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Research Article

Development and validation of STEM motivation scale for middle school students

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Abstract: Understanding motivational beliefs such as expectancy and value that shape students' persistence and decision to pursue a STEM career, obtaining valid and reliable measures for these dimensions, and developing strategies using this data are critically important to ensure students' persistence in the STEM pipeline. Therefore, this study aims to develop a tool to measure middle school students' STEM motivations within the expectancy and value concepts framework. The trial version of the scale was conducted on 967 middle school students in the 5th, 6th, 7th, and 8th grades. The study group was randomly divided into two groups. EFA was conducted on the data obtained from the first sub-group (n=479), and CFA was performed using the data obtained from the second sub-group (n=488). The results of a series of CFA performed to test three different models developed based on the theoretical structure, Model 3, the second-order single-factor structure composed of 5 sub-dimensions was found to be a successful model. This measurement tool would allow determining motivational beliefs within the expectancy-value concept that can be targeted to encourage students' interest in STEM fields, as well as help design interventions for these structure(s), and evaluate the effectiveness of these interventions.

1. INTRODUCTION

In the last few decades, as technological and industrial advances have accelerated, the demand for STEM (Science, Technology, Engineering, and Mathematics) workforce has begun to increase markedly. Since the number of jobs that require STEM knowledge and skills is rising (Langdon et al., 2011), more STEM professionals are needed to meet this increasing demand (Ball et al., 2017; Hermans et al., 2022; Razali, 2021). Accordingly, STEM education, which refers to teaching and learning in the fields of science, technology, engineering, and mathematics (Gonzalez & Kuenzi, 2012), is considered an important approach to meeting STEM workforce demands for the competitive world of the 21st century (Breiner et al., 2012; Çorlu et al., 2014; Kuenzi, 2008; Kuo et al., 2019; Luo et al., 2021; National, Research Council [NRC], 2011; National Science and Technology Council [NSTC], 2018; PCAST, 2010).

Despite STEM education being widely recognized as crucial for societal advancement and human development, recent reports indicate a decline in the number of students pursuing STEM

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majors and entering STEM careers (pipeline problem in STEM) (Griffith, 2010; Hinton Jr. et al., 2020; Sanders, 2009; van den Hurk et al., 2019; Yahaya et al., 2022). Too many students lose their interest in science and mathematics at early ages and make an early exit from the STEM pipeline (Sanders, 2009). Students' reluctance to pursue a STEM career or decline in interest in STEM careers are considered a major STEM problem in many parts of the world (Bøe et al., 2011; Hossain & Robinson, 2012; Perez et al., 2019).

Although studies examining possible reasons for the decline in STEM interest in the last decade highlighted many factors (see, van den Hurk et al., 2019; Wang & Degol, 2013), psychological studies have revealed that it is partly an issue of motivation (Rozek et al., 2017). Motivation refers to the power that stimulates an organism to start and act toward a specific behavior, and explains the intensity, direction, and persistence of this behavior (Petri & Govern, 2012). In the previous studies, some motivation-related factors such as interest, perceived value, feeling competent in STEM disciplines, belief in success, and considering STEM topics as personally interesting and important were found to affect students' willingness to pursue a STEM career (Perez et al., 2019; Robnett & Leaper, 2012). Students' motivation for STEM can be therefore argued to play an important role in interest and continuous engagement in this field, as well as in choosing a STEM career (Chen & Dede, 2011; Joseph et al., 2019; Luo et al., 2019, Robnett & Leaper, 2012; Wang, 2013; Wang & Degol, 2013).

Motivation researchers have introduced many theories based on internal and external factors to explain how motivation affects one's choices, determination, and performance (Bandura's Self-efficacy theory, Covingtoh's Self-worth theory, Ryan and Deci's Self-determination theory, Weiner's Attribution theory, Eccles-Parsons et al.'s Expectancy-value theory, etc.) Among these contemporary educational psychology theories, the Expectancy-value theory (EVT) is particularly focused on the relation of beliefs, values, and goals to actions (Eccles & Wigfield, 2002). Therefore, the EVT has inspired many education-related studies and practices for more than one-quarter of a century (Trautwein et al., 2012).

1.1. Expectancy – Value Theory (EVT)

EVT is an important theory developed to understand individuals' motivational beliefs (Eccles & Wigfield, 2020), which is widely used in education to explain and predict students' achievement, persistence, and aspirations (Loh, 2019). This theory assumes that students' motivation to perform achievement tasks (e.g., an effort to do homework or exhibit a skill, engaging in specific activities, or using strategies to develop skills) is determined by their expectation of success in a task and the value they attached to the task (Dotterer, 2022; Rosenzweig et al., 2019). In simpler terms, individuals' motivation for success is a function of their belief in their abilities and the value they place on the task (Wigfield et al., 2009).

Among the components of the EVT, the expectation of success is defined as individuals' beliefs about how well they will perform in future achievement tasks (Meyer et al., 2019; Rosenzweig et al., 2019; Wigfield & Gladstone, 2019). In this context, one's expectations for success predict achievement-related factors including performance, persistence, and choices. For example, when students believe that they are competent in mathematics and expect their successes to continue, they are likely to show good performance in mathematics (Eccles et al., 1983). On the other hand, students with low expectations are more likely to procrastinate on academic tasks (Wu & Fan, 2017).

According to EVT, an individual's expectations of success in any task are strongly influenced by his/her confidence in performance (self-efficacy) or beliefs about his/her ability to perform the task (self-concept beliefs) (French et al., 2023). Ability beliefs are children's evaluations of their current competencies or abilities (Wigfield & Gladstone, 2019). Therefore, many researchers in the field of EVT combine beliefs regarding skills with expectancy values rather than simply measuring expectations (Rosenzweig et al., 2019). Although they have different origins, many empirical studies have also shown that expectations overlap with self-efficacy (Appianing & Van Eck, 2018). Self-efficacy refers to one's beliefs about their performance in events that affect their life. These beliefs that they can complete a particular task are important predictors of activity choices, willingness to expend effort, and persistence (Bandura, 1997). Thus, scholars sometimes measure self-efficacy instead of expectations or beliefs about skills (Wigfield & Eccles, 2000).

Another component of the EVT, subjective task value, refers to the quality of a task or activity that increases or decreases the probability of being selected by the person (Eccles & Harold, 1991). The incentives during the performance of the task are associated with this component (Gråstén, 2016). When a task is perceived as motivating (seen as important, beneficial, enjoyable, etc.) from an individual's perspective, the likelihood of that task being completed increases (Barron & Hulleman, 2015; Schoenherr, 2024). Conversely, when there is no reason or incentive for the task, it leads to the task not being done (Wentzel & Wigfield, 1998).

