Educational Administration: Theory and Practice
2025, 31(02), 01-09
ISSN: 2148-2403
https://kuey.net/

Research Article

STEM Vocational Interest Among Rural Students: Variations by Marginalization Level

Verónica Hernández-Mena[1]*, Deneb Elí Magaña Medina[2]

[1]*PhD in Economic and Administrative Studies, currently a postdoctoral fellow at the National Council of Humanities, Science and Technology at the Universidad Juárez Autónoma de Tabasco –Academic Division of Economic and Administrative Sciences. Her lines of research have focused on intervention in Health and Education Administration, with a gender focus and studies on STEM disciplines. Email: veroh114@gmail.com ORCID: https://orcid.org/0000-0001-7250-4281
[2]PhD in Administrative Sciences Socioeconomic Management. She belongs to the National System of Researchers, level II. Leader of the consolidated academic body: Management and Organizational Behavior. Lines of research on research and technological development activities, interest in careers in STEM disciplines, leadership and behavior in higher education organizations and research groups in Mexico. Universidad Juárez Autónoma de Tabasco –Academic Division of Economic and Administrative Sciences. Email: deneb.magana@ujat.mx ORCID Code: https://orcid.org/0000-0002-8579-596X

Citation: Verónica Hernández-Mena et al. (2025), STEM Vocational Interest Among Rural Students: Variations by Marginalization Level, *Educational Administration: Theory and Practice, 31(02), 01-09*
Doi: 10.53555/kuey.v31i2.10019

ARTICLE INFO

ABSTRACT

The observed gap between the international need for specialized human capital in scientific and technological disciplines and the decline in university enrollment in these areas has raised concerns about the economic future of regions related to knowledge production. The objective of this research is to determine the differences perceived by high school students living in localities with varying degrees of marginalization, among the variables: Family Support, Teacher Support, Peer Support, Expectations, and Self-efficacy in relation to Interest in STEM careers. A quantitative, correlational, and explanatory study is presented, with a sample of 828 students from 13 rural high school institutions. Through statistical tests of linear regression, bivariate correlation, and Student's t-test, it was shown that the model and its variables explain 50% of the interest in university degrees in STEM and revealed some interesting differences between population groups living in different conditions of marginalization. The importance of family support and the perception of self-efficacy in both populations was identified, as well as the influence of teachers, mainly on students living in localities with a High Level of Marginalization. Likewise, differences were observed in the significance of career expectations, being higher for those with a Lower Level of Marginalization.

Keywords: Rural students, marginalization, STEM

Introduction

The scientific and technological growth of nations is closely related to economic growth and the ability to generate opportunities for social well-being, value, and wealth for their citizens (Comisión Económica para América Latina y el Caribe [CEPAL], 2004). Current economies require specialized human capital focused on research, engineering, and technology (García & Sánchez, 2017) that contributes to meeting the needs of the industry and generating competitive advantages, through the strengthening of disciplines globally known as STEM, an acronym for science, technology, engineering, and mathematics.

Statistics predict that the need for human capital in STEM in 2025 will be 12.1% higher, as opposed to the projected increase for other occupations (3.8%) (Danish Technological Institute, 2015). However, globally, there is a [gradual distancing of young people from STEM studies and a low demand for scientific and technological careers (Biel-Maeso et al., 2022), creating an imbalance between the supply and demand of specialized human resources.

In Mexico, university enrollment data show a significant decline in STEM-related disciplines (Asociación Nacional de Universidades e Instituciones de educación Superior (ANUIES), 2018), despite the increasing demand for professionals in industries such as Automotive, Biotechnology, Energy, Information Technology, and Aerospace (Fundación México-Estados Unidos para la Ciencia, 2018.). This issue becomes even more relevant when considering the marked socioeconomic differences between the country's regions, placing the southeastern region at a clear educational and economic disadvantage compared to the central and northern states.

An example of this is the state of Tabasco, where the level of social lag is classified as Medium (Subsecretaría de Planeación Evaluación y Desarrollo Regional [SEDESOL], 2018), with marked gaps between urban and rural localities. More than half of the state's population (54%) lives in poverty (38.9% moderate and 14% extreme) (Secretaría de Bienestar, 2023), meaning they earn less than the welfare line, which prevents them from covering the minimum needs of food and non-food baskets ((Consejo Nacional de Evaluación de la Política de Desarrollo Social [CONEVAL], 2016). It is noteworthy that 43% of the population lives in rural communities (Instituto Nacional de Estadística y Geografía [INEGI], 2020b), which complicates access to quality education opportunities, as well as incentive and training programs. Additionally, unemployment rates are the highest in the country (Instituto Nacional de Estadística y Geografía [INEGI], 2024), despite the state's potential in oil, livestock, and agriculture, and its proximity to the country's main ports and consumption centers (Secretaría de Economía [SE], 2017).

