

# Motivations Matter: Predicting Entrepreneurship Education MOOC Course Completion with a Decision Tree Approach

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## Abstract

Online entrepreneurship education (EE) courses experienced a sharp 66% spike in demand around March 2020, attributed to the COVID-19 pandemic and the subsequent surge in digital entrepreneurship uptake. Completion rates serve as a key indicator of online MOOC efficacy, with students' psychological attributes and contextual factors often examined as explanatory variables in assessing online course completion. This mixed-methods study explores influential factors in student retention in an EE Massive Open Online Course (MOOC) by using survey responses from 222 Malaysian youths who voluntarily registered for an EE MOOC, which was active from February to October 2021. A Decision Tree approach was chosen to predict the course completion likelihood based on sociodemographic and psychological factors, while qualitative content analysis was conducted to explore participant course enrollment motivations from their textual responses. The results indicated that entrepreneurial intention (EI) does not necessarily translate into EE MOOC completion. Instead, internal locus of control and socioeconomic factors held more priority in predicting completion status. These results were reflected in the students' thematic narratives from their textual responses. Both completed (CP) and dropout participants (DP) expressed similar entrepreneurial interests and, indeed, in the transferability of entrepreneurial skills and knowledge beyond entrepreneurial settings. However, there was a distinction in clarity; most CPs had well-defined and detailed enrolment goals, whereas the narratives from DPs were mainly ambiguous. Overall, the study contributes to the methodological discussion of using decision tree modelling, expands the application of Social Cognitive Career Theory (SCCT) and informs practical implications in online EE context.

*Keywords:* Decision tree, online entrepreneurial education, distance learning, entrepreneurial intention, online completion rate

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In the first quarter of 2024, Coursera, the world's leading MOOC (Massive Open Online Course) platform, gained 7 million new registered learners, thus its total number of learners amounted to 148 million (Coursera, 2024). The soaring prominence of online learning has compelled scholarly interest in student retention (Moore & Fetzner, 2019), especially given the high dropout rates traditionally associated with online learning in MOOCs (Toledo et al., 2020). Retention rates have become increasingly regarded as an indicator of institutional efficacy (Moore & Fetzner, 2019); institutions with low retention rates often face reduced profits and challenges in maintaining operations (Liu et al., 2019). Attention to MOOC completion rates may thus enable administrators to allocate resources and budget more effectively for coming fiscal years (Lee & Choi, 2011).

Simultaneously, the constantly evolving economic landscape and learner demographics link completion rates with educational access. Marked inequalities exist within the different social strata of online learners; studies indicate that students most likely to succeed in MOOCs tend to be those who are already educationally and socioeconomically privileged (Emanuel, 2013). The potential of MOOCs to provide universal access to education is further hampered by its "one-size-fits-all" format of lessons, which lacks accommodation for the needs of its diverse learners (Kizilcec et al., 2017). These issues extend to the realm of online entrepreneurship education (EE), which has gained importance since the COVID pandemic, when demand for online EE courses rose by 66% following the boom in digital entrepreneurship during the lockdown (Mescon & van Rest, 2021). Still then, Liguori and Winkler (2020) describe how the widespread adoption of online EE remains challenged due to two major gaps: the underdevelopment of tools and capacity to teach EE online, and scarce academic literature on online EE. In this respect, attrition in online MOOC courses is a worthy focus of attention for researchers and practitioners in EE, as they seek to leverage emerging technologies to benefit the new generation of entrepreneurs (Toledo et al., 2020). In recognition that teaching an entrepreneurial mindset may demand non-traditional approaches to online MOOC education, Liguori and Winkler (2020) have issued a call for more scholarship and resources to adapt EE to its evolving landscape. In tandem with Ng's (2019) call for research that focuses on the needs of diverse online learners through differentiation, this study thus responds by looking into the contextual dimensions surrounding completion rates of online EE MOOC. In a review of online course completion studies between 1999 and 2009, student psychological attributes emerged as the most frequently researched category of explanatory factors (Lee & Choi, 2011). Accordingly, studies have found a strong link between internal locus of control (ILOC) and persistence in online SDL courses (Hart, 2012; Stritto et al., 2023). As such, the current study specifically asks the following questions:

To what degree do psychological variables account for the completion rate of an EE MOOC?

Similarly, to what degree do sociodemographic variables account for the completion rate of an EE MOOC?

In lieu of the conventional logistic regression method, this study proposes a Decision Tree approach for answering the aforementioned research questions in predicting the likelihood of completion among participants in an EE MOOC. The results will then be further

contextualised by considering the participants' motivations for entering the online course. Although prevalent in other disciplines, such as medical research, the decision tree method is utilised less frequently in psychological research (Batterham et al., 2009; Namazkhan et al., 2020). A decision tree not only identifies the most important variables linked to the completion of EE MOOC, but also illustrates the interactions between two or more predictors in the model by providing a visual representation of the relationship between variables. The method provides the advantage of being flexible enough to handle both categorical and continuous data, as well as variables that have missing values, as compared to regression. Therefore, a decision tree is anticipated to offer a more comprehensive understanding of the variables associated with the successful completion of an EE MOOC.

