beliefs. Encouraging mentorship programs, observational learning from role models, and positive reinforcement in social contexts can create opportunities for adolescents to internalize experiences that enhance confidence and decision-making skills (Beatson et al., 2020; Taylor & Betz, 1983).

Theoretically, these findings contribute to the understanding of the dynamic interplay between social and cognitive factors in adolescent career development. The results reinforce the mediating role of self-efficacy within the framework of social cognitive career theory (Lent et al., 1994), demonstrating that social intelligence alone is insufficient to foster career maturity without the presence of strong self-belief. Practically, educational and counseling programs should prioritize interventions that strengthen adolescents' self-efficacy through structured mastery experiences, mentorship, and role-model exposure. Facilitating peer-based social learning activities may also help translate social intelligence into tangible self-efficacy gains, thereby indirectly improving career maturity.

Despite the robustness checks conducted in this study, several limitations should be acknowledged. First, the relatively modest sample size may limit the generalizability of the findings, particularly across different cultural, educational, or socioeconomic contexts. Although Monte Carlo simulations and power analyses indicated that the regression model achieved adequate statistical power and stable parameter estimates, future studies should replicate these findings using larger and more diverse samples to strengthen external validity.

Second, the cross-sectional design of the study restricts causal inference. Longitudinal research is needed to examine the developmental dynamics between social intelligence, self-efficacy, and career maturity over time, particularly to clarify potential indirect or mediating

ISSN 2598-6368 (online) / ISSN 1693-7236 (print)

mechanisms. Third, all variables were measured using self-report instruments, which may introduce common method bias and social desirability effects. Future research may benefit from incorporating multi-informant assessments, behavioral indicators, or longitudinal tracking of career-related outcomes. Finally, although social intelligence did not show a direct effect on career maturity in this study, its significant association with self-efficacy suggests potential indirect pathways. Future studies are encouraged to explicitly test mediation or moderated mediation models, as well as to include contextual variables such as social support, school climate, or mentoring experiences, to provide a more comprehensive understanding of adolescent career development.

Conclusion

Based on the results of the analysis, it shows that social intelligence does not have a significant effect on career maturity, which is reflected in the insignificance in the first model. In contrast, self-efficacy is proven to be a strong and significant predictor of career maturity in the second model. These results indicate that self-efficacy plays an important role in predicting career maturity, while social intelligence does not provide a significant contribution. Overall, these findings provide an understanding that the self-efficacy factor is more relevant in shaping career maturity compared to social intelligence. Meanwhile, the sensitivity analysis confirms the robustness of these hierarchical regression findings. Specifically, the contribution of self-efficacy to career maturity remains stable and statistically supported in data simulations, while social intelligence shows inconsistent and very small effects in both models. These results strengthen the interpretation that social intelligence is not a significant predictor in influencing career maturity when self-efficacy has been controlled, possibly due to overlapping variance or concept redundancy. In addition, the narrow confidence limits and stable estimates in the simulation indicate that the model performance is not too sensitive to data fluctuations, which supports the generalization of this model to broader applications, even though the number of participants in the empirical data testing is below one hundred. This shows that the model remains stable and robust even with a relatively small sample, so these findings can be applied in a larger context with more confidence.

Acknowledgment

The researcher extends sincere gratitude to all collaborators for their invaluable support and seamless cooperation, which played a crucial role in the successful completion of this study. Special thanks are also directed to the adolescent participants who generously devoted their time and shared their experiences. Their meaningful involvement has provided rich insights that significantly contributed to the depth and quality of this research.

Declarations

Author contribution. NMJ: conceptualisation, data collection, guiding the research framework, reviewing the literature, and writing the original draft. DYN: data curation, formal analysis, methodology, review and improvement of the manuscript, validation, and visualisation.

Funding statement. The study was self-funded, with no external financial contributions from public institutions, private companies, or charitable foundations.

Conflict of interest. No potential conflicts of interest, whether financial or non-financial, were identified as having any influence on the conduct or results of this research.

Additional information. This study followed national and institutional ethical guidelines. As only anonymized, non-identifiable data were used, formal ethical approval was not required. Research procedures adhered to the 1964 Helsinki Declaration and subsequent amendments. Data are not publicly available due to confidentiality, but the R code can be obtained from the corresponding author upon justified request.

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