In this context, promoting the study of STEM disciplines becomes relevant as a strategy to reduce social inequalities. According to data from the National Occupation and Employment Survey (ENOE), the highest-paying professional fields are Architecture, Engineering, and Physical-Mathematical Sciences, with Physics being the highest-paying career (Secretaría del Trabajo y Previsión Social, 2022), which represents an opportunity for social mobility. Additionally, the state's industry increasingly requires better human resources, opening opportunities for more dignified jobs, mainly in renewable energy, agroindustry, and petrochemicals, with oil mining contributing the most to the state's GDP (Instituto Nacional de Estadística y Geografía [INEGI], 2021).

Some authors suggest that there is greater interest in studying STEM careers in populations with lower social development (Aschbacher et al., 2010); however, given the context described, the structural differences that limit access to these careers cannot be ignored. Unlike urban areas, where there are appropriate spaces for the study and development of these disciplines, rural localities face various challenges, including the scarcity of resources to offer specialized courses or programs in educational institutions (Burton et al., 2014).

Identifying how the degree of marginalization of students' residence influences their interest in university STEM careers will broaden the perspective and generate strategies to encourage interest, improve access patterns, and reduce school dropout rates, enabling the generation of high-level human resources that meet the requirements of Tabasco's industry. This research aimed to determine the differences among high school students from rural institutions, considering the degree of marginalization of their locality of residence, in relation to Interest in university STEM careers. To this end, the following variables were analyzed: Family Support, Teacher Support, Peer Support, Expectations, and Self-efficacy.

Literature Review

Vocational Interest in STEM

Vocational choice is a complex process that encompasses cognitive and emotional elements, making it difficult to predict interest in studying STEM disciplines (Maltese et al., 2014). However, it has been studied that personal characteristics, psychological state, contextual characteristics, and the educational environment are fundamental elements in this process (Krapp, 1999). Various studies worldwide have shown some variables that influence the choice of university STEM careers (Aschbacher et al., 2014; Hasni & Potvin, 2015; Ing, 2014; Perera & McIlveen, 2017; Vázquez-Alonso & Manassero-Mas, 2015), among which the following stand out: Family Support, including parental education level, occupation, job stability, socioeconomic status, and support in extracurricular activities; the school environment and Teacher Support (Vázquez-Alonso & Manassero-Mas, 2015), as well as the attitudes of classmates and friends (Peer Support) (Osborne et al., 2003). These studies highlight that individuals who receive support from their communities have more opportunities to show and consolidate scientific interests, orienting themselves toward STEM vocations (Aschbacher et al., 2010; Hillman et al., 2016). Undoubtedly, gender is also an important predictor for vocational choice, as stereotypes can negatively influence the perception of STEM-related abilities, as well as their involvement and interest in developing future careers in these areas (Garduño & Reyes, 2022).

Social Support

Adolescence is a stage of high vulnerability for individuals, making the support they receive from their environment essential for development and adaptation (Orcasita & Uribe, 2010). Social support represents a fundamental component for individual and family well-being, primarily responding to processes of change and personal development, and is crucial in preventing and reducing deficiencies in the academic process, acting as a physical and psychological protective factor (Manrique-Millones et al., 2020).

Generally, two types of support can be observed: informal, stemming from interactions with family and friends; and formal, developed in groups, such as the school environment; both being equally important and necessary. The emotional, material, and informational support provided by the environment becomes a protective factor, helping individuals face risky situations, reinforce their self-esteem, and, in general, create an environment of well-being and a positive perception of their surroundings (Chavarría & Barra, 2014). In this way, the advice, comments, and expectations of those around them influence their perception of their own abilities for optimal development in STEM areas.

Self-efficacy

Academic performance and motivation are directly related to the perception of self-efficacy. Students' perceived confidence in their own abilities is decisive in vocational choice (Moakler & Kim, 2014). In general, those who show achievements and confidence in mathematics and high school averages are more likely to choose and complete a degree in STEM. The perception of self-efficacy in STEM activities has a positive influence on professional interest, making it essential to pay attention to career stereotypes among students and attempt to transform these conceptions into more friendly, realistic, and diversified ones (Luo et al., 2021).

Expectations

The imagined future, monetary benefits, social recognition, and self-satisfaction generate expectations that impact academic interest and are a critical mediator in the choice of university careers (Nugent et al., 2015), in such a way that individuals are more likely to choose to engage in an activity if they consider that it will have valuable results in their future (Roller et al., 2018). Both self-efficacy and expectations predict professional interest in STEM, this relationship emphasizes the subjective values attributed to tasks, such as interest, cost, achievement, etc.; but also shows the influence of beliefs and the social and cultural environment surrounding the student, who, through comments and perceptions from those around them, goals, and obstacles, will determine their career inclinations (Vázquez-Alonso & Manassero-Mas, 2015), however, students' stereotypical beliefs about these disciplines are negative vocational predictors (Luo et al., 2021).

Sociocultural Context

The social and cultural environment in which individuals develop directly influences personal development, ideas, and behaviors, linked to the relationship with groups that share political, religious, scientific, and technological interests. Thus, the sociocultural level is directly related to career choice, showing significant differences between groups. It has been observed that members of segregated groups show greater willingness and interest in science, mathematics, and technology; likely due to expectations of improvement and better living conditions; however, they are not the ones who continue this vocational path (Aschbacher et al., 2014; Christensen et al., 2014).