## Literature Review

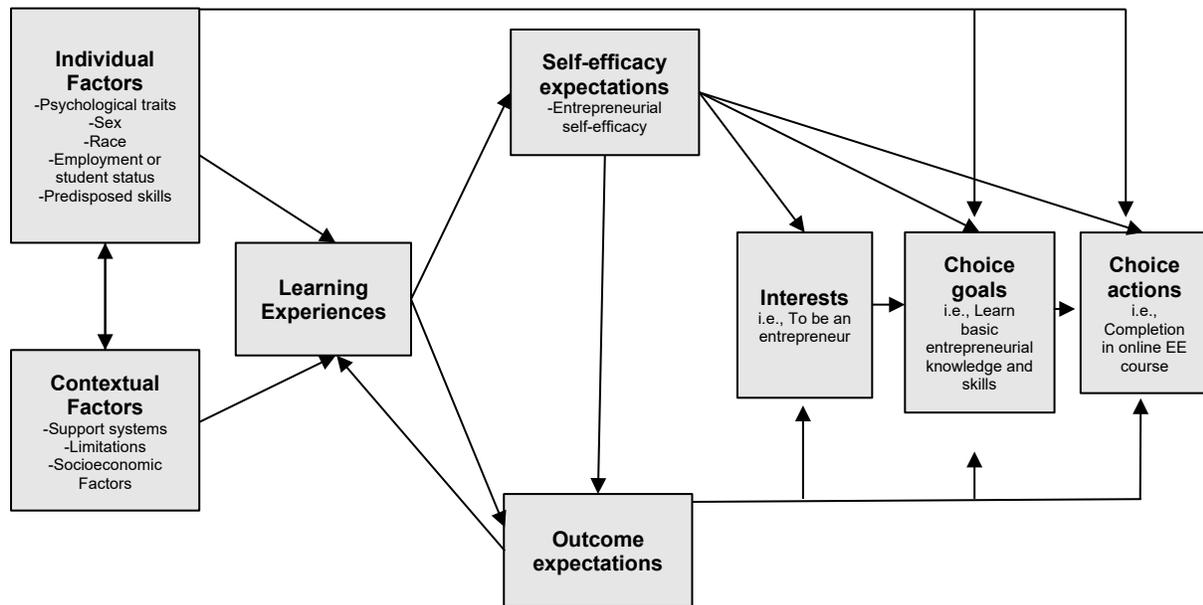
### *Theoretical Framework*

Inquiry into this study is guided by the Social Cognitive Career Theory (SCCT) developed by Lent et al. (2002), which places a strong emphasis on the influence of personal, contextual, and socio-cognitive variables on a person's formation of career interests, job objectives, and performance. SCCT underscores the development of career interests, which are largely determined by several key socio-cognitive beliefs: (1) self-efficacy – a person's belief in their ability to formulate and perform a course of action required to achieve their goals, (2) outcome expectations—beliefs about the overall impact of an individual's actions, with the two initial variables influencing (3) goals—cognitive representations connecting means to desired outcomes. Indeed, SCCT proposes a complex interplay between goals, self-efficacy, and outcome expectations in behavioural self-regulation (Lent et al., 2002). These three core socio-cognitive beliefs operate alongside a multitude of other individual factors (e.g., psychological traits, gender, race, ethnicity, predisposed skills), contextual factors (e.g., support systems, limitations, socioeconomic status), and behavioural factors (e.g., choice action). Collectively these elements may support or inhibit the goals individuals established, ultimately influencing the actions they take to achieve those goals (Lent & Brown, 2019).

The SCCT framework, particularly the Interest Development Model (Lent et al., 2002), posits how personal and contextual influences produce differential learning experiences. These experiences subsequently alter self-efficacy and outcome expectations, which directly affect interest formation, ultimately impacting goal-setting and consequent actions taken towards those goals to sustain that interest. The influence of SCCT in the current study's theoretical framework is illustrated in Figure 1 below. This study postulates that SCCT is particularly relevant in underscoring the relationship between personal and contextual affordances with the retention of participants in an EE MOOC, operationalized in this study as a form of choice action directed towards the course completion for goal-related purposes.

**Figure 1**

*SCCT Illustration of How Contextual Factors Ultimately Affect Completion in an EE MOOC. Adapted from the Interest Development Model by Lent et al. (2002, Pp. 269)*



In past studies, SCCT held significant utility in explaining the adoption of online courses (Ray et al., 2019) and in illustrating how background individual and contextual constraints may ultimately lower career goals (Flores et al., 2017; Fouad & Santana, 2017). Thus, SCCT's Interest Development Model serves as this study's foundational perspective in understanding the significance of background inputs (i.e., socioeconomic and psychological traits), which affect entrepreneurial self-efficacy beliefs and outcome expectations, and in turn, entrepreneurial interest (EI). Consequently, these components direct the participation in goal-directed activity (i.e., completion and retention in an EE MOOC in the pursuit of goal-related purposes).

### **Online Learning Completion Rates**

Over the past two decades, numerous studies have found that online course completion rates may be lower than those of traditional F2F courses, subsequently featuring simultaneous, or even alternative, research focus on withdrawal rates (Rahmani et al., 2024; Visser et al., 2002). In a study on an online psychology course designed to replace its pre-existing F2F counterpart, it was found that the online course had more than twice the withdrawal rate of the F2F course (Garratt-Reed et al., 2016). A study on 221 MOOCs revealed completion rates to hover at an average of 12.6% (Jordan, 2015). Inversely, a study on 92 credit-bearing Psychology classes within the same college revealed no significant differences in retention rates between online and traditional instructional formats (Nguyen, 2011). Given such inconclusiveness, retention is unlikely to be explained by course format alone, suggesting that underlying socio-cognitive processes may offer greater explanatory strength. Hence, SCCT is used in this study to provide a theoretical lens to understand learner persistence and disengagement.

In studying online course retention, student psychological attributes emerged as the most frequently researched category of explanatory factors in a review of online course completion studies between 1999 and 2009 (Lee & Choi, 2011). Internal locus of control (ILOC) was found to be highly associated with persistence in online SDL courses (Hart, 2012; Stritto et al., 2023). Defined as the degree to which people believe they have control over their lives (Levenson, 1981), ILOC may encourage higher classroom engagement, probing, and constructive problem-solving (Hart, 2012). From an SCCT perspective, ILOC reinforces learner's self-efficacy beliefs, which sustain persistence in online learning environments. Self-confidence amongst students was found to be a useful predictor of student persistence (Stephen et al., 2020), facilitating elevated self-expectations for academic achievement and a strong belief in their capacity to fulfill those expectations (Holder, 2007).

Additionally, entrepreneurial self-efficacy (ESE), defined by one's belief in their capability to successfully execute entrepreneurial tasks and roles (Chen et al., 1998), has been shown to foster goal commitment, task effort, and persistence amongst entrepreneurs (Cardon & Kirk, 2015; Trevelyan, 2011). This finding is supported by studies that found positive links between ESE and EI (Chen et al., 1998; Liu et al., 2019), known as the best predictor of planned behavior to start a business (Krueger et al., 2000). EE strengthened this pathway by enhancing EI through shaping self-efficacy (Hoang et al., 2020; Liu et al., 2019), reflecting the SCCT pathway towards interest formation in entrepreneurship via self-efficacy and outcome expectations. However, these studies largely examine learners who have received EE, focusing on outcomes such as heightened EI. Far less is known about what pushes learners to finish EE in the first place. SCCT posits that developed interests and goals should guide choice actions, including course completion. This study, therefore, examines whether EI predicts retention in an EE MOOC, operationalized as a choice action within the SCCT framework.

### ***Entrepreneurship Education in Developing Contexts***

While the intervention effects of online EE on students remain under-researched, general EE research suggests that the benefits seen in traditional settings may be replicated online. A critical review of hard outcome studies showed consistent positive results on university-based EE impacts (Rideout & Gray, 2013), highlighting higher rates of business start-ups and other entrepreneurial success than their comparison groups. Nonetheless, whether EE translates into entrepreneurial success largely depends on the local circumstances and structures within which it is delivered, wherein entrepreneurship can either be enabled or constrained (Urbano et al., 2019). Previous Malaysian studies on youth's EI accentuated the need to localize entrepreneurial-related interventions as their results showed that psychological traits, parental income, and the urban-rural context influenced youth's EI and perception of entrepreneurship (Nungsari et al., 2021, 2023). Inequalities also exist in larger contexts—the environmental conditions for potential entrepreneurs were found to be much more favorable in developed countries compared to developing economies, whose barriers include inefficient, unstable policies, a lack of effective EE in university and society, negative societal perception of entrepreneurs, and restrictive sociocultural norms towards market participation (Guerrero et al., 2021). This study thus holds implications that connect to the wider transformative potential of open education for emerging economies; indeed, Zhang (2022) describes how the emergence of cross-institutional, cross-cultural MOOC researchers yields the potential of reshaping education initiatives of entire

regions, but particularly impactful for the Global South, where internet connectivity and online learning proliferates rapidly each day (Zhu et al., 2020).