Task values vary depending on task characteristics and their impact on the individual's motivation to complete the task. The values, therefore, are unique to the task (Eccles et al., 1983; Wigfield & Eccles, 1992). These values are also subjective because beliefs about an activity are students' own beliefs, and every student is different (Wigfield & Cambria, 2010). For example, success in mathematics is valuable for some students, whereas it might not be valuable for other students (Eccles, 2011). Subjective task value is positively affected by three components namely, attainment value (importance), intrinsic value (interest), and utility value, whereas it is negatively affected by cost value (Eccles et al., 1983; Eccles, 2005; Rosenzweig et al., 2019; Wigfield et al., 2017; Wigfield & Gladstone, 2019).

Eccles et al., (1983) defined attainment value (importance) as the personal importance attributed to succeeding in a task. For example, learning to play a new instrument can be a way for a musician to improve his/her musical skills. In this case, the attainment value of learning to play a new instrument will be high for the musician. In addition, this value is related to one's self-identity (Eccles, 2005). Tasks are considered important when they are consistent with one's self-scheme, gender, ethnicity, and other personality traits or when the task allows one to express their important aspects or affirm themselves (Eccles, 2011; Wigfield et al., 2009; Wigfield & Eccles, 2002). If one wants to affirm him/herself with a task that requires skills or effort, the attainment value of this task increases (Eccles & Harold, 1991).

Intrinsic value refers to the natural and immediate pleasure experienced by an individual during engagement in an activity or their subjective interest in that activity (Eccles & Wigfield, 1995; Partridge, 2013; Wigfield et al., 2009). For example, if a student shows interest in activities carried out in a lesson and finds them entertaining, this student's intrinsic value probably increases, and s/he would show more effort in the lesson than other students (Ball et al., 2017; Barutcu, 2017; Yurt, 2016). EVT argues that if the intrinsic value of a task is high, the person will be intrinsically motivated to fulfill this task (Eccles & Wigfield, 2002). In some aspects, this component is similar to intrinsic motivation and interest concepts (Wigfield, 1994). However, it should be considered that these structures are based on different theoretical traditions (Wigfield & Cambria, 2010).

Utility value refers to the perceived benefit of the activity (Wentzel & Wigfield, 1998). In other words, it defines how a task fits one’s future plans (e.g., career goals) (Wigfield, 1994). If one finds the task important for their future goals or receives promotions if it is accomplished, they may engage in it (Shin et al., 2019). For example, an additional foreign language course taken by a student may help enhance their language skills, be more effective in international relations, and expand job opportunities. Therefore, taking an extra foreign language course would be highly beneficial for their future career, resulting in high value of benefit. In a sense, this component includes more “external” reasons such as achieving the desired result (Eccles et al., 1999; Wigfield & Eccles, 2002).

The fourth value proposed in the EVT, the cost value, negatively affects student motivation (Barron & Hulleman, 2015; Meyer et al., 2019). This value is conceptualized in terms of fear of social consequences of the task (such as negative reactions from peers, parents, and colleagues) (Eccles, 2011), fear of failure, concerns about performance, amount of effort required for success, and opportunities lost as a result of a choice (Wigfield & Eccles, 2002). The high cost of a task compared to its benefit may cause the individual to avoid that task (Loh, 2019). For instance, completing a math assignment can be cited as an example of task cost. The student must invest time and energy to complete the assignment, potentially sacrificing other activities. According to EVT, there are three different types of cost: the effort required to succeed in the task, lost time that can be spent on other activities, and negative psychological outcomes related to struggle or failure on the task (Barron & Hulleman, 2015; Eccles et al., 1983).

1.2. The Current Study

Due to the growing need to pursue a STEM career, raising a continuous interest in STEM is important (Romine & Sadler, 2016). Previous reports indicated that motivation -an important factor that should be targeted to promote learning- (Williams & Williams, 2011) plays a critical role in educational outcomes (Walters et al., 2016). High motivation not only helps students in the learning process but also leads them to value what they learn and develop an interest in future careers (Beerenwinkel & von Arx, 2016). Accordingly, students' motivations can be targeted to increase their interest in STEM fields (Rosenzweig & Wigfield, 2016).

The middle school period is an important stage for the development of students while getting prepared for a rapidly changing future. Many researchers highlighted the importance of the secondary education stage for improving interest in STEM and choosing a STEM field (Christensen & Knezek 2017; English, 2017; Moreno et al., 2016). The STEM skills acquired in this period paved the way for a successful STEM career (Knezek et al., 2013). Brown et al. (2016) observed that middle school students' STEM beliefs and attitudes changed after experiencing the STEM curriculum. Sadler et al., (2012) found that students' career preferences before starting high school are the most powerful predictor of their career preferences when graduating from high school. Tai et al., (2006) reported that middle school students who are interested in a science career are more likely to graduate with a science degree. Consistent with this, Dabney et al., (2012) found that the probability of choosing a STEM career for a student who is not interested in STEM is significantly lower compared to a student who is interested in STEM since middle school. In this regard, measuring middle school students' motivational beliefs such as expectancy and value which shape their decisions to continue a STEM career, obtaining valid and reliable measurements of these dimensions, and designing interventions based on the obtained data are very important to ensure students' persistence in the STEM pipeline.

Considering the long history of Eccles's EVT which is used to understand students' motivational beliefs, many measurement tools are developed based on this theory for different academic levels (primary school, middle school, high school, college, etc.) and fields (mathematics, English, STEM, physical education, critical thinking, Master's degree, etc.) to measure students' motivations (see Appianing & Van Eck, 2018; Barron & Hulleman, 2015; Eccles & Wigfield, 1995; Valenzuela et al., 2011; Wigfield & Eccles, 2000; Xiang et al., 2003). Scales developed by Eccles et al. from these measurement tools are highly preferred due to their factor structure, good psychometric properties, and ability to show the relationships between success and choice (Wigfield et al., 2009). On the other hand, there are measurement tools -although not based on EVT- using some motivational constructs including expectancy/value structures developed to measure students' motivations (Glynn et al., 2011; Jones, 2009, 2018). After a literature survey, detailed information was obtained on some measurement tools, as shown in Table 1.