It has been shown that the sociocultural level conditions parents' educational practices, students' self-esteem levels, as well as psychosocial development, which implies expectations of social and academic success (Alonso & Román, 2014) In the study conducted by (Everis (2014), it was observed that 44% of students with a high sociocultural level choose STEM studies, while only 24% of those with a low level follow this path, showing a concerning difference.

Rural Population and Marginalization

Marginalization is the set of disadvantages faced by individuals and families living in a community or locality and is conceived as a structural social problem, characterized by a lack of development opportunities and the capacities to acquire them. The marginalization index allows for the dimensioning and visualization of those social sectors in this position, stratifying them into 5 degrees, using information available in population censuses. According to statistics, rural populations concentrate the lowest socioeconomic levels in Mexico, showing that people living in remote and dispersed settlements present high degrees of marginalization and social lag. In these areas, extreme poverty reaches 17.4% of the population, compared to urban areas where this indicator is at 4.4% (Consejo Nacional de Población [CONAPO], 2019).

As previously mentioned, the state of Tabasco has a high concentration of rural populations (Instituto Nacional de Estadística y Geografía [INEGI], 2020a), implying high sociocultural and economic lag, as well as limited access to quality educational opportunities, as the academic performance of students in rural environments shows a higher degree of failure and school dropout than in urban environments. The limited access to incentives, training, and STEM projects discourages interest in the area and distances youth from scientific and technological interest (Polasek & Kolcic, 2006).

Methodology

The study design is non-experimental and cross-sectional, without deliberate manipulation of variables and collecting data at a single point in time. This allows for the observation of the phenomenon, as well as the description and analysis of population behavior (Cortés & Iglesias, 2004). The study is developed with a quantitative approach, correlational and explanatory scope, seeking to analyze the relationships between the established variables and explain the differences in the studied population groups (Hernández & Mendoza, 2018).

Participants

The population consisted of students enrolled in rural high school institutions in the state of Tabasco, selecting those near areas (within a 60 km radius) with the highest educational offerings in STEM undergraduate programs. Through non-probabilistic quota sampling (Chica & Castejón, 2006), 828 students from 13 rural institutions in 5 municipalities of Tabasco were chosen. To establish the rural characteristic, the search and location were based on the microregions established by the National Institute of Statistics and Geography

(INEGI, 2019). Additionally, a variable related to the level of marginalization of the students' localities of residence was generated, using microregion statistics from (Instituto Nacional de Estadística y Geografía [INEGI], 2023) highlighting that one-third reside in populations with a high degree of marginalization (Table 1).

Table 1. Degree of Marginalization of the Locality of Residence of the Surveyed Population.

Degree of Marginalization	Frequency	Percentage
Very low	117	14.1
Low	195	23.6
Medium	206	24.9
High	273	33.0
Total	791[1/]	95.5[1/]

Note. ^1/^The difference with the total number of students surveyed corresponds to missing data.
Source. Own elaboration with data from INEGI, 2023.

Data Collection Procedures

After preliminary talks with school authorities, authorization was requested to apply the questionnaire, and the number of participating students from each selected institution was established, ensuring diversity and gender parity to provide greater certainty to the results. Voluntary participation of the students was requested, with prior informed consent. Data collection was carried out through a self-administered questionnaire, with the support of the research group.

The questionnaire was designed based on a documentary review of other instruments used worldwide that measure the variables of interest from which items were adopted and adapted to the study environment, which was qualitatively validated by a group of experts with publications on vocations in STEM disciplines. To understand the participants' reactions, they were presented with a set of questions in the form of statements, asking for their response through a Likert scale with five response options: 1. Strongly Disagree, 2. Disagree, 3. Neither Agree nor Disagree, 4. Agree, and 5. Strongly Agree (Muñiz, 2018).

Data analysis

Cronbach's Alpha coefficient showed that the instrument has a high level of reliability, ensuring internal consistency, with values close to .80: Family Support, .84; Peer Support, .78; Teacher Support, .85; Self-efficacy, .83; Interest, .79; and Outcome Expectations, .82 (Cronback LJ, 1951).

Upon obtaining a Kaiser-Meyer-Olkin (KMO) result = .95 and Bartlett's sphericity with significance values of *p* < .000, it was shown that the criteria for conducting Exploratory Factor Analysis (EFA) were met (Zalazar-Jaime & Cupani, 2018), to validate the construct.

Thus, an Exploratory Factor Analysis (EFA) was conducted using the maximum likelihood factor extraction method with direct oblimin rotation, resulting in total variances with acceptable percentages, above 51.06% (Hernández-Mena, 2021; Magaña Medina et al., 2022). Through structural equations, the measurement models for each variable were analyzed, with the support of AMOS software version 26. To ensure that the estimation results were not affected by normality issues, the AMOS bootstrap method was used (with 2,000 repetitions and a 95% confidence interval) (Rojas-Torres, 2020). The maximum likelihood estimation method was used to calculate the goodness-of-fit indices, absolute fit, and incremental fit, obtaining highly satisfactory values (Table 2).