Collectively, these studies indicate that while EE has clear benefits, its outcomes in developing contexts are inextricably linked to the sociodemographic and structural conditions that shape learners' engagement. This highlights the necessity to examine both psychological elements and sociodemographic characteristics in elucidating who persists and completes EE MOOCs.

## Methodology

Building on the above literature, the present study investigates how psychological and sociodemographic variables encourage learners' persistence in a voluntary EE MOOC. We employed a convergent mixed-methods design (QUAN + QUAL; Creswell, 2013) that analyzed survey responses from Malaysian youths who went through an EE MOOC. The survey data included demographic and psychological assessment information, which was used as input for the decision tree algorithm. The purpose was to determine how these factors influence and interact with one another in order to predict course completion. Subsequently, the textual data from the survey was inductively analyzed for their motives for course participation using qualitative content analysis, and a comparison was made between participants who completed the course ("Completed Participants" [CP]) and those who did not ("Dropout Participants" [DP]). The findings were collectively interpreted in the discussion section to gain a comprehensive understanding of the research questions (Creswell, 2013).

Materials and analysis code for this study are available from the corresponding author upon reasonable request.

### *Participants and EE MOOC Details*

Our participants are 18- to 28-year-old Malaysian youths who voluntarily registered for an EE MOOC, which was active from February to October 2021 and allowed registration throughout this period. This EE MOOC was funded by Citi Foundation [G-IDS-20207103] and aimed to deliver entrepreneurial training to Malaysian youth and facilitate the starting point of their entrepreneurial journey. The course was promoted through social media platforms and by sending email invitations to Malaysian universities. With the course's SDL approach, participants were given the autonomy to complete 23 short course modules consisting of recorded lectures, local case studies, reading materials, and assignments at their own pace. As an incentive for course completion, eligible participants could apply to a business incubation program by submitting their business proposal before the course deadline.

The MOOC recorded a completion rate of 19.86% out of 569 participants. The data analyzed in this paper were taken from the participant's registration survey on the Qualtrics Online Survey platform prior to course enrolment. The informed consent form was provided within the registration survey, in which participants consented to the utilization of their data for research and programmatic objectives. After excluding 31 participants whose survey responses were flagged as invalid (Buchanan & Scofield, 2018; Curran, 2016), 538 participants remained, which included 427 dropouts (incomplete course progress) and 111 completed participants. To

achieve an evenly matched sample ( $N = 222$ ), we used the R packages “optmatch” and “MatchIt” to randomly draw 111 dropouts from the larger pool and age-match them to the 111 completers, thereby ensuring comparability across groups. Table 1 presents our participants’ characteristics. The average age of participants is  $22.144 \pm 2.704$ , while the median age is 22.

**Table 1***Characteristics of Participants, N=222*

Variable	Completion Status				Total	
	Dropout, n=111		Completed, n=111		n	%
	n	%	n	%		
<b>Gender</b>						
Female	77	34.68%	69	31.08%	146	65.77%
Male	34	15.32%	42	18.92%	76	34.23%
<b>Employment Status</b>						
Not working	62	27.93%	72	32.43%	134	60.36%
Self-employed	8	3.60%	6	2.70%	14	6.31%
Full-time	19	8.56%	14	6.31%	33	14.86%
Part-time/Freelancing	22	9.91%	19	8.56%	41	18.47%
<b>Student Status</b>						
No	39	17.57%	36	16.22%	75	33.78%
Yes	72	32.43%	75	33.78%	147	66.22%
<b>Residential State<sup>a</sup></b>						
Low-Income States	9	4.09%	18	8.18%	27	12.27%
Moderate-Low-Income States	15	6.82%	14	6.36%	29	13.18%
Moderate-High-Income States	28	12.73%	31	14.09%	59	26.82%
High-Income States	57	25.91%	48	21.82%	105	47.73%
<b>Entrepreneurial Status</b>						
Not thinking of starting a business	9	4.05%	14	6.31%	23	10.36%
Thinking about starting a business	23	10.36%	28	12.61%	51	22.97%
Taking steps of starting a business	62	27.93%	59	26.58%	121	54.50%
Have started a business in the last 3 years in any form, such as full time, part time, online, side hustle or freelance	17	7.66%	10	4.50%	27	12.16%
<b>Household Income<sup>b</sup></b>						
Low (Less than RM2,200)	16	7.21%	16	7.21%	32	14.41%
Moderate-Low (RM2,200 - RM3,199)	18	8.11%	17	7.66%	35	15.77%
Moderate (RM3,200 - RM4,999)	29	13.06%	24	10.81%	53	23.87%
Moderate-High (RM5,000 - RM10,999)	28	12.61%	34	15.32%	62	27.93%
High (RM11,000 and above)	20	9.01%	20	9.01%	40	18.02%
<b>Parental Educational Status</b>						
Completed primary education	9	4.46%	10	4.95%	19	9.41%
Completed secondary education	32	15.84%	39	19.31%	71	35.15%
Completed pre-university education	5	2.48%	2	0.99%	7	3.47%
Completed vocational education	2	0.99%	2	0.99%	4	1.98%
Completed tertiary education	53	26.24%	48	23.76%	101	50.00%
<b>Entrepreneurial Parents</b>						
No	85	38.29%	79	35.59%	164	73.87%
Yes	26	11.71%	32	14.41%	58	26.13%

*Note.* <sup>a</sup> According to the median household income (Department of Statistics Malaysia, 2021), the states were grouped: High-Income (Kuala Lumpur, Putrajaya, Selangor), Moderate-High-Income (Johor, Melaka, Pulau Pinang, Negeri Sembilan), Moderate-Low-Income (Terengganu, Sabah, Pahang, Sarawak) and Low-Income (Perak, Kedah, Perlis, Kelantan).

<sup>b</sup> MYR = Malaysian Ringgit, 1 USD was approximately equivalent to 4.14 MYR in 2021.

### ***Data Collected***

The participant's registration survey contained items that represent different SCCT components. Participant's individual factors were represented by certain sociodemographic information and psychological traits, while residential state, household income, parental educational status, and entrepreneurial parents formed the basis for contextual factors. Additionally, the survey collected participants' textual responses to these two questions: "What do you hope to achieve through this programme?" and "Which industry do you want to own a business in? Please list out answers with elaboration. If you do not have the intention to start a business, please state "N/A" as your answer." These questions were expected to elucidate participants' outcome expectations, interests, and choice goals per the SCCT theoretical framework. Besides theoretical relevance of the survey components, the survey was reviewed by the instructors of the EE MOOC for comprehensibility and program relevance, with the additional purpose of understanding participant profiles to inform future course design. Minor wording adjustments were made for enhanced clarity and face validity.