Table 1. *Information on measurement tools.*

Developed by	Measurement tool	Sample	Theory	Number of items
Eccles & Wigfield (1995)	Children's self and task perceptions in the domain of mathematics	Middle & high school students	Expectancy-Value Theory (Eccles et al., 1983)	19
Glynn et al. (2011)	Science Motivation Questionnaire II	College students	Bandura's social cognitive theory (Bandura 1977-1986)	25
Jones (2012/2022)	MUSIC Inventory (Middle/High School Student version)	Middle school students	The MUSIC Model of Academic Motivation (Jones, 2009,2018)	18
Kosovich et al. (2015)	Expectancy-Value-Cost Scale	Middle school students	Expectancy-Value Theory (Eccles et al., 1983)	10
Appianing & Van Eck (2018)	Value-Expectancy STEM Assessment Scale (VESAS)	College students	Expectancy-Value Theory (Eccles et al., 1983)	15
Luo et al. (2019)	STEM Continuing Motivation (STEM-CM)	Middle school students	Continuing motivation Maehr (1976)	25
Kızılay et al. (2019)	Motivation Scale for STEM Fields	High school students	ARSC model Keller (1979)	22
Gök (2021)	STEM Attitude and Motivation Survey	Middle school students	---	34

As seen in Table 1, some tools are developed based on different theories to measure students' motivations at different academic levels. The measurement tool developed by Eccles and Wigfield (1995) measures middle and high-school students' motivations in mathematics. On the other hand, the "Expectancy-Value-Cost Scale" developed by Kosovich et al. (2015) employs expectancy/value and can be adapted for certain content fields such as mathematics and science. Another measurement instrument -although not based on the expectancy/value theory- was developed by Glynn et al. (2011). Science motivation questionnaire-II (SMQ-II) consists of different motivational structures (intrinsic motivation, self-determination, self-efficacy, career motivation, and grade motivation) and is frequently used to measure student motivation in science disciplines (biology, physics, and chemistry). Besides, the music model developed by Jones (2009, 2018) combines different motivation theories -also includes the EVT- and focuses on motivation in a specific event and explains factors motivating one to participate in a specific event in a specific discipline (mathematics, science, etc.). In general, each tool used by researchers to measure student motivation is developed to assess a specific area. Although mathematics or science is a part of STEM, as indicated in many definitions (see Bybee, 2010; Gonzalez & Kuanzi, 2012) STEM is a holistic approach and is composed of the disciplines in its content. Therefore, measurement tools developed for a specific discipline may yield indirect outcomes while measuring motivation in STEM. This is why we focused on STEM motivation for the measurement tool we developed. Additionally, as previously mentioned, the middle school years are a critical period for the development of students' motivational beliefs. It is seen that 5 of the measurement tools given in Table 1 are designed for middle school students. Plus, three of these measurement tools (Eccles & Wigfield, 1995; Jones, 2009, 2018; Kosovich et al., 2015) are designed for a specific discipline (e.g., science, mathematics). Luo et al. (2019) and Gök (2021) developed measurement tools focusing directly STEM motivation of middle school students. However, neither measurement tool was based on the EVT. In this study, unlike the previously mentioned measurement tools, we focus specifically on STEM and use the EVT to assess middle school students' expectancies and values related to their STEM motivation. We believe that such a tool will make valuable contributions to the existing literature in this field.

This study outlines the development process of a tool based on the concepts of expectancy and value to measure middle school students' STEM motivation. This tool can be used to assess students' STEM motivation, design intervention strategies to retain students in this field, and evaluate the effectiveness of these interventions.

2. METHOD

2.1. Study Group

The current study involved students who were attending a state middle school in the 2020-2021 academic year in Turkey. The study group consisted of 967 students (316 5th graders; 110 6th graders; 266 7th graders; and 275 8th graders) who voluntarily completed the Turkish version of the trial survey. The study group was randomly divided into two groups for analysis. Exploratory Factor Analysis (EFA) was performed on the data obtained from the first sub-group (n=479) and Confirmatory Factor Analysis (CFA) was conducted on the data collected from the second sub-group (n=488). The gender and grade information of the students in the 1st and 2nd groups are shown in Table 2.

Table 2. *Gender and grade information of the students in the 1st and 2nd sub-groups.*

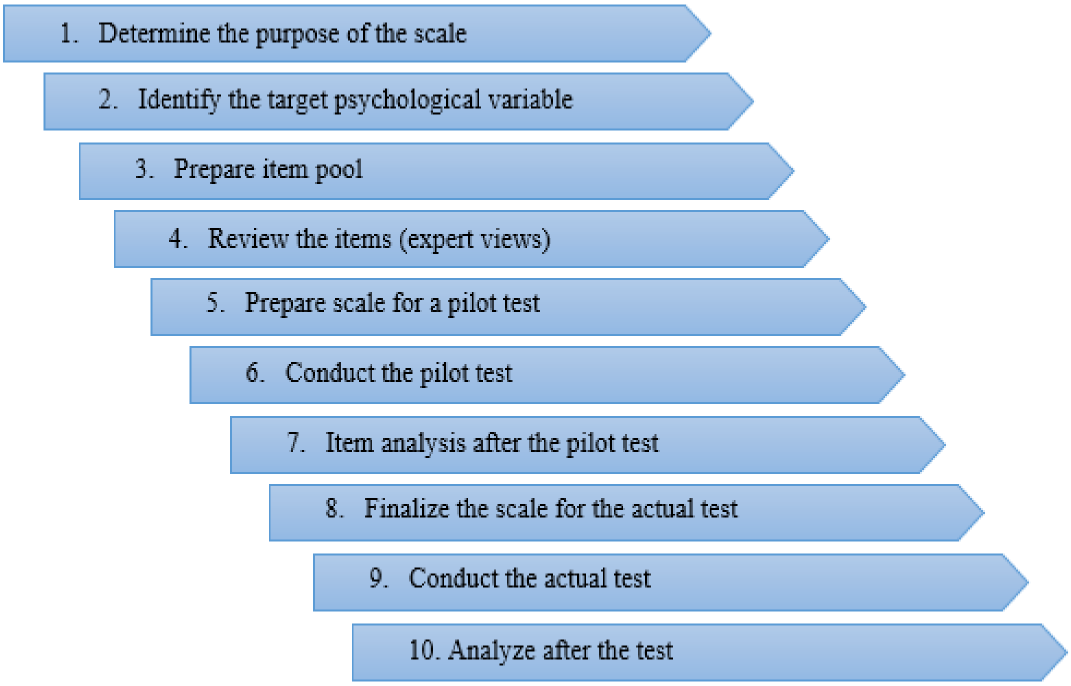
	First sub-group				Second sub-group		
Grade Level	Gender	*f*	%	Grade Level	Gender	*f*	%
5th Grade	Male	75	15.7	5th Grade	Male	86	17.7
	Female	79	16.5		Female	76	15.6
6th Grade	Male	19	3.9	6th Grade	Male	23	4.7
	Female	38	7.9		Female	30	6.1
7th Grade	Male	60	12.5	7th Grade	Male	60	12.2
	Female	63	13.2		Female	83	17
8th Grade	Male	70	14.6	8th Grade	Male	55	11.3
	Female	75	15.7		Female	75	15.4
Total		479	100	Total		488	100