Table 2. Fit Indices of the Measurement Models for Each Studied Variable.

Variable	CMIN/DF	SRMR	AGFI	TLI	CFI	RMSEA
Valores esperados	1 a 3	<.08	≥ .90	≥ .90	≥ .95	<.06
Family Support	1.85	.01	.98	.99	.99	.03 [.00-.07]
Peer Support	1.44	.00	.99	.99	.99	.02 [.00-.07]
Teacher Support	2.45	.01	.98	.99	.99	.04 [.00-.08]
Self-efficacy	2.19	.01	.98	.99	.99	.03 [.00-.07]
Expectations	0.79	.00	.99	1.02	1	.00 [.00-.04]
Interest	3.36	.01	.98	.98	.99	.05 [.00-.12]

Note. N= 828. Reference values taken from: (Arias, 2008; Manzano & Zamora, 2010).

Results

The capture and analysis of the collected data were performed using the IBM SPSS Statistics 25 program, verifying data integrity, for which incomplete questionnaires were discarded, and missing and atypical data were identified. Through descriptive statistics, the sample and data distribution were characterized. The gender distribution of the sample was very homogeneous, with 50.5% (418) men and 49.5% (410) women, aged

between 17 and 21 years. All of them study in rural schools, and only 22% live in an urban area, while 78% reside in a locality considered rural.
To contrast the research hypotheses, the t-test was used to establish the differences between the population groups. Finally, a hierarchical regression analysis was performed to explain the variable Interest in STEM disciplines in the two studied population groups (Kerlinger & Lee, 2002).
To explain students' interest in STEM disciplines based on the degree of marginalization, the 5 defined levels (very low, low, medium, and high) were divided into only two groups, with the first two levels in the first population group called Low Marginalization Level, and the last two as High Marginalization Level. Subsequently, a hierarchical regression analysis was performed to explain the variable Interest in STEM disciplines in the two defined population groups (Kerlinger & Lee, 2002).

Analysis of variance

Through the statistical analysis of variance, the means of two or more independent populations with normal distribution and homogeneous variance were compared simultaneously (Ho & Lin, 2003). The statistical results showed that all the studied variables present significant differences in the comparison of the population groups, except for self-efficacy. Teacher Support is the variable with the largest effect size at 38%, with the highest mean in the high marginalization level (see Table 3).

Table 3. Student's t-test and Effect Size of the Model Variables

Variable	Degree of Marginalization				t	D Cohen
	Low		High			
	M	DE	M	DE		
Family Support	3.99	0.81	4.12	0.74	-2.18*	-0.16
Peer Support	3.85	0.72	4.01	0.64	-3.16**	-0.23
Teacher Support	3.82	0.79	4.11	0.72	-4.98***	-0.38
Self-efficacy	3.68	0.74	3.75	0.69	-1.19	-0.09
Interest	3.57	0.90	3.75	0.87	.2.74**	-0.20
Expectations	3.93	0.69	4.03	0.62	-2.13*	-0.15

Note. N= 828. *p<.05, **p<.01, ***p<.001

Correlation

Table 4 shows the bivariate correlation analysis between the study variables and the level of marginalization, highlighting again the impact of Teacher Support.

Table 4. Mean, Standard Deviation, and Correlations Between the Degree of Marginalization of the Surveyed Population and the Model Variables.

Variable	M	DE	M	F	P	D	AF	I	E
DOM	2.80	1.070	1						
F	4.03	0.80	0.09**	1					
P	3.90	0.70	0.10**	0.58**	1				
D	3.91	0.79	0.19**	0.50**	0.59**	1			
AF	3.70	0.73	0.07*	0.48**	0.51**	0.53**	1		
I	3.62	0.91	0.11**	0.50**	0.48**	0.50**	0.65**	1	
E	3.96	0.68	0.09**	0.53**	0.54**	0.53**	0.48**	0.50**	1

Note. *p<.05, **p<.01, ***p<.001. DOM= Degree of Marginalization, F=Family Support, P= Peer Support, D= Teacher Support, AF= Self-efficacy, I= Interest, E= Expectations.

Regression analysis

The linear regression analysis of the model, based on the low marginalization level, highlights that the variables positively and significantly predict interest, explaining 50% of the variance (R^2^=50, *p*<.001) (Table 5). The highest values are found in Family Support (β=.50, *p*<.001) and Self-efficacy (β=.62, *p*<.001), while Expectations have fewer influence (β=.16, *p*<.001).

Table 5. Linear Regression of the Model Variables for Interest in STEM in Individuals with Low Marginalization Level.

