Konin Language Studies
Faculty of Humanities and Social Sciences, University of Applied Sciences in Konin, Poland
KSJ 11 (1). 2023. 11-31
http://ksj.konin.edu.pl
doi: 10.30438/ksj.2023.11.1.1

Adult reading motivation: A factor analysis study

Abdelouahed Bouih
Moulay Ismail University, Meknes, Morocco
https://orcid.org/0000-0002-2197-9479
abdelouahed.bouih@gmail.com

Bendaoud Nadif ✉
Moulay Ismail University, Meknes, Morocco
https://orcid.org/0000-0001-6278-1808
bendaoudnadif@umi.ac.ma

Driss Benattabou
Moulay Ismail University
Moulay Ismail University, Meknes, Morocco
https://orcid.org/0000-0003-4240-1390
d.benattabou@umi.ac.ma

Abstract

This study aims primarily to explore the factor structure of the *Adult Reading Motivation Scale* (ARMS) using a sample of EFL university students in Morocco. As part of a larger battery, a questionnaire on reading motivation (RM) and socio-biographical data was completed by 180 participants of undergraduate and graduate level students. Using parallel analysis (PA) and minimum average partial (MAP) prior to exploratory factor analysis (EFA) with both oblique and orthogonal rotation methods, a four-factor structure emerged showing mostly good construct reliability (composite reliability). Further, results also showed acceptable discriminant validity using the Fornell-Larcker criterion and the Heterotrait-monotrait (HTMT) ratio despite insufficient convergent validity (average variance extracted). Overall, our findings were revealed to be comparable to previously reported results in existing literature. The study concludes by making recommendations for future research.

Keywords: adult motivation; convergent validity; construct reliability; factor analysis; reading motivation

1. Introduction

The present paper attempts to examine the psychometric properties of the *Adult Reading Motivation Scale* (ARMS) and its implementation in a Moroccan English-speaking academic setting. The paper consists of three major sections along with an introduction and a conclusion. The first section is devoted to a theoretical background delineating the explanation of the main key terms of the study including reading and reading motivation, and explores previous reports regarding the factor structure of the ARMS instrument. The second section presents the methodology of research along with the research design, research questions and hypotheses and a description of the research instruments. The next section is concerned with the presentation of the major findings which crop up from the processing of data screening, factor and validity analysis. The fourth and last section discusses the results of this research and evaluates it in the light of the prevailing literature surrounding this topic. The study then ends with a conclusion and makes recommendation for potential future research.

2. Literature review

2.1. Reading motivation and its importance to language learning

As a common practice, an intriguingly complex process, and a human language skill, reading has naturally been a major interest for both theorists and practitioners (Watkins & Coffey, 2004). Reading is a motivated behavior (Aarnoutse & Schellings, 2003). It expresses a specific interest for reading (Guthrie et al., 2006). Reading motivation (RM, henceforth) "refers to intentions or reasons for reading" (Schiefele et al., 2012, p. 429) and researchers have investigated it among both children and adults. Guthrie et al. (1999) define RM as "the individual's goals and beliefs with regard to reading" (p. 199). RM has also been regarded as a process which "activates and guides reading behavior." (Aarnoutse & Schellings, 2003, p. 387), and it comprises "goals for reading, intrinsic and extrinsic motivation, self-efficacy, and social motivation for reading" (p. 387). Brittain (1970) elaborates more on the issue arguing that reading motivation is a complex construct which encompasses aspirations, style, and cognitive aspects, which unapologetically defies the essence of any mechanizing and reductionist view of reading as a dynamically scalable phenomenon.

Reading has countless benefits and far-reaching effects at multiple levels for the individual specifically and society at large. For instance, Krashen (1993) reports ample evidence showing that reading is good for language acquisition and literacy development. In terms of language performance, studies also show that reading literacy predicts “receptive vocabulary, general information, spelling, sight vocabulary, verbal fluency, and reading comprehension even after controlling for age, recognition memory” (Echols et al., 1996, p. 296). There is some research evidence indicating that the earlier the reading, the more it is correlated with “spelling, vocabulary, verbal fluency, word knowledge, and general information” (Cunningham & Stanovich, 1991, p. 264; see Cunningham & Stanovich, 1997). Moreover, it was found that reading skills predict reading habits and also reading habits predict reading skills in a consolidating manner and that the earlier the better (Leppänen et al., 2005), and that in general reading habits correlate positively with comprehension and vocabulary (Cain & Oakhill, 2011). Likewise, it was also observed that reading behavior and habits depend on the level of education and the reading language proficiency (Mokhtari & Sheorey, 1994) and on taking reading courses (Chua, 2008), just as socio-demographic variables such as milieu (urban or rural) and social class also play a role in determining reading habits (Hughes-Hassell & Rodge, 2007).