As seen in Table 2, the first sub-group has a balanced distribution of gender in all grade levels (5, 6, 7, 8). The highest-class size in this sub-group was observed in 5th grade with 75 boys and 79 girls (n=154), whereas the lowest class size was in 6th grade with 19 boys and 38 girls (n=57). Similar to the first sub-group, the second sub-group also had a balanced distribution of gender in all grade levels. Plus, as in the first sub-group, the highest-class size was observed in 5th grade with 86 boys and 76 girls (n=162), and the lowest class size was in 6th grade with 23 boys and 30 girls (n=53). In general, both sub-groups had a balanced distribution of gender and grade level.

2.2. Scale Development

As shown in Figure 1, the scale development steps proposed by DeVellis (2003, s.60-137) were followed during the scale development study. As mentioned before, it is an interesting fact that STEM motivation is an important factor to retaining students in a STEM field, and accordingly, measuring directly STEM motivations instead of motivation in each discipline (mathematics, science, etc.) is considered important by the researchers. Therefore, this study was aimed at developing a measurement tool for secondary students’ STEM motivations. Accordingly, to measure middle school students’ STEM motivations, the EVT introduced by Eccles et al. *(*1983) was studied in detail, and comprehensive definitions of the components of this theory were made. Then considering the scales developed based on the expectancy-value theory and components of the theory of Eccles et al. (1983), 35 items were prepared with a 5-point Likerttype scale (1: Strongly Disagree, 2: Disagree, 3: Neutral, 4: Agree, 5: Strongly Agree). Some examples of the scale items are presented in Table 3.

Figure 1. *DeVellis's scale development steps*



Expert opinions were received to determine whether the items were appropriate to measure the intended characteristic. Accordingly, the items were sent to 2 assessment and evaluation experts, 2 STEM experts, 1 expert studying STEM motivation, and 3 doctoral students who received STEM education for review. Two assessment and evaluation experts, 2 STEM experts, and 3 doctoral students provided opinions on the items. Based on the expert opinions, 2 items were removed from the scale, and 2 items were revised. Then the revised version of the scale consisting of 33 items (six cost items were negatively worded) was examined by a language expert and then by two science teachers regarding language and understandability. The scale was then decided to correct in spelling-grammar and is understandable for middle students. However, to further test the understandability, the scale was applied to a small group of 5th graders (n=30). Before the application, the students were informed about the scale and it was stated that the definition of STEM field, STEM field professions, and courses in the scale were explained at the bottom of the scale. As the students did not have any understandability issues while responding, the scale was decided to be understandable and ready for implementation.

Table 3. *Some examples for the scale items.*

Dimension	Item No.	Item with English
Expectancy	Item 1	STEM alanlarında diğer alanlara kıyasla daha başarılı olacağıma inanıyorum. [I believe I will be more successful in STEM fields than in other disciplines.]
Attainment value	Item 12	STEM alanlarında öğreneceklerimi önemsiyorum. [I care about the things I learn in STEM fields.]
Utility value	Item 16	STEM alanlarına yönelik öğrendiklerim iyi bir meslek sahibi olmamı sağlayacaktır. [Things I learn in STEM fields will allow me to gain a good profession.]
Intrinsic value	Item 21	STEM ile ilgili etkinlikler eğlencelidir. [STEM-related activities are fun.]
Cost value	Item 31	STEM ile ilgili bir etkinliğe zamanımı harcamak istemem. [I don't want to spend my time in a STEM-related activity.]

After receiving the required ethical permission to conduct the study, the scale was applied to students who voluntarily agreed to participate in the study. Following this practice, the study group composed of volunteer students was randomly divided into two subgroups. EFA was conducted for the pilot study using the data obtained from the first sub-group. On the other hand, CFA was performed for the actual study using the data obtained from the second sub-group.

2.3. Data Analysis

To examine the psychometric properties of motivation measures obtained from the developed scale, analysis was conducted using IBM SPSS Statistics version 22.0 and LISREL version 8.8. Before the analysis, the negatively worded items (cost items) were reversely scored. Furthermore, missing data were examined by Little's MCAR (Missing Completely at Random) test. The results of the test conducted on the dataset showed the dataset contains random patterns (χ^2=1955.839, p<.000) (Garson, 2015). Accordingly, it was decided that the missing data would not lead to problems in analysis, and assignments were made using the EM algorithm for missing data. Afterward, the study group was randomly divided into two sub-groups to examine the psychometric properties of the scale. To get evidence related to the construct validity of the measures, EFA was conducted on the data obtained from the first sub-group using direct oblimin rotation (since the structures of the theory are correlated) with SPSS ver. 22.0. Since it is the commonly used method in Social Science, Principal Component was used as the factor-extracting method in this study. The appropriateness of these data for EFA was assessed based on the Kaiser criterion (Kaiser, 1960) and Bartlett's Test of Sphericity. Additionally, scree plots and interpretability criteria were used to determine the number of factors.