### **Psychological Batteries.**

We measured EI using six items from Liñán and Chen (2009) with a seven-point Likert scale. Entrepreneurial self-efficacy was measured using six items, using five-point Likert scale (Wilson et al., 2007). Furthermore, we assessed self-esteem using ten items, half of which are negative items (Rosenberg, 1989). As for Likert scale, the items use a four-point Likert scale which starts from zero (strongly agree). The IE-4 (Kovaleva, 2012) comprised of four items which two items measure internal locus of control (ILOC) while the rest measure external locus of control (ELOC). A binary measure of risk-return preference was used (Barbosa et al., 2007; Reynolds, 2000). Participants will be coded as "0," as having a low risk tolerance, if they chose "A business that would provide a good living, but with little risk of failure, and little likelihood of making you a millionaire" while participants who choose "A business that was much more likely to make you a millionaire but had a much higher chance of going bankrupt" will be coded as "1."

After going through confirmatory factor analysis (CFA) without including LOC items as their number of items are below three, we removed one item from ESE and one item from RSES for having standardized factor loading below .40. A second CFA showed an adequate fit (CFI = .925; TLI = .915; SRMR = .059; RMSEA = .063) with the standardized factor loading of items ranging from .429 to .894. The average variance extracted (AVE) of each variable was at least .40, and the  $\sqrt{\text{AVE}}$  was greater than the correlation between the variables. Composite reliabilities for each variable were above the cut-off value of .60 (Bagozzi & Yi, 1988) and .70 for assessing Cronbach's alpha. Although ESE and RSES have lower AVE, their reliability and discriminant validity scores were above the threshold of .60 (Fornell & Larcker, 1981) and thus convergent and discriminant validities are established (Table 2).

**Table 2***Reliabilities, Average Variances Extracted and Correlations Between Variables*

	Variable	$\alpha$	CR	AV						
				E	1	2	3	4	5	
1	Entrepreneurial Intention	.908	.910	.630	(.793)					
2	Entrepreneurial Self-Efficacy	.783	.792	.440	.427 ***	(.663)				
3	Self-esteem	.863	.869	.437	.361 ***	.468 ***	(.661)			
4	Internal Locus of Control	-	-	-	.384 ***	.395 ***	.352 ***	-		
5	External Locus of Control	-	-	-	-	-.066	-.121	-.057	-	
	Mean				.147*	5.399	3.783	1.927	3.838	2.633
	Standard Deviation					.950	.645	.469	.750	.739

*Note.*  $\alpha$  = Cronbach's alpha, AVE = average variances extracted, CR = composite reliability, \*\*\* = correlation is significant at .001 (two-tailed), \* = correlation is significant at .05 (two-tailed). Numbers within parentheses are the square roots of the AVEs.

For the decision tree model, we predict the likelihood of participants completing the online EE course (Choice action; 1 = Completed, 0 = Dropouts) using the above-mentioned psychological traits and the following sociodemographic characteristics: sex, student status, employment status, median household income of the residing Malaysian state, parental education level, household income, entrepreneur parents, and entrepreneurial experience.

***Data Analysis******Decision Tree.***

On RStudio software version 2023.06.1, the first author completed all quantitative procedures and analyses. Before analysis, she replaced outliers with computed values from the K-nearest neighbor method (Aguinis et al., 2013). Data normality was assumed since the z-score calculated from their skewness and kurtosis is below 3.29 (Kim, 2013).

To identify the more relevant factors related to MOOC completion, a decision tree model was chosen over logistic regression due to several advantages, such as simplifying complex relationships between variables, robustness to outliers, and easy handling of missing values, but both methods of analysis were done to compare model performance (Batterham et al., 2009; Song & Lu, 2015). Receiver operating characteristic (ROC) curves for the decision tree and the logistic regression were plotted to assess the performance of each approach by comparing the areas under the curve (Ying et al., 2022).

After standardizing all continuous variables, the “rpart” R package was used to model the decision tree. The minimum sample size for each node to split was  $n = 15$ , and branching was limited to five levels. The decision tree reveals the probability of a Malaysian youth completing the EE MOOC having the specific characteristics (first number below the nodes in Figure 2), as

well as the percentage of participants falling into each category (second number below the nodes in Figure 2). Notably, by following a path from the root node (the top) to a leaf node (the bottom), determine the group of participants whose probability of course completion is specified. In order to ascertain the factors that account for the completion of the EE MOOC in the decision tree, it is necessary to descend from the highest branch to the lowest branch, which corresponds to the characteristics of Malaysian youth included in each category.

### Qualitative Content Analysis

The responses to the two survey questions were considered as a single unit of analysis for each participant and were examined using inductive content analysis (Elo & Kyngäs, 2008; Graneheim et al., 2017). As the initial step, the first and third authors thoroughly examined each textual input in order to comprehend the entirety of the content. The third author employed open coding to generate a comprehensive set of content-characteristic words, known as codes, in order to describe all facets of the content. These codes are organized in coding sheets where the code description and representative quotes were listed. The first author reviewed the coding sheets to validate the codes before applying the codes to a quarter of the data. The agreement rate between the first and third authors was determined by calculating the pooled Cohen's Kappa coefficient (De Vries et al., 2008). If  $\alpha > .8$  is not achieved, a debriefing session will be conducted to determine areas of disagreement, and a revised version of the coding sheets will be produced. The third author will recode the data with this new version. The process was iterated three times until a consensus of  $\alpha = .804$  was ultimately reached. The researchers viewed this reflective process as a necessary means to avoid pitfalls associated with an inductive approach, which is to prevent surface descriptions of the data and reduce preconceived biases (Graneheim et al., 2017).