Schutte and Malouff (2007) found that adult reading motivation in particular is related to both enjoyment of reading and reading patterns. Additionally, studies revealed that reading motivation predicts word reading, comprehension, summarization and text reading speed (McGeown et al., 2015). Lau and Chan’s (2003) study showed that there is a relationship between reading underachievement and poor intrinsic motivation. Overall, there is enough evidence to allow the conclusion that motivated reading behavior is linked to and reinforces the reader’s good reading habits and skills, which in turn increases the individual’s chances of becoming a good reader.

2.2. Measurement of dimensionality of reading motivation

There are multiple tools for assessing reading motivation, and a substantial number of these scales are designed specifically for children (Davis et al., 2018). Examples of these scales are the *Reading Self-Perception Scale* (RSPS, Henk & Melnick’s, 1992); the *Me and My Reading Profile* (MMRP, Marinak et al., 2015); the *Early Literacy Motivation Scale* (ELMS, Wilson & Trainin, 2007); and the *Motivation Read Profile*, (MRP, Gambrell, et al., 1996). In their review of reading motivation scales, Davis et al. (2018) reported a considerable number of reading motivation scales the vast majority of which are designed for an age range of k-12, with the exception of the *Adult Reading Motivation Scale* dedicated to adults between 18-77 years. This measure; however, has comparatively received substantially far less attention than its age-range-specific counterparts, as its competing adult-specific measures are virtually non-existent.

There are multiple studies that have examined the factor structure of a wide range of reading motivation scales either centrally through exploratory and/or confirmatory factor analysis (e.g., Griffi et al., 2020; Henk et al., 2012; Schiefele & Schaffner, 2016; Katrancı, 2015; Pecjak & Peklaj, 2006; Vallerand et al., 1992; Watkins & Coffey, 2004) or as part of the methodology while investigating related phenomena (e.g., Guthrie et al., 2007; Kim, 2011; Lin et al., 2012) where the target population is mostly children, and adolescents to a lesser extent. This sort of studies is not uncommon. However, comparatively speaking, considerably less numerous studies have targeted an adult population using the *Adult Reading Motivation Scale* (e.g., Dhanapala & Hirakawa, 2016), and even less so using the ARMS (e.g., Schutte & Malouff, 2007). As far as the former study is concerned, using principal component analysis (PCA) with an oblique rotation, the authors identified four factors for the ARMS: "Reading as part of self" (11 items), "Reading efficacy" (3 items), "Reading for recognition" (3 items), and "Reading to do well in other realms" (4 items).

As the literature surrounding adult RM is notably scant and the construct is under-researched, the concept requires in our estimation urgent attention and calls for further research, particularly in what seems to be previously understudied or novel contexts. In the present study, we explore the ARMS structure in the Moroccan context without overlooking its comparison with other findings documented in earlier reports.

3. Methodology

3.1. Research design

The main purpose of the present investigation is to conduct an exploratory and validational analysis of the ARMS scale using primarily factor analysis techniques and empirical evidence in support of the standard existing ARMS factor structure and subsequently evaluate its fitness, focusing on the four sub-construct based structure. For this purpose, numerous statistical procedures are used at different levels of the factor analytical procedure.

First, we set out to explore the number of factors constituting the ARMS using principal component analysis (PCA), being one of the widely used methods to conduct dimensionality reduction of observed data into factorizable components at the exploratory stage. After performing PCA, both Horn's (1965) parallel analysis (PA) and Velicer's (1976) minimum average partial (MAP) are used for factor retention, having been demonstrably shown to be measurably more effective than competing classical alternatives (Courtney & Gordon, 2013; Ledesma & Valero-Mora, 2007). The obtained model is then compared to the existing standard version of the original four-factor based model at the sub-construct item level.