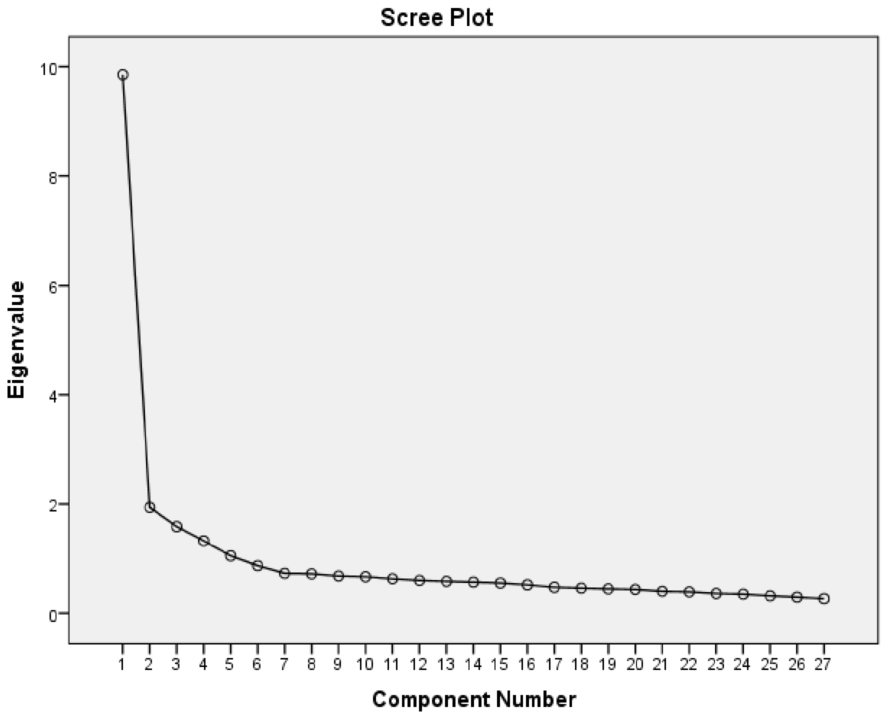
The EFA conducted for the factor structure of the scale and the second-order factor model developed based on the EVT from the 33-item scale were evaluated together. According to the results of these evaluations (discussed in the next section), the scale was revised to 27 items. Alternative first-order and second-order measurement models were defined based on the factor structure of the 27-item scale and were tested by a series of CFA using the data obtained from the second sub-group. In the model specification, for each latent variable, one-factor loading per latent variable was fixed to 1. Before CFA, to test the multivariate normality assumption, z values for Multivariate Kurtosis (z=26.723, p<.000) and skewness (z=57.258, p<.000) were calculated. χ^2 value (χ^2=3992.596, p<.000) for Multivariate Kurtosis and skewness was also computed. The results indicated that the dataset does not meet the multivariate normality assumption. Accordingly, for parameter estimation, the Robust Maximum Likelihood method was used. Accordingly, the Satorra-Bentler χ^2(S-Bχ^2) value was calculated and evaluated (Brown, 2006, s.76). In the CFA, an adequate fit of the measurement models to the data (GFI≥.90, CFI≥.95, NFI≥.90 & RMSEA≤.08) was assessed as evidence for construct validity (Schermelleh-Engel et al., 2003). Both for EFA and CFA, items with loadings higher than .32 were considered an appropriate indicator of the measured construct (Tabachnick & Fidell, 2007). On the other hand, in EFA, items loaded on two or more factors with loadings greater than .10 were considered cross-loading. As evidence for the reliability of these measures, Cronbach's alpha values were calculated using SPSS software version 22.

3. RESULTS

Firstly, EFA was conducted on the data obtained from the first sub-group (n=479). The KMO value (KMO=.949) and results of Bartlett's test of sphericity (χ^2=6831.4, p≤.05) indicated that EFA is feasible for this dataset. The EFA results supported a 5-factor solution, and these 5 factors explained 53.945% of the total variance. However, for one item, the main loading was found to be below .32, and five items had cross-loadings. Therefore, the 9th item was removed since it had the lowest factor loading (λ=.29), and EFA was conducted again. The analysis results showed that items 13, 28, and 29 did not load their expected factor, they rather loaded another factor with a higher loading value. These items were, therefore, removed from the scale, each time one item, and another EFA was performed after the removal of each item. Then items 14 and 18 were removed, respectively since these cross-loaded factors cause a high inter-correlation between factors, prevent the discrimination of factors, and make it difficult to determine the factor structure. An EFA was conducted again after the removal of each item.

After item removal procedures, a final EFA was conducted on the 27-item scale (KMO=.946, for Bartlett's Test of Sphericity χ^2=5653.59, $p\leq.05$), and a 5-factor solution with an eigenvalue greater than 1 was obtained (Figure 2).

Figure 2. *Scree-plot graph for a 5-factor solution*



The eigenvalue of the first factor is 9.854, and it explains 36.496% of the total variance. However, the eigenvalues of the remaining 4 factors varied between 1.049-1.939, and each of these factors explains only a small amount of variance. The eigenvalues, explained variance, and factor loadings are shown in Table 4.

Considering the theory and the items loaded on the factors, the first factor was called "Intrinsic value", the second factor was "Cost", the third factor was "Utility", the fourth factor was "Expectancy", and the fifth factor was called as "Attainment". All factor loadings were above .32. The factor loadings values varied between λ=.627 and .844 for the first factor; between λ= .530 and .769 for the second factor; between λ=.422 and .753 for the third factor; between λ= -.480 and -.798 for the fourth factor; and finally, varied between λ=-.529 and -.638 for the fifth factor. The EFA results indicate that the final version of the scale consisting of 27 items can measure middle school students' STEM motivation over the expectancy, utility value, attainment value, intrinsic value, and cost dimensions defined in the theory.

In addition to the EFA, the validity of the measurements obtained from the scale was tested with CFA conducted on the expectancy-value model (Model 1). This model was developed based on the EVT. As explained in the EVT section, expectancy for success and task value are the two main components of this theory. On the other hand, according to the EVT, task value is positively affected by three factors namely, attainment/importance value, intrinsic value, and utility value (usefulness of the task), whereas, is negatively affected by cost value (Eccles, 2005; Rosenzweig et al., 2019; Wigfield et al., 2017). Accordingly, in the second-order factor model, expectancy and value were higher-order factors; Intrinsic value, Cost, Utility, and

Attainment were first-order factors, and the related items were defined as indicators. According to the calculated fit indexes (χ^2=850.90, *df*=491, GFI=.88, NFI=.96, CFI=.98, and RMSEA=.039), the model showed a good fit to the data. However, the examination of individual parameter estimates (standardized solution) showed that higher constructs were highly correlated, and the Heywood case was observed for the coefficient (β=1.01) indicating the predictive strength of the value higher construct for the attainment first-order construct.