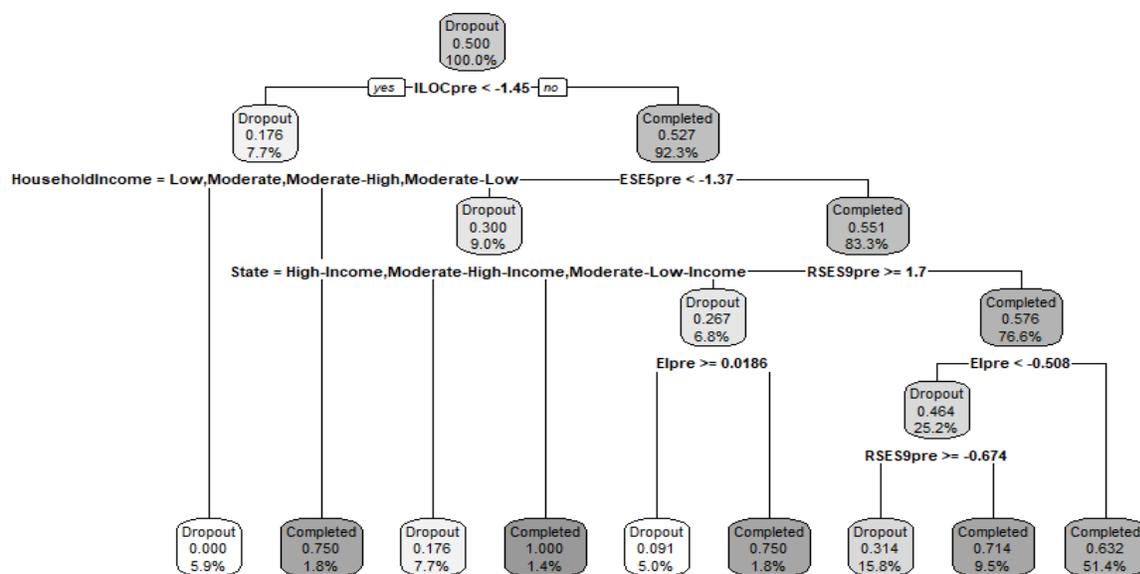
These codes were categorized into higher-order subcategories to initiate the abstraction phase; these subcategories were then the subject of group discussion until consensus was reached. Throughout the discussion, the subcategories were reviewed against the research question to maintain qualitative rigor. Subsequently, the researchers formulated general descriptions of the participants' motives for joining the EE MOOC from the codes and subcategories. Lastly, the main categories were developed and reviewed until consensus was achieved.

## **Results**

### ***Decision Tree***

The resulting decision tree (Figure 2) has a total of 16 nodes among which nine are leaf nodes. Figure 2 indicates that six out of 13 variables are essential predictors in explaining EE MOOC completion rate, which are ILOC, ESE, RSES, EI, residing Malaysian state, and household income.

**Figure 2**  
*Decision Tree for Predicting EE MOOC Completion Rate in Malaysian Youth*



*Note.* First number in each node box represents the probability of course completion in this branch, while the second number in each node box indicates the percentage of participants that end up in this branch. The color of the node boxes reflects the fitted value of the probability of course completion in each branch: darker hue of grey represents stronger probability of course completion while the least probability is accompanied by a lighter hue of grey.

The resulting decision tree revealed that internal LOC (ILOC) was the most strongly associated with course completion, where participants with extremely low ILOC values stood at 17.6% probability of completing the EE MOOC and 52.7% probability for those with higher ILOC. However, branching from ILOC, there were also various ranges of other indicators. Besides, there were several results worth noting from the decision tree. From the branch of low ILOC participants, a wealthy family background (>RM11,000/month) was needed to compensate for their deficit in ILOC to increase their probability to 75%. For participants in the medium-to-high ILOC group, the following influential predictors were ESE and RSES.

Interestingly, given the condition of being in the advantageous group of medium-to-high ILOC and high ESE (55.1%), a high RSES lowered the probability of course completion to 26.7%, which applied to other branches with RSES. Surprisingly, EI was not among the top predictors in the decision tree model. Other than household income, the resident Malaysian state also yielded an encouraging result that participants from low-income states harboring normal-to-high ILOC and low ESE have an extremely high chance (100%) of completing this course, albeit only 1.4% of our sample are in this category.

### Model Performance

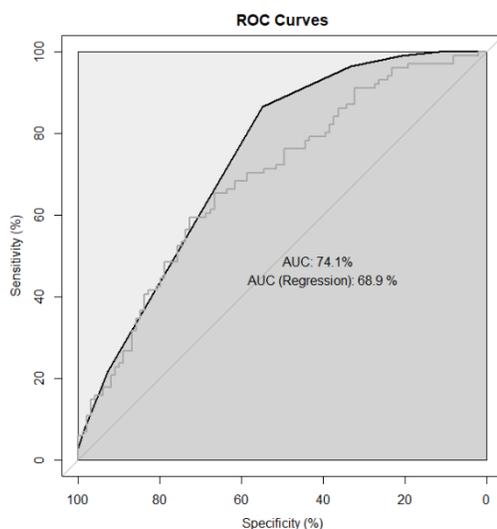
In order to examine the decision tree approach's performance in predicting course completion probabilities, it was compared to logistic regression. The regression provided no significant predictors, and only two variables showed a p-value below .10, which are

entrepreneurial status ( $OR_{\text{Not-thinking vs Started-a-business}} = .277 [.064, 1.191], \chi^2 = 3.0, p = .084$ ) and ESE ( $OR = 1.675 [.925, 3.032], \chi^2 = 2.9, p = .089$ ).

For both the decision tree and logistic regression models, ROC curves are presented and compared in Figure 2. The area under the decision tree ROC curve (74.134%) is significantly greater than the area under the logistic regression ROC curve (68.927%),  $\chi^2[1] = 4.029, p = .045$ . This result showed that the decision tree has significantly better predictive power than logistic regression.

### Figure 3

*Receiver Operating Characteristic Curves for the Decision Tree and the Logistic Regression Model in Predicting Entrepreneurial Education MOOC Completion*



*Note.* The black line represents the ROC curve of the decision tree model while the ROC curve of the logistic regression model is shown with a grey line.

### *Qualitative Content Analysis*

There were three final thematic categories that described Malaysian youths' motivation for enrolling in an EE MOOC. These categories underscore the similarities and distinctions between the CP and DP (Table 3). The excerpts were lightly edited for readability.

**Table 3***Main Categories, General Descriptions, Sub-Categories, and Representative Quotes*

Main Category	General Descriptions	Sub-category	Representative Quote
Furthering Ambition	Formed / Forming Ambition	Meaningful	...currently studying business studies ... not depending 100% from it to guide me to be a great entrepreneur. I want to know others perspective and views, the fresh ideas...I want to create my dream to own my own company. To help more people in need...I'm attracted to open company either provide raw foods or frozen or I can just open my own Cafe and make it different...Besides that I got my own taste to decorate the restaurant... [Nordin]
		Developed business idea	
Seeking Answers	Unclear ambition	Career prospects	I wish to upskill myself and gain insights into the corporate world. I also wish to improve my networking skills [Kai]
		-	Fashion, music and arts ... would love to start business as I have passion in them but there are still so many uncertainties in starting a business thus I would like to learn more before I decide to become an entrepreneur [Layla]
Lower Drive	Ill-defined ambition	-	Just exploring for now. No idea yet. Something learning-based. [Kang]
		-	Learn something [Ying]
	Unmet needs	Desire social connection	... more connection with people , it's really good to emerge ourselves with people who has the same interest with us. [Jing Wei]
		Desire resource support	... pathway to venture out and gain practical knowledge such as grant application, collaborations and partnerships, government funding workshops, etc. [Krish]

Note. C = CP, D=DP

Furthering Ambition.