Variable	B	95%CI	β	R^2	ΔR^2
Step 1: F	.56	[.47-.64]	.50***	.25***	.25***
Step 2: P	.40	[.29-.51]	.33***	.32***	.07***
Step 3: D	.30	[.20-.40]	.27***	.37***	.05***
Step 4: AF	.52	[.43-.64]	.62***	.48***	.11***
Step 5: E	.21	[.11-.32]	.16***	.50***	.01***

Note. N = 273; *p<.05, **p<.01, ***p<.001. F=Family Support, P= Peer Support, D= Teacher Support, AF= Self-efficacy, E= Expectations, CI = Confidence Interval for β.

When performing the same analysis for the high marginalization level, it is shown that all variables significantly explain interest in STEM careers, with 51% of the variance (R^2^=51, *p*<.01) (Table 6).
In this group, Family Support also significantly explains interest in STEM (β=.45, *p*<.001), as does Self-efficacy (β=.53, *p*<.001).

Table 6. Linear Regression of the Model Variables for Interest in STEM in Individuals with High Marginalization Level.

Variable	B	95%CI	β	R^2	ΔR^2
Step 1: F	.53	[.40-.65]	.45***	.20***	.20***
Step 2: P	.38	[.21-.55]	.28***	.26***	.05***
Step 3: D	.33	[.18-.48]	.27***	.31***	.05***
Step 4: AF	.66	[.53-.78]	.53***	.50***	.19***
Step 5: E	.18	[.02-.33]	.13*	.51**	.00*

Note. N = 273; *p<.05, **p<.01, ***p<.001. F=Family Support, P= Peer Support, D= Teacher Support, AF= Self-efficacy, E= Expectations, CI = Confidence Interval for β.

In both marginalization levels, the model significantly explains interest in STEM disciplines, with a slight difference between the two population groups.

Discussion and Conclusions

The marked structural differences in access to education depending on the context, rural or urban, in which students develop in the state of Tabasco, where there is a high level of social inequality, highlights the need to establish strategies, from public policy, that take into account socioeconomic characteristics, to understand and contribute to reducing gaps (Consejo para la Evaluación de la Educación del tipo Medio Superior A.C. [COPEEMS], 2019). It is noteworthy that higher education, the growth of enrollment, and terminal efficiency are key to social mobility; however, it is necessary to address other factors, such as equal opportunities and the availability of quality jobs that provide better development opportunities (Perezchica, 2023), through a holistic understanding of the societies targeted by policies.
The studied model and the variables included in it largely explain interest in STEM disciplines in students living in communities with a Low Level of Marginalization, with only a 1 percentage point difference compared to those with a High Level, providing an interesting perspective on what happens socially and personally with students regarding their professional interests related to STEM. In both populations, Family Support and the perception of Self-efficacy were variables with a high degree of significance, being slightly higher in students with a Low Level, which provides a perspective on where strategies to attract students to the area should focus. The effect of Teacher Support on students with a High Level of marginalization stands out, clearly showing the influence that teachers have on students; the fewer development opportunities the localities where they live present, the greater the influence that their teachers can have on their professional decisions. Teacher Support is fundamental for making vocational decisions; therefore, if teachers are convinced of the importance of these, they generate spaces for student engagement, recognizing interesting and fun STEM learning methods and models, which can impact student learning outcomes (Nurfirani & Kristayulita, 2024). However, it should not be ignored that teachers also face difficulties in fulfilling their tasks, as they largely depend on the level achieved by students in previous levels of education (Guevara Benítez et al., 2008), as well as the infrastructure they must carry out their work, which in these environments is scarce.
Another variable worth highlighting is Career Expectations, which, although they explain the model to a lesser extent compared to the other variables, shows the degree of significance between one population and another. While for students with a high level of marginalization, they do not represent an important significance, for those living in localities with a Low Level of Marginalization, these are highly influential. This can be understood by the differences in access to development opportunities. The fewer opportunities the environment provides, the ability to visualize opportunities also decreases.
Limitations due to socioeconomic conditions are related to the possibility of leaving professional studies unfinished, which frequently happens in rural communities (Raczynski & Román, 2014), despite the fact that upon completing high school, this population reports a 60% interest in continuing their professional studies; to achieve this, they largely depend on access to scholarships or combining work and study (Weiss et al., 2008), clearly showing the importance of generating evidence-based public policies that take into account social, economic, and cultural differences. The results and analysis of this research globally conclude that incentive programs and scholarships targeted at these high marginalization groups are needed to promote not only interest in STEM disciplines but also the training of teachers who contribute to the generation and maintenance of this interest.

It is important to highlight that there are efforts, from different areas, to combat the problem, so policy planning should consider the path already traveled. In vulnerable environments, spaces for collaboration and the development of technological skills have been created, promoting equity in STEM education, seeking the democratization of access to education through interactive learning, contributing to a sense of belonging (González-Nieto et al., 2020), which have shown important results in bringing students closer to these disciplines.
Methodologically, in this research, a sociocultural diverse sample was sought; however, social desirability in responses can generate bias that limits and hinders the generalization of findings. This leaves a basis for ideally replicating the study in other regions, contexts, and age groups, allowing the observation of the model's behavior under other conditions. The importance of including variables related to gender in future research is highlighted, as evidence shows that stereotypes can deter women from seeking careers in these fields, increasing the gender gap in STEM, due to the entrenched belief that STEM disciplines are more suitable for men (Garduño & Reyes, 2022), a situation that is accentuated in rural communities and with high social lag.