Table 4. *EFA analysis results.*

Factors	Items	F1	F2	F3	F4	F5	Eigenvalue	Explained variance
Intrinsic value	26	**.844**	.030	-.018	.032	.065	9.854	36.496%
	25	**.762**	-.029	-.015	-.055	-.030		
	22	**.761**	.113	-.055	-.049	-.103		
	21	**.712**	.053	-.052	-.062	-.042		
	24	**.637**	-.005	.097	.006	-.071		
	23	**.636**	-.106	.037	-.061	-.201		
	27	**.627**	-.021	.089	-.143	.183		
Cost value	32	.021	**.769**	-.015	-.099	-.069	1.939	7.128%
	30	-.095	**.759**	.002	-.016	.136		
	33	.033	**.730**	-.073	-.211	.023		
	31	.361	**.530**	.116	.207	-.189		
Utility value	19	-.051	-.071	**.753**	-.145	.046	1.586	5.873%
	17	-.008	.036	**.711**	.018	.022		
	20	.046	.046	**.698**	.012	-.135		
	16	.033	-.010	**.639**	-.044	-.196		
	15	.313	-.062	**.422**	-.132	.138		
Expectancy	3	-.032	.035	.065	**-.798**	.038	1.325	4.906%
	1	.010	.020	.052	**-.768**	-.047		
	7	.211	-.081	.091	**-.655**	.111		
	2	.116	.092	-.066	**-.643**	-.183		
	4	.140	.083	.006	**-.588**	-.071		
	6	-.023	.153	.142	**-.565**	-.157		
	5	.131	.231	.067	**-.480**	-.088		
Attainment value	12	.112	.071	.210	.013	**-.638**	1.049	3.885%
	11	.057	.094	.286	-.051	**-.613**		
	10	.064	-.159	-.169	-.263	**-.572**		
	8	.037	.021	.324	-.110	**-.529**		

After the 33-item version of the scale was determined to be not successful by the CFA, a revised scale consisting of 27 items was obtained using EFA results. In addition to Model 1 defined for analysis of the 33-item scale, two measurement models (Model 2 and Model 3) were also defined and CFA analyses were conducted on these models using the data obtained from the 2nd sub-group. Accordingly, a 5-factor measurement model, Model 2 (expectancy, intrinsic value, utility value, attainment value, and cost value were considered factors, and the items were considered indicators) consistent with the 5-factor solution obtained by EFA was defined and tested. However, the EFA results indicated that the variance explained by the intrinsic value factor was 36.496%, and there might be other structure(s) over the determined factors. The sub-dimensions (utility, attainment, cost, and intrinsic values) under the expectancy and value constructs of the theory are often highly correlated with each other or loaded on a factor (Eccles & Wigfield, 1995). Furthermore, Trautwein et al. (2012) found strong relations between expectancy and value beliefs. It is, therefore, highly possible that strong relations exist between expectancy and value as well as between the sub-dimensions of value. Accordingly, another second-order factor model (Model 3) based on the EVT was defined and tested. In this model, expectancy, intrinsic value, utility value, attainment value, and cost value were considered first-order factors; motivation was a second-order factor, and the items were considered indicators. Fit statistics for the models developed based on the 27-item scale are shown in Table 5.

Table 5. *Model fit indices for the tested models (27-item scale).*

Model	Chi-Square	*df*	GFI	NFI	CFI	RMSEA
Model 1	586.64	320	.89	.96	.98	.041
Model 2	477.69	314	.91	.97	.99	.033
Model 3	515.87	319	.91	.96	.99	.036

As seen in Table 5, the fit indices of Model 1 (obtained based on the 27-item scale) display an acceptable fit to the data. According to the test of the model, factor loading estimates (λ's) and unique variances (ε's) vary between .49-.85 and .28-.76, respectively. On the other hand, the examination of the correlations between latent variables (see Table 6) indicated a strong correlation between expectancy and value factors (r=.94; p<.05). Furthermore, the evaluation of individual parameter estimates (standardized solution) showed that higher-constructs were highly correlated with each other, and Heywood case was observed for the coefficient (β=1.03) indicating the predictive strength of value higher-construct for the attainment first-order construct. Accordingly, Model 1 was decided to be not consistent with the measures obtained from the 27-item scale.

Table 6. *Correlation matrix for Model 1.*

	Exp.	Value	Att.	Uti.	Int.	Cost
Exp.	1.00					
Value	.94	1.00				
Att.	--	.98	1.00			
Uti.	--	.86	.85	1.00		
Int.	--	.86	.85	.74	1.00	
Cost	--	.70	.69	.60	.60	1.00

Similar to Model 1, Model 2 (obtained based on the 27-item scale) also showed an acceptable fit to the data. The factor loading estimates (λ=.42 - .75; p<.05) obtained by the test of the model pointed out that the indicators of this model are accurate indicators of the constructs and dimensions of the model. However, the correlations between latent variables (see Table 7) varied between .37-.83. Furthermore, high correlations were found between expectancy value and attainment value (r=.83; p<.05); and between attainment value and utility value (r=.83; p<.05). These findings indicated that the dimensions of the scale do not discriminate well, and the model do not represent the factor structure of the measures sufficiently.

Table 7. *Correlation matrix for Model 2.*

	Exp.	Att.	Uti.	Int.	Cost
Exp.	1.00				
Att.	.83	1.00			
Uti.	.66	.83	1.00		
Int.	.74	.66	.57	1.00	
Cost	.54	.47	.40	.59	1.00

Like other models, Model 3 (obtained based on the 27-item scale) also displayed an acceptable fit to the data. Standardized estimates for both factor loadings (λ's = .42–.75) and unique variances (ε's = .44–.83) indicated that the items of the 27-item scale are appropriate indicators of their respective factors and can produce measures with acceptable levels of error. On the other hand, in addition to the evidence of construct validity for the measures, the coefficients indicating the predictive strength of the latent variable in the model (see Table 8) for 5 factors were found to be high (they varied between .60-.91). Second-order measurement model (Model 3) with standardized solutions is shown in Figure 3.