Furthermore, the four factors of our obtained model are examined for their consistency using composite reliability (CR) to evaluate the level of consistency of items constituting latent factors (Hair et al., 2019) before proceeding to the evaluation of model factors with respect to their convergent validity through the average variance extracted (AVE) designed to measure the convergence between the underlying variables that make up any given latent factor (Hair et al., 2019). At the final phase, we use the hetero-trait mono-trait (HTMT) ratio to evaluate the discriminant validity of the underlying factors in our model (Hair et al., 2019).

3.2. Research question and hypotheses

Based on the reviewed literature and the standard ARMS configuration as validated by the original author, we advance two hypotheses derived from one research question in the Moroccan context: *Does the evidence from the Moroccan context support the standard ARMS four factor structure?*

- H1: The evidence from the Moroccan context supports the standard ARMS structure at the factor level.
- H2: The evidence from the Moroccan context supports the standard ARMS structure at the item-level.

3.3. Sampling procedure

The sample was composed of 112 (62%) male students and 68 (38%) female students of the total of 180 EFL learners/participants who took part in the study from various universities. The most frequent age bracket was 20-25 years old making nearly (36%) followed by 25-30 years old making approximately (27%) of the sample. The most frequently reported diploma was the BA, representing roughly (40%) as 72 participants reported having a bachelor's degree. The mean score for reading motivation was (M = 3.28, SD = .44).

3.4. Measurement instruments and administration procedure

The *Adult Reading Motivation Scale* is a 5-point Likert scale. The ARMS has an internal consistency of .85, as it demonstrated acceptable validity for the four subscales making the total reading motivation scale represented by the sum of all the subscales: "Reading as part of self;" "Reading efficacy;" "Reading for recognition;" "Reading to do well in other realms" (Schutte & Malouff, 2007). The scale ranges from "strongly disagree" to "strongly agree" and it was designed specifically to measure reading motivation levels in adults. Data were gathered through questionnaires given to students from different universities which are Mohammed V University in Rabat, Moulay Ismail University in Meknes, Moulay Slimane University in Beni Mellal, and Ibn Tofail University in Kenitra emanating from different regions from Morocco. The collected data was processed through Microsoft Word, Excel (2007), SPSS (20) and AMOS (24).

4. Results

4.1. Data preparation, multicollinearity and normality testing

The study conducted missing data analysis, outlier detection, normality and multicollinearity assessments. Our data set showed no missing data. Data were assessed for multivariate outliers. Using a cutoff *p* value of .001 while implementing the Mahalanobis distance test (Tabachnik & Fidell, 2013), one multivariate outlier was identified and removed. As for multivariate normality, our analyses show that RM data follows a normal distribution pattern ($W(179) = .988$, $p = .154$).

4.2. Reading motivation: Exploratory factor analysis and internal consistency

The Kaiser-Meyer-Olkin measure of sampling adequacy ($KMO = .774$) and the Bartlett's test of sphericity ($\chi^2(210) = 1112.051$, $p < .001$) indicate that the ARMS scale items are reliably factorizable (See Table 1), while PCA of ARMS scale items yielded a seven-factor solution (See Table 2 and Figure 1) explaining a total of 64.910% of the variance.

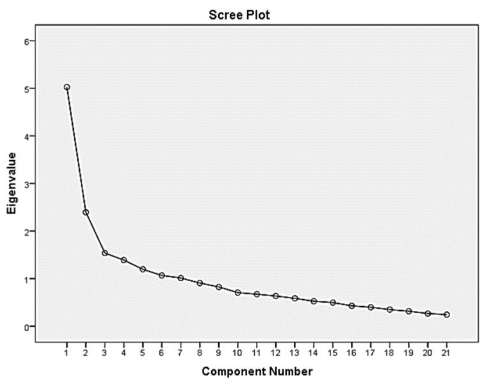

Figure 1 Scree plot of reading motivation

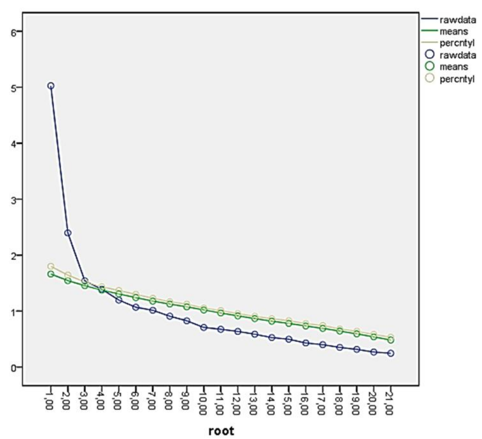

Figure 2 Raw and simulated eigenvalues plot of reading motivation

Table 1 KMO and Bartlett's test of reading motivation scale items

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.774
Bartlett's Test of Sphericity	Approx. chi-square	1112.051
	df	210
	Sig.	.000