References

1. Alonso, J., & Román, J. M. (2014). Nivel sociocultural, prácticas educativas familiares y autoestima de los hijos en edades tempranas. Revista de Investigación Educativa, 32(1), 187–202. https://doi.org/10.6018/rie.32.1.173421
2. Aschbacher, P. R., Ing, M., & Tsai, S. M. (2014). Is Science Me? Exploring middle school students' STE-M career aspirations. Journal of Science Education and Technology, 23(6), 735–743. https://doi.org/10.1007/s10956-014-9504-x
3. Aschbacher, P. R., Li, E., & Roth, E. J. (2010). Is science me? High school students' identities, participation and aspirations in science, engineering, and medicine. Journal of Research in Science Teaching, 47(5), 564–582. https://doi.org/10.1002/tea.20353
4. Asociación Nacional de Universidades e Instituciones de educación Superior (ANUIES). (2018). Anuarios Estadísticos de Educación Superior - ANUIES. Anuarios Estadísticos de Educación Superior. http://www.anuies.mx/informacion-y-servicios/informacion-estadistica-de-educacion-superior/anuario-estadistico-de-educacion-superior
5. Biel-Maeso, M., Montesinos, V. S., María, A., & Martín, G. (2022). Stem a análisis: evolución de las matriculaciones en titulaciones universitarias y Formación Profesional. Revista de Estilos de Aprendizaje Journal of Learning Styles, 15(E1), 135–149. www.revistaestilosdeaprendizaje.com
6. Burton, E. P., Kaminsky, S. E., Lynch, S., Behrend, T., Han, E., Ross, K., & House, A. (2014). Wayne school of engineering: Case study of a rural inclusive STEM-focused high school. School Science And Mathematics, 114(6), 280–290. https://doi.org/10.1111/ssm.12080
7. Chavarría, M. P., & Barra, E. (2014). Satisfacción Vital en Adolescentes: Relación con la Autoeficacia y el Apoyo Social Percibido. Terapia Psicológica, 32(1), 41–46. https://doi.org/10.4067/s0718-48082014000100004
8. Chica, A. A., & Castejón, J. L. (2006). Elaboración, análisis e interpretación de encuestas, cuestionarios y escalas de opinión. Vicerrectorado de calidad y armonización europea. Universidad de Alicante.
9. Christensen, R., Knezek, G., & Tyler-Wood, T. (2014). Student perceptions of science, technology, engineering and mathematics (STEM) content and careers. Computers in Human Behavior, 34, 173–186. https://doi.org/10.1016/j.chb.2014.01.046
10. Comisión Económica para América Latina y el Caribe [CEPAL]. (2004). Desarrollo productivo en economias abiertas. Organización de las Naciones Unidas. https://repositorio.cepal.org/bitstream/handle/11362/13057/S0400002_es.pdf;jsessionid=E53F5CFA55A84E260E2A0D7C15FACB8A?sequence=1
11. Consejo Nacional de Evaluación de la Política de Desarrollo Social [CONEVAL]. (2016). InfoPobreza. Página Oficial. http://sistemas.coneval.org.mx/InfoPobreza/
12. Consejo Nacional de Población [CONAPO]. (2019). Localidades rurales. http://www.conapo.gob.mx/es/CONAPO/Localidades_rurales
13. Consejo para la evaluación de la educación del tipo medio superior A.C. (2019). Estadística del PC-SINEMS – Copeems. https://www.copeems.mx/dim/estadistica-del-pc-sinems/
14. Cortés, M., & Iglesias, M. (2004). Generalidades sobre Metodología de la Investigación. In Colección Material Didáctivo (Vol. 10). Universidad Autónoma del Carmen. http://www.unacar.mx/contenido/gaceta/ediciones/metodologia_investigacion.pdf
15. Cronback LJ. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16(3), 297–334. https://doi.org/10.1007/BF02310555
16. Danish Technological Institute. (2015). Does the EU need more STEM graduates? (Issue 120). Office of teh European Union. https://doi.org/10.2766/000444
17. Everis. (2014). Factores influyentes en la elección de estudios científicos, tecnológicos y matemáticos. In Everis, e-motiva, Generalitat de Catalunya Departament d'Ensenyament (pp. 1–80). http://s3-eu-west-1.amazonaws.com/e17r5k-datap1/everis_documents_downloads/estudio+vocaciones.pdf