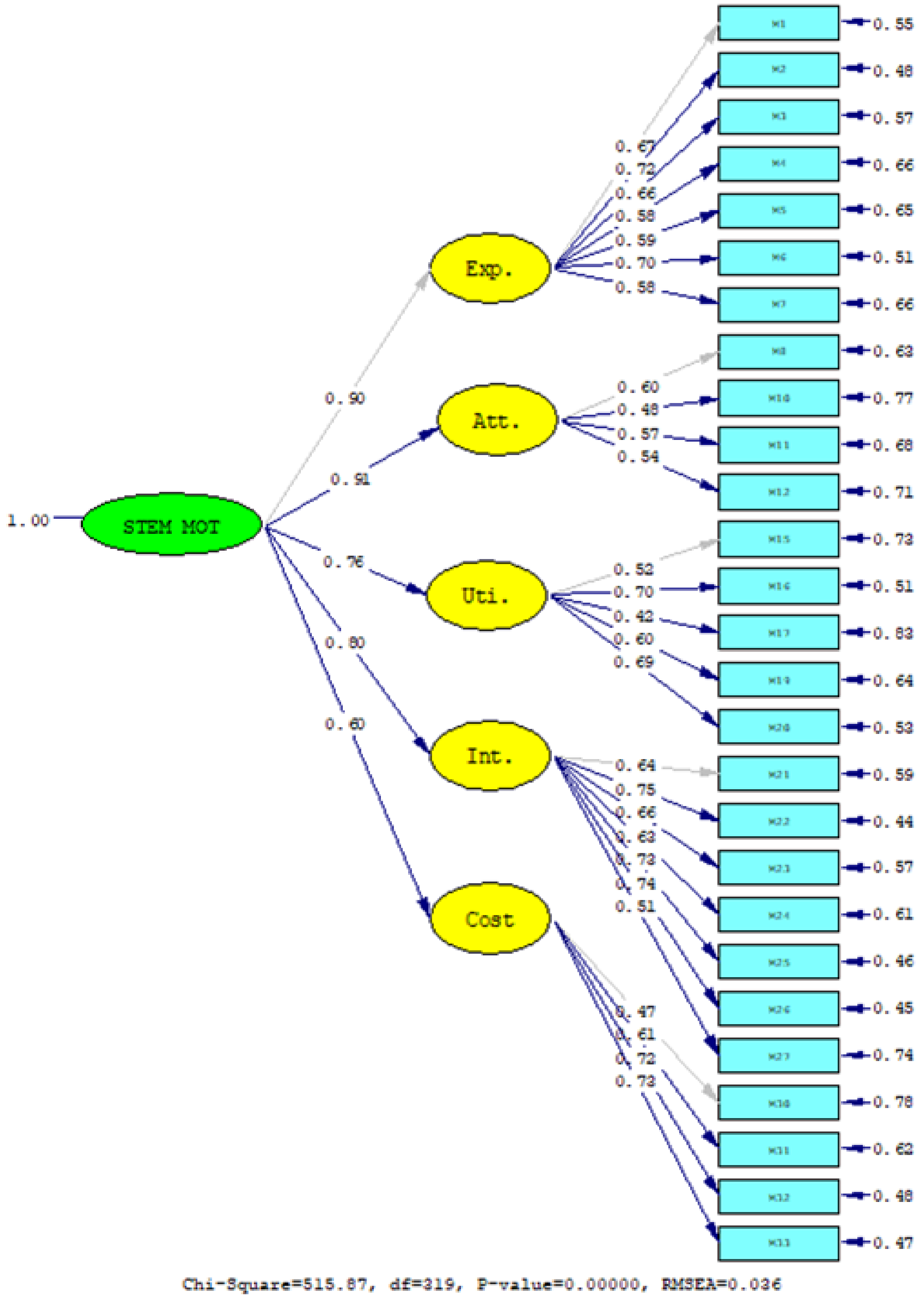
Table 8. *Correlation matrix for Model 3.*

	Mot.	Exp.	Att.	Uti.	Int.	Cost
Mot.	1.00					
Exp.	.90	1.00				
Att.	.91	.82	1.00			
Uti.	.76	.69	.61	1.00		
Int.	.80	.72	.73	.61	1.00	
Cost	.60	.54	.55	.48	.46	1.00

The results of a series of CFAs indicated that Model 1 does not adequately represent the factor structure, due to a high correlation between the expectancy and value factors, as well as the occurrence of a Heywood case. Additionally, Model 2 and Model 3 have similar fit indexes. However, it should be noted that Model 2 does not adequately represent the factor structure as the dimensions fail to discriminate effectively. Brown (2006) argued that if the results of CFA show strong relationships between certain factors, it is not appropriate to claim that these factors represent distinct dimensions of the structure. This finding also suggests poor discriminant validity. Additionally, in our study, a factor with a significantly higher eigenvalue compared to other factors was observed in EFA. Moreover, the high correlations between the attitude/experience and utility/attitude factors in the first-order CFA model indicate the possible presence of a second-order factor that could account for the common source of these correlations between the factors. Hence, adopting a second-order CFA model that demonstrates a comparable fit to Model 2 and incorporates a second-order factor to account for the strong correlations among the factors appeared to be a more logical approach (Iversen, et al., 2022). Based on these reasons, it was decided that utilizing Model 3 instead of Model 2 would be more suitable for this study. The second-order measurement model (Model 3) with standardized solutions is shown in Figure 3.

As seen in Figure 3 for Model 3, the Chi-square value was found to be statistically significant according to the construct validity findings of measures obtained from the 27-item scale. However, the Chi-square is sensitive to sample size (Bergh, 2015). For models with 75-200 cases, a Chi-square test is mostly a reasonable measure of fit. But for larger models (with 400 cases or more), the Chi-square is statistically significant almost always (Kenny, 2015). For that reason, examining the χ^2/df ratio is recommended (Şimşek, 2007; Waltz et al., 2010). In our study, the χ^2/df ratio for the final model was calculated as 1.61. Schermelleh-Engel et al., (2003) stated that $0 \leq \chi^2/df \leq 2$ indicates a perfect fit. Additionally, considering fit indexes described by Schermelleh-Engel et al., (2003), among the other fit indexes calculated, the GFI value displayed an acceptable fit (.90≤GFI<.95), whereas, NFI (.95≤NFI≤1.00), CFI (.97≤CFI≤1.00), and RMSEA (0≤RMSEA≤.05) values indicate a perfect fit. Based on these findings, it can be argued that the model provides a good fit to the data. Furthermore, the factor loadings varied between .42 and .75 and the error variances were acceptable. According to Tabachnick and Fidell (2007), factor loadings greater than .71 are considered perfect, greater than .63 are very good, greater than .55 are good, greater than .45 are good/acceptable, and finally, factor loadings greater than .32 are weak. Therefore, our findings indicate that the items represent the related factors and can make measurements with acceptable errors. Accordingly, Model 3 was decided as the valid model of the 27-item version of the STEM Motivation Scale. These findings revealed that the 27-item version of the scale can measure middle school students' STEM motivation through expectancy, intrinsic value, utility value, attainment value, and cost value dimensions.