This category narrates how enrolling in this EE MOOC enabled our participants to further their pre-course ambitions that were in the process of being formed. For those who

wished to start a business, similar expressions of their goals recurred in both groups, such as “learn on how to start,” “how to manage,” and “maintain” a “successful business” through the online course. Both groups held similar motivations to start a business; CP expressed meaningful hopes to create a business that could “help people directly” and “solve a big problem in society,” while DP pursued ideas “for the betterment of society” or to “help underprivileged people.”

However, CP’s expressed ambitions differed from DP’s by having indicators of a developed business idea. These include the visualization of their business clientele, ideation of a backup business plan, and recognition of competitors in their targeted industry:

Jiyan: ... a unique cafe where I can serve food to people according to their health conditions, body weight, [their] diet plans and etc... can be a personal nutritionist at the same time! So I will be having a backup for the moment. Another plan which is plan B is opening a [24-hours] shop ... full of vending machine.

Besides being indicators of ideational development, these characteristics were often accompanied by other relatively detailed elaborations of the business plan, further solidifying their association with a fleshed-out ambition/idea. Jiyan’s excerpt continued with a delineation of the participant’s job scope along with the vending machines’ intended role within their Plan B:

Jiyan: ... some workers are being uncomfortable to work until late night. So this vending machines will take over their job...My job will only be filling the machines with goods, collecting money, refilling coins and cleaning or service the machines.

Other than entrepreneurial ambition, a portion of participants from both groups recognized the transferability of entrepreneurial skills and knowledge in the non-entrepreneurial career context. Although some generally expressed the desire to “gain new perspectives” and “knowledge” for “the future,” some participants explicitly mentioned that they “wish to upskill and gain insights into the corporate world” as some skills were deemed as “applicable to any field.”

More importantly, these developmental indicators situate their ambition ideation within an active process of evolution, from an ambition that is “forming” to one that is “formed.” As the action directly resulted from their ambitions; their participation in the EE MOOC is contextualised as an extension of this process.

Carlene: At the end of the program, I hope to be better equipped with knowledge on how businesses are created and developed, so that I could better assist with the Management if I work in Human Resources.

### Seeking Answers.

However, not all successful participants apply to the motivational process based on a fleshed-out ambition. Many expressed ambiguous, unclear ambitions—seeking “insights,” “new knowledge,” or “awareness and education” for an undefined subject. Nevertheless, those with

unclear course learning goals compensated by seeking answers:

Hai Wen: These are somethings I would love to start business as I have passion in them but there are still so many uncertainties in starting a business thus I would like to learn more before I decide to become an entrepreneur.

In explicit acknowledgement of their uncertainty, CP sought “to get a clearer picture,” “have a better frame of guidance,” or understand the “thought process and decision making before attempting” —creating an alternative motivational conduit towards course completion.

**Lower Drive.** Similar to CP, ill-defined responses were manifestly present amongst DP as well, albeit with a larger presence. Facing the question of what their learning intentions were towards the course, one- or two-words answers were common: “Learn something,” “Satisfaction,” “Education,” “Community,” or “Knowledge.” This is reflected in the range of the excerpts’ wordcount (DP: 1-129; CP: 2-331). Even amongst more pointed answers, a high number were generic and unfocused:

Zhang: More skills and gained more experience; I'm still not sure about which industry I have interest on.

Chen: I am not thinking of starting a business; Entrepreneur knowledge, that I may use in future.

Compared to CP who sought answers to their uncertainty, however, DP had no such response, thus leaving the ambiguous status of their ambitions as is—with no resolution.

Another group of DP had clear but misguided course goals. Some saw the EE MOOC as a socializing opportunity – to “get more connection with people,” “network with other entrepreneurs,” or “engage with like-minded individuals.” Others requested resource-specific support, such as “seed funding” or “grant application” and “government funding” advice. Finally, participants who had already started a business sought support on their relatively more complicated issues, such as to “expand their business,” make their “business well-known,” or to “improve business analytics and social media presence.”

The format and curriculum of the EE MOOC left these expectations unfulfilled: In terms of the former, the only social feature on the platform interface of the course was a comment/chat section, which was underutilized. Meanwhile, the course content did not include or guarantee any material resource support, save for an opportunity to win seed funding for their business proposal. Finally, those who sought guidance on a more intermediate level perhaps found little value in the course content, which was catered towards beginners with a more introductory and theoretical level of entrepreneurship knowledge.

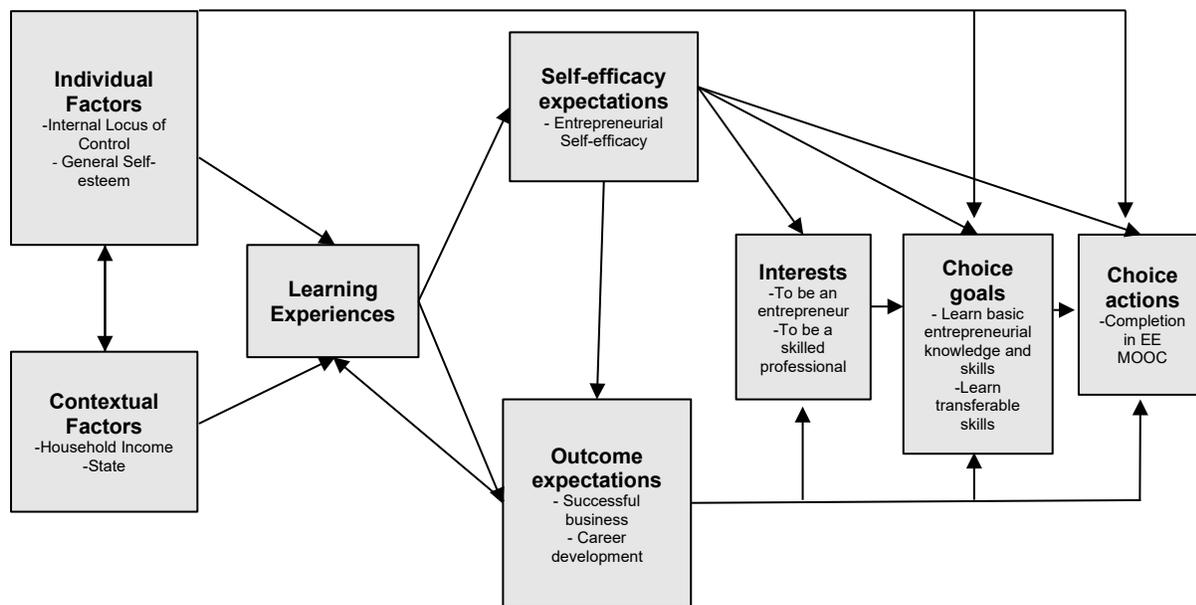
These unmet needs, combined with ill-defined ambitions, suggest an overall weaker character of motivation amongst DP to pursue course completion, thus culminating in their thematic essence: an environment of Lower Drive.