18. Fundación México-Estados Unidos para la Ciencia (FUMEC). (2018). Retrieved August 28, 2018, from https://www.fumec.org/
19. García, M. de L., & Sánchez, M. G. (2017). Sistemas de innovación y capital humano calificado. Avances y retos en México. XXII Congreso Internacional de Contaduría, Administración e Informática., 1–32. http://congreso.investiga.fca.unam.mx/docs/xxii/docs/9.18.pdf
20. Garduño, E., & Reyes, A. (2022). Mujeres y educación en STEM : una mirada con perspectiva de género. Apuntes para México. https://www.movimientostem.org/wp-content/uploads/2022/02/Mujeres-y-educacion-en-STEM-una-mirada-con-perspectiva-de-genero.pdf
21. González-Nieto, N., Ching-Chiang, C., Fernábdez-Cárdenas, J. M., Reynaga-Peña, C., Cid-de-León, D., de-León-Lastras, A., & Cortés, A. J. (2020). FabLabs in vulnerable communities: STEM education opportunities for everyone. Int J Interact Des Manuf , 14, 1535–1555. https://doi.org/https://doi.org/10.1007/s12008-020-00744-y
22. Guevara Benítez, Y., Hermosillo García, Á., López Hernández, A., Delgado Sánchez, U., René García Vargas, G., & Pablo Rugerio Tapia, J. (2008). Habilidades matemáticas en alumnos de bajo nivel sociocultural. Acta Colombiana de Psicología, 11(2), 13–24. http://www.redalyc.org/articulo.oa?id=79811202
23. Hasni, A., & Potvin, P. (2015). Student's interest in science and technology and its relationships with teaching methods, family context and self-efficacy. International Journal of Environmental and Science Education, 10(3). https://doi.org/10.12973/ijese.2015.249a
24. Hernández, R., & Mendoza, C. P. (2018). Metodología de la investigación: las rutas cuantitativa, cualitativa y mixta (McGraw Hill, Ed.; 1st ed.).
25. Hernández-Mena, V. (2021). Apoyo Social, Autoeficacia y Expectativas de resultado: Factores asociados al interés por Estudios Universitarios en CTIM, en alumnos de instituciones educativas rurales. [Universidad Juárez Autónoma de Tabasco]. https://ri.ujat.mx/handle/20.500.12107/3522
26. Hillman, S. J., Zeeman, S. I., Tilburg, C. E., & List, H. E. (2016). My attitudes toward science (MATS): the development of a multidimensional instrument measuring students' science attitudes. Learning Environments Research, 19(2). https://doi.org/10.1007/s10984-016-9205-x
27. Ho, C., & Lin, Z. (2003). Analysis and Application of Grey Relation and ANOVA in Chemical–Mechanical Polishing Process Parameters. The International Journal of Advanced Manufacturing Technology, 21, 10–14.
28. Ing, M. (2014). Can parents influence children's mathematics achievement and persistence in STEM careers? Journal of Career Development, 41(2), 87–103. https://doi.org/10.1177/0894845313481672
29. Instituto Nacional de Estadística y Geografía [INEGI]. (2020a). Censo de Población y Vivienda 2020. https://www.inegi.org.mx/programas/ccpv/2020/
30. Instituto Nacional de Estadística y Geografía [INEGI]. (2020b). Información por entidad. Tabasco. Población Rural y Urbana. https://cuentame.inegi.org.mx/monografias/informacion/tab/poblacion/distribucion.aspx?tema=me#:~:text=Tabasco&text=79%20%25%20de%20la%20poblaci%C3%B3n%20vive,localidades%20rurales%20y%204%2C189%20urbanas.
31. Instituto Nacional de Estadística y Geografía [INEGI]. (2021). Producto Interno Bruto por entidad federativa, para tabasco en 2020.
32. Instituto Nacional de Estadística y Geografía [INEGI]. (2023). Marco geoestadístico - Catálogo único de claves de áreas geoestadísticas estatales, municipales y localidades. Sistema de Consultas. https://www.inegi.org.mx/app/ageeml/
33. Instituto Nacional de Estadística y Geografía [INEGI]. (2024). Programas de Información. Desocupación. In Comunicado de prensa INEGI (Issue 162/18). https://doi.org/DOI 10.1016/j.colsurfa.2009.03.031
34. Kerlinger, F. N., & Lee, H. B. (2002). Investigación del comportamiento (McGrawHill, Ed.; 1st ed.).
35. Krapp, A. (1999). Interest, motivation and learning: An educational-psychological perspective. European Journal of Psychology of Education, 14(1), 23–40. https://doi.org/10.1007/BF03173109
36. Luo, T., So, W. W. M., Wan, Z. H., & Li, W. C. (2021). STEM stereotypes predict students' STEM career interest via self-efficacy and outcome expectations. International Journal of STEM Education, 8(1). https://doi.org/10.1186/s40594-021-00295-y
37. Magaña Medina, D. E., Hernández-Mena, V., Aguilar Morales, N., & Sánchez Escobedo, P. A. (2022). Apoyo de pares y expectativas de resultado en STEM: desarrollo y validación de un instrumento. Revista Electrónica de Investigación Educativa, 24(e31), 1–13. https://doi.org/https://doi.org/10.24320/redie.2022.24.e31.4274
38. Maltese, A. V., Melki, C. S., & Wiebke, H. L. (2014). The Nature of experiences responsible for the generation and maintenance of interest in STEM. Science Education, 98(6), 937–962. https://doi.org/10.1002/sce.21132
39. Manrique-Millones, D., Millones-Rivalles, R., Dominguez-Lara, S., Pineda-Marín, C., & Manrique-Pino, O. (2020). Social Support in Higher Education: Evidence of Validity and Reliability in the Peruvian Context*. Universitas Psychologica, 19, 1–11. https://doi.org/10.11144/Javeriana.upsy19.sshe