Figure 3. *Second-order measurement model for STEM Motivation Scale (27-item form)*



Finally, to obtain evidence for the reliability of the measures, Cronbach's Alpha values were examined. Accordingly, Cronbach's Alpha values for the measures obtained from expectancy, utility, attainment, intrinsic value, and cost sub-scales were calculated as α=.878, α=.760, α=.700, α=. 878, and α=.729, respectively. Plus, Cronbach's Alpha of the total scale was found to be α=.921. These α values indicate an acceptable level of reliability. CFA findings and these α values were considered validity and reliability evidence for the 27-item form of the STEM Motivation Scale for middle school students.

4. DISCUSSION, CONCLUSION and RECOMMENDATIONS

Examination of the education period from early childhood education to college graduation is a key step for increasing the number of students interested in STEM and maintaining this interest until they receive a STEM degree (Nariman, 2021). Students' interest, persistence, and effort in STEM fields represent the whole students' achievement expectations and value perceptions for the STEM field (Açıksöz et al., 2020). To understand motivational beliefs, such as expectancy and value, that predict students' success and academic effort (Trautwein et al., 2012) and influence their persistence decisions, valid and reliable measures of these dimensions are essential. On the other hand, the lack of a reliable and practical motivation measurement tool in the literature for middle school students makes it difficult for researchers or program evaluators to determine the effectiveness of educational interventions designed to increase student motivation (Kosovich et al., 2015).

The theory introduced by Eccles et al. (1983) is composed of two main structures namely, expectancy and value. This model assumes that expectancy and value directly affect performance, persistency, and task choices (Trautwein et al., 2012). However, the sub-dimensions (utility, attainment, cost, and intrinsic value) of the expectancy and value constructs are highly correlated or loaded on a single factor mostly (Eccles & Wigfield, 1995). Thus, observing high correlations between expectancy and value as well as between value sub-dimensions is highly likely. In the current study, the results of both 33-item and 27-item scales showed that high correlations exist between factors of the 2-factor model defined based on the theory; therefore, expectancy and value constructs do not discriminate well. Consistent with our results, Trautwein et al. (2012) reported high correlations between expectancy and value beliefs.

Additionally, in the same study, Trautwein et al. (2012) found that some relationships between the sub-dimensions of value (expectancy, attainment, cost, and intrinsic value) were lower than the relationship between expectancy and value, especially, the relationship between cost and utility subdimensions was found to be low. Consistent with these, our findings indicated that the cost sub-dimension showed lower correlations compared to the relationships between other sub-dimensions. Considering other studies in which the cost sub-dimension was addressed as an empirically different construct than the expectancy and value (see Kosovich et al., 2015), it is an expected result that the cost sub-dimension did not show a higher correlation, unlike the other dimensions in our study.

EVT suggests that students' motivation for success and behaviors (preferences) are a function of their beliefs regarding their skills (expectancy) and perceived importance (value) for a specific task (Eccles et al., 1983; Wigfield et al., 2009). Considering the framework of STEM, the participation of students in STEM as well as their performance and persistence in this field can be defined as a combination of expectancy for success and perceived value in this field. Model 3, the best model according to our findings, includes all expectancy and value constructs. Moreover, this model's sufficient fit to the relevant data as well as both factor loadings and standardized unique variance estimates were good indicators of the corresponding factors can be considered evidence for the construct validity of the measures obtained from the 27-item scale. Therefore, the developed measurement tool can predict the motivation component of 5 factors based on the EVT, and the 27-item scale can yield valid measures regarding middle school students' motivation. In addition to this, reliability results for the measures obtained from the scale showed that sub-dimensions and overall scale yield measures with an acceptable level of reliability. Based on these findings, it can be argued that the STEM Motivation Scale can address students' expectancy and the value they place on the field of STEM as a whole and can provide reliable and valid measures for middle school students' STEM motivations.

4.1. Use of the Scale for Research and in Teaching Environments

According to Steinmayr et al. (2019), in the limited number of studies that examined some motivational constructs as predictors of students' academic success, most of the motivational constructs predicted academic success more than intelligence, and particularly, students' ability self-concepts and task value were more powerful for predicting success. On the other hand, Areepattamannil et al. (2011) found that motivation is a predictor of academic success. However, Kulwinder Singh (2014) stated that the relationship between motivational beliefs and learning outcomes is still uncertain. In this regard, the measurement tool developed in this study can be used to explain relationships between students' motivational beliefs and academic success in STEM discipline.

Appianing and Van Eck (2018) emphasized that if one's expectations and value beliefs are high, this person is likely to stay in STEM fields, make an effort, and graduate from these fields, but otherwise, the opposite happens. Additionally, raising motivation in a specific field may help gain interest in a certain field including a future career (Hidi & Renninger, 2006). Using this measurement tool, program makers and practitioners can measure middle school students' STEM motivational beliefs, especially in formal settings and also in informal settings. Considering the constructs included in the measurement tool, the motivational dimensions of students that need to be improved can be identified and intervention practices targeting this dimension can be performed. For example, practices focusing benefits of a task or discipline can be carried out for students who were identified with lower utility value, on the other hand, practices improving self-efficacy beliefs can be implemented for students who consider themselves inadequate (those with lower expectancy) for an activity or discipline. In this regard, this measurement tool can be a guide for determining strategies aiming to improve students' STEM motivation or designing curricula according to these needs.

Furthermore, aiming for student motivation only in a certain period might be insufficient to meet future STEM workforce needs. Although our study was carried out for middle school STEM fields, we know that students may leave STEM in the further educational stages. This is why we consider validating this measurement tool by implementing it in different education levels (high school, university) important. Moreover, this measurement tool, which we believe is important in terms of its potential contribution to further research and intervention strategies, was validated by the data collected from a specific socio-cultural population and in an urban region in Turkey. Accordingly, validating this measurement tool with populations of different languages and cultures would contribute to the validity and reliability studies of the scale.

4.2. Conclusion

Since students' preference, persistence, and performance in STEM fields, whose importance is constantly rising in today's world, are partly shaped by students' motivation, more studies are needed to understand motivation dynamics. This measurement tool, which can make valid and reliable measurements, allows for determining motivational beliefs within the expectancy-value concept that can be targeted to encourage students' interest in STEM fields as well as help design interventions for these structure(s) and evaluate the effectiveness of these interventions.

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Contribution of Authors

All authors have equally contributed to all section of this study. The authors read and approved the final manuscript.

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