### Re-Contextualization

In Figure 4, the results from the previous two sections are summarized in the context of this paper's theoretical framework.

**Figure 4**

*Re-Contextualization of the Results in the Adapted SCCT Framework Illustrating the Journey Towards Completion in an EE MOOC*



## Discussion

This paper examined whether student retention in a voluntary EE MOOC could be explained by their sociodemographic characteristics and psychological variables using a decision tree model while contextualizing the results with the participants' reasons for enrolling in the course.

With the inputs from 222 Malaysian youths, the decision tree model successfully categorized the participants into distinguishable subgroups of participants with virtually zero probabilities of course completion to 100%. The importance of the individual factors in predicting completion status was dependent on the ILOC level before starting the EE MOOC. The decision tree model presented an optimistic view of the method, outperforming the logistic regression model regarding predictive power. A complex model with a large number of predictors will cause overfitting in regression-type analysis, and the solution is to either increase the sample size or revisit the predictor selection again (Babyak, 2004). However, the decision tree approach handles overfitting issues by setting branch-stopping rules (Song & Lu, 2015). Furthermore, essential factors that the regression may have overlooked were important predictors of the EE MOOC completion rate for certain subgroups of participants. However, the overlooked predictors in the regression model and the absolute probabilities (0 and 100%) of course

completion for the subgroups of participants could be due to the comparably low number of participants in contrast with previous studies using a decision tree approach (Batterham et al., 2009; Namazkhan et al., 2020; Reissová et al., 2020). To overcome this sample size limitation, we interpreted the decision tree model in the context of the participants' course enrollment motivations. The qualitative evidence not only triangulated the quantitative outcomes but also revealed alternative motivational pathways that the decision tree could not capture. This combination strengthens the credibility of the findings while highlighting the limitations of relying solely on statistical predictors.

This paper offers insight into the influences of personal agency and motivations on EE MOOC completion, which aligns with Rahmani et al.'s (2024) study that shows learner motivation has the largest impact on student retention. Particularly, the decision tree results highlighted ILOC to be the strongest predictor associated with EE MOOC completion, with medium-to-high ILOC participants being more likely to complete the course. Given that these individuals tend to perceive the outcomes of their lives to be determined by their own agentic actions and decisions (Suretha & Stanz, 2004), there is a likelihood that CP completed the course being motivated by a desire to improve their lives and knowledge at their own volition. It could be surmised that ILOC also encourages persistence in EE MOOC learning, in line with a study by Hart (2012), observing similar results in online learning in general. This notion is supplemented by our extracted themes from the textual data, which show that CP completed the EE MOOC to actively pursue their entrepreneurial goals, having reported more developed business ideas and a determination to find answers to their uncertainties, similar to the characteristics associated with successful learning (Liu & Chi, 2012). Inversely, DP have unclear entrepreneurship goals, suggesting lower motivations to study the subject and a lower likelihood of completing the EE MOOC. Thus, per SCCT assumptions (Lent et al., 2002), it could be inferred that when participants enter the EE MOOC with a strong goal in mind, it strengthens their personal conviction to complete the program as a stepping stone (i.e. choice action) towards "said" goal.

However, motivation to complete the EE MOOC may not necessarily be entrepreneurial-based. As shown in Figure 2, EI interestingly plays an unexpectedly smaller role in this present study. Despite EE generally having been observed to positively impact EI (Hoang et al., 2020; Nabi et al., 2017), the present study indicates that EI does not, in turn, necessarily translate into the likelihood of participants completing the EE MOOC and is possibly irrelevant to certain groups of participants. This finding is, unfortunately, incongruent with the EE MOOC developer's goal of promoting entrepreneurial activities. We have two possible explanations for this.

First, we postulate participants to have been motivated to complete the EE MOOC with more holistic goals—in effect, by considering entrepreneurship as a transferable skill set (e.g., communication, strategic thinking, and leadership) (Salceanu et al., 2021). This perspective is echoed by Jones (2010), who argues that EE is not solely about producing entrepreneurs but about equipping learners with lifelong skills that are valuable across occupations. Furthermore, our content analysis highlighted that several CPs planned to take the EE MOOC to advance their careers and learn business skills for that purpose. Additionally, participants with low-to-moderate self-confidence—indicated by their RSES—were found to have higher completion

rates, perhaps driven by their learning of transferable skills which has been recognized to increase self-confidence in learners (Winarsunu et al., 2023). This is supported by the notion that students with low prior skills and knowledge tend to derive greater benefits from education (Flores et al., 2012), providing larger motivational incentive to complete.

Secondly, strong EI might not be relevant to EE course completion. Participants with strong EI might find the course misaligned with their expectations, especially since digital platforms often lack the interaction and practice-based activities needed to sustain motivation (Chen et al., 2021). This helps explain why dropout participants were often characterized by unmet support needs, suggesting that both motivational gaps and course design features shape persistence. Moreover, EE exposure itself can prompt new reflections on entrepreneurship, which in some cases may dampen rather than strengthen EI and lead to dropout. Nabi et al.'s (2017) review highlights this heterogeneity, showing that students with prior exposure or already high intentions sometimes report weaker—or even negative—responses to EE. From an SCCT perspective, their experiences in the EE MOOC may have reshaped their outcome expectations and self-efficacy beliefs in ways that dampened their EI, reducing their motivation to persist. This nuance complicates the EE MOOC developer's goal of fostering entrepreneurial activity, as strong EI does not uniformly translate into course completion.

Similar to our SCCT model (Figure 1), this study also found interactions between sociodemographic background and individual attributes affect the participants' choice goal and actions (EE MOOC completion), leading to differing outcomes. In regard to household income, low-ILOC participants were unlikely to complete the EE MOOC unless they came from high-income families. The comparatively lower completion from their lower-income family counterparts indicates that the combination of low ILOC and socioeconomic status serve as a contextual barrier. In SCCT terms, contextual barriers may limit an individual's self-efficacy and outcome expectations (Flores et al., 2017), affecting their career goals and their desire to finish the EE MOOC. Indeed, as the qualitative content analysis on DP reported respondents desiring business-based guidance in addition to social and resource-based support, we hypothesize that low-income participants may be less motivated to complete the EE MOOC if it fails to meet their support-specific expectations.