40. Moakler, M. W., & Kim, M. M. (2014). College major choice in STEM: Revisiting confidence and demographic factors. Career Development Quarterly, 62(2), 128–142. https://doi.org/10.1002/j.2161-0045.2014.00075.x
41. Muñiz, J. (2018). Introducción a la Psicometría. Teoría clásica y TRI (Pirámide, Ed.; 1st ed.).
42. Nugent, G., Barker, B., Welch, G., Grandgenett, N., Wu, C. R., & Nelson, C. (2015). A model of factors contributing to STEM learning and career orientation. International Journal of Science Education, 37(7). https://doi.org/10.1080/09500693.2015.1017863
43. Nurfirani, P., & Kristayulita, K. (2024). Pengaruh Pembelajaran Science, Technology, Engineering and Mathematics (STEM) terhadap Hasil Belajar Siswa. Kognitif: Jurnal Riset HOTS Pendidikan Matematika, 4(1), 451–459. https://doi.org/10.51574/kognitif.v4i1.1565
44. Osborne, J., Simon, S., & Collins, S. (2003). Attitudes towards science: A review of the literature and its implications. International Journal of Science Education, 25(9), 1049–1079. https://doi.org/10.1080/0950069032000032199
45. Perera, H. N., & McIlveen, P. (2017). Vocational interest profiles: Profile replicability and relations with the STEM major choice and the Big-Five. Journal of Vocational Behavior, 106(2018), 84–100. https://doi.org/10.1016/j.jvb.2017.11.012
46. Perezchica, J. E. (2023). La educación superior en México: obligatoriedad, gratuidad y movilidad social. RECIE. Revista Electrónica Científica de Investigación Educativa, 7, 1–12. https://doi.org/10.33010/recie.v7i0.1955
47. Polasek, O., & Kolcic, I. (2006). Academic performance and scientific involvement of final year medical students coming from urban and rural backgrounds. Rural and Remote Health, 6(2), 530.
48. Raczynski, D., & Román, M. (2014). Evaluación de la educación rural. Revista Iberoamericana de Evaluación Educativa, 7(3), 9–14. https://revistas.uam.es/index.php/riee/article/view/3098
49. Rojas-Torres, L. (2020). Robustez de los índices de ajuste del análisis factorial confirmatorio a los valores extremos. Revista de Matemática: Teoría y Aplicaciones, 27(2), 383–404. https://doi.org/10.15517/rmta.v27i2.33677
50. Roller, S. A., Lampley, S. A., Dillihunt, M. L., Benfield, M. P. J., & Turner, M. W. (2018). Student attitudes toward STEM: A revised instrument of social cognitive career theory constructs (Fundamental). ASEE Annual Conference and Exposition, Conference Proceedings, 2018-June.
51. Secretaría de Bienestar. (2023). Informe anual sobre la situación de pobreza y rezago social 2023. Tabasco. https://doi.org/10.0%
52. Secretaría de Economía [SE]. (2017). Información económica y estatal. Tabasco. http://www.explorandomexico.com.mx/city/70/Villahermosa/photo/mexico/1795
53. Secretaría del Trabajo y Previsión Social. (2022). Tendencias actuales del empleo profesional. Primer trimestre 2011. Reporte. https://www.observatoriolaboral.gob.mx/static/estudios-publicaciones/Tendencias_empleo.html
54. Subsecretaría de Planeación Evaluación y Desarrollo Regional [SEDESOL]. (2018). Informe anual sobre la situación de pobreza y rezago social 2018 (p. 6). SEDESOL. http://www.sedesol.gob.mx/work/models/SEDESOL/Informes_pobreza/2014/Municipios/Oaxaca/Oaxaca_050.pdf
55. Vázquez-Alonso, Á., & Manassero-Mas, M.-A. (2015). La elección de estudios superiores científico-técnicos: análisis de algunos factores determinantes en seis países. Revista Eureka Sobre Enseñanza y Divulgación de Las Ciencias, 12(2), 264–277. https://doi.org/10.498/17251
56. Weiss, E., Guerra, I., Guerrero, E., Grijalva, O., & Ávalos, J. (2008). Jóvenes y bachillerato en México : el proceso de subjetivación , el encuentro con los otros y la reflexividad. Ethnography and Education Journal, 3(1), 17–31. http://www.propuestaeducativa.flacso.org.ar/archivos/articulos/18.pdf
57. Zalazar-Jaime, M. F., & Cupani, M. (2018). Adaptación de las escalas de expectativas de resultado, metas de progreso y satisfacción académica en estudiantes universitarios. Revista Electrónica de Investigación Educativa, 20(3), 105. https://doi.org/10.24320/redie.2018.20.3.1675