Inversely, medium-to-high-ILOC participants residing in low-income states were overwhelmingly likely to complete the EE MOOC. This phenomenon may be driven by a desire to overcome a lack of business venture and knowledge-building opportunities in lower-income states, a similar situation faced by Chinese rural youth entrepreneurs, who find rural infrastructure, resources, and market access inferior to urban areas (Yuan et al., 2022). Thus, considering ILOC's role in overcoming contextual barriers is crucial to reconciling both sociodemographic factors' contradictory results. As per SCCT (Flores et al., 2017), low sociodemographic standing typically constrains an individual's self-efficacy and outcome expectations, but a strong ILOC may provide the “push” needed to motivate participants to overcome their sociodemographic barrier (Nungsari et al., 2021), allowing them to pursue greater opportunities expediently afforded by EE MOOCs.

This study acknowledges limitations in its scope and findings. Firstly, the study used data from a small voluntary sample size from a single EE MOOC, which allowed for important

observations but limited generalizability and introduced a risk of both the decision tree and regression models “overfitting” the data. Nonetheless, these early insights point to the value of entrepreneurial skills beyond strictly entrepreneurial contexts. While preliminary, these patterns highlight potentially fertile directions for future research with larger and more diverse samples, as well as across different educational settings. Additionally, the present study investigated the effects of background psychological and sociodemographic factors on course completion, but it did not consider participants’ relationship to the course’s pedagogy and content, which may have affected their retention. Course structure, teaching methods, and content quality are examples of factors well-known to influence retention (Jordan, 2015; Lee & Choi, 2011); by excluding these factors, we risk over-attributing dropout to individual traits rather than course-level features. Furthermore, the decision tree's sole SCCT “interest” component was EI, and the overall results suggest that non-entrepreneurial motivations have a more significant impact on EE course completion. It is feasible to augment the accuracy rate of the model by incorporating additional non-EI “interest” variables in future studies. Finally, this study took place during COVID-19, when participants’ motivations and constraints were atypical. High dropout rate could partly reflect pandemic-related stressors or limited digital access (Mathrani et al., 2022), instead of enduring patterns of typical MOOC retention. Thus, future research could further clarify the effects of psychological and sociodemographic factors on EE MOOC completion, without the potential proximal influence of COVID-19.

### ***Implications for Research***

The discussion of this paper’s findings leads to two broad contributions to future research, which are the following: (a) the potential of using decision tree modelling to map out potential interactions in complex datasets to scrutinize in follow-up studies and (b) expands SCCT application in EE MOOCs’ completion rates.

While contemplating the usage of decision tree over regression, performing moderation analysis by incorporating interaction terms into the logistic regression equation can make it more similar to the decision tree model. However, determining which interaction to investigate poses challenges, especially in complex datasets with diversifying variables, necessitating a selection approach and reducing parsimony (Batterham et al., 2009). This decision tree approach identifies important interactions to be explored in a follow-up study, demonstrating its applicability in exploratory studies with data collected beyond research purposes. For example, student course registration data, client databases, and census data. Consequently, it provides the foundation for specific follow-up studies aimed at validating and expanding the results.

Additionally, the decision tree approach contributes to the discourse in SCCT literature with its novel application in EE MOOCs by mimicking the relationships between the components in the SCCT model to an extent (Lent & Brown, 2006). Firstly, the impact of psychological traits and sociodemographic factors on vocational-related educational pursuits is not uniform but context-dependent, as evidenced by the intricate conditions shown in Figure 2 that must be met prior to successful course completion. Furthermore, the potential for generalizing the findings beyond the Malaysian context is presented by the fact that SCCT endorses our findings. Secondly, our initial assumption that youth with EI would be a strong contributor to EE MOOC completion was flawed. This EE MOOC was designed to support youth’s EI and advance them towards their entrepreneurial goal. Nevertheless, the results

contradicted this notion, as the decision tree demonstrated the minor role of EI in facilitating course completion. In contrast, ILOC has the largest explanatory power in course completion. This highlights the role of personal agency that SCCT champions and offers avenues for nurturing certain traits in facilitating strong and clear goals. The textual data revealed an additional “interest” that emphasizes career development while sharing common choice goals and actions with those with EI “interest” (Figure 4) as they acknowledged the transferability of entrepreneurial skills.

### ***Implications for Practice***

Our study highlights three key considerations for the pedagogy and execution of EE MOOC. First, personal motivations—both entrepreneurial and non-entrepreneurial—influence EE MOOC retention, due to the versatility in the application of entrepreneurial skills. Depending on the course content creator’s intent, it would be practical for EE MOOC practitioners to consider framing their course content to be more holistic in its outcome. Teaching entrepreneurship as a transferable skill set that can be applied to business and other career scenarios (Salceanu et al., 2021), rather than merely the ability to start and run a company, may make the online EE course knowledge more appealing to a wider range of participant motivations, encouraging retention. In contrast, these findings also showed that EE MOOC alone is insufficient in promoting entrepreneurship and practitioners should consider designing a broader entrepreneurship program that incorporates other elements outside EE, as suggested in the sub-category “Unmet needs” from the content analysis (Chen et al., 2021). Second, ILOC—beliefs in personal agency and self-confidence—increases classroom participation, investigation, and active problem-solving (Hart, 2012). Thus, educational content that encourages participants to take ownership and responsibility for their future may strengthen their ILOC (Lowes & Lin, 2015), improve their self-regulation, and make them more proactive in course content (Liu & Chi, 2012). Lastly, contextual barriers affect the likelihood of participants completing the EE MOOC, highlighting the need for a strong entrepreneurial support network for youth from lower sociodemographic backgrounds, who often lack the opportunities, infrastructure, and resources to succeed in entrepreneurship (Yuan et al., 2022). Online EE practitioners may seek to strengthen their impact on lower sociodemographic communities by incorporating informal collaborative support networks, which include mentorship and collaborations between entrepreneurs, that serve as substantial alternatives to the “institutional voids” that characterize the entrepreneurial environment of developing nations (Guerrero et al., 2021).

## **Conclusion**

Intending to assess EI’s role in student retention in a voluntary EE MOOC, the present study utilized survey data from 222 youths. Upon situating the decision tree outcomes within the framework of students’ course enrollment objectives, the results unexpectedly emphasize that EI alone does not suffice to motivate students to complete the course. Furthermore, the narrative derived from the textual data and the hierarchical significance of ILOC support the notion that, in addition to imparting educational content, the course design should actively consider students’ mindsets and motivations. Besides, youth’s internal traits intersect with their socioeconomic context to form differing reactions towards the EE MOOC’s contents. The study contributes to the current literature in terms of (1) methodological discussion of using decision tree modelling, (2) expanding the discussion of vocational-related educational pursuits as context-dependent, and

(3) highlighting the possible motivators for completing EE to be beyond the pursuit of an entrepreneurial career path, and entrepreneurial skills being transferable in workplace settings.

## **Declarations**

### **Ethics Statement**

This study was approved by their institution's review board (ASB-IRB-2021-2). All procedures involving human participants complied with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments. Informed consent was obtained from all participants.

### **Conflicts of Interest Statement**

The authors declare no conflicts of interest related to the research, authorship, or publication of this article. The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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