Table 2 Principal component eigenvalues, parallel analysis eigenvalues and Velicer's average squared partial correlations

Component	Initial eigenvalues	Simulated eigenvalues	Average squared partial correlations
1	5.027	1.662181	.0532
2	2.397	1.543810	.0198
3	1.539	1.453969	.0181
4	1.390	1.372652	.0197
5	1.196	1.306407	.0217
6	1.068	1.240786	.0262
7	1.014	1.177332	.0304
8	.908	1.125820	.0362
9	.826	1.075591	.0423
10	.707	1.019561	.0493
11	.674	.965517	.0576
12	.636	.913526	.0682
13	.586	.865393	.0807
14	.526	.819264	.0990
15	.497	.779002	.1176
16	.430	.733720	.1461
17	.400	.690494	.1750
18	.350	.642119	.2332
19	.316	.592397	.3068
20	.268	.538557	.4751
21	.246	.481902	1.0000
Total variance explained	64.910	-	-

Note. Extraction method: Principal component analysis

EFA was conducted using the twenty one RM scale items. The four-factor solution (see Table 3) was chosen over solutions accommodating more factors. The cumulative variance explained by the factors is 49.300.

Table 3 Obliquely rotated reading motivation factor correlation matrix (N = 179)

Factor		1	2	3	4
1	Reading as part of self	—			
2	Reading to do well in other realms	.398	—		
3	Reading for recognition	.138	.275	—	
4	Reading efficacy	.299	.169	-.012	—

Note. Extraction method: Principal component analysis; Rotation method: Promax with Kaiser normalization

Table 4 Orthogonally rotated factor loadings for the 21 items of the *Adult Reading Motivation Scale*

Items	Factor loadings			
	1	2	3	4
Factor 1: Reading as Part of Self				
It is very important to me to spend time reading	.807			
In comparison to other activities, reading is important to me	.707	.358		
If a book or article is interesting, I don't care how hard it is to read	.689			
Without reading, my life would not be the same	.688			
My friends sometimes are surprised at how much I read	.650			.359
My friends and I like to exchange books or articles we particularly enjoy	.638			
Reading helps make my life meaningful	.547	.394		
I like hard, challenging books or articles	.511			.349
I set a good model for others through reading	.454	.374		
I am a good reader	.453	.417		.408
Factor 2: Reading to Do Well in Other Realms				
I read to improve my work or university performance		.796		
I do all the expected reading for work or university courses		.701		
Work performance or university grades are an indicator of the effectiveness of my reading		.514		
If I am going to need information from material I read, I finish the reading well in advance of when I must know the material		.317		
Factor 3: Reading for Recognition				
I like others to question me on what I read so that I can show my knowledge.			.818	
It is important to me to have others remark on how much I read			.764	
It is important to me to get compliments for the knowledge I gather from reading			.699	
Factor 4: Reading Efficacy				
I don't like reading material with difficult vocabulary				.636
I read rapidly	-.304			.562
I am confident I can understand difficult books or articles	.311		-.311	.435
I don't like reading technical material				.412
Eigenvalues	4.243	2.256	2.154	1.699
Variance	20.206	10.744	10.259	8.090

Note. Extraction method: Orthogonal. Rotation method: Varimax with Kaiser normalization. Loadings < .3 are suppressed

The final part of the study consisted in eveluating internal consistency using the classical Cronbach's Alpha and the more robust version of internal reliability namely, CR, in addition to convergent and discriminant validity. Internal consistency for each of the subscales was examined using Cronbach's alpha (see Table 5). The value were revealed to be good for "Reading as part of self" (10 items; .85); acceptable for "Reading to do well in other realms" (4 items, .70); poor for "Reading for recognition" (3 items; .55), and very low for "Reading efficacy" (4 items, .31). No substantial increases in alpha values were achieved by eliminating items for any of the four subscales.

Table 5 Descriptive statistics and Cronbach's Alpha for the ARMS factors (N = 179)

Factors	Items	*M(SD)*	Skewness	Kurtosis	Min	Max	Cronbach's α
Reading as part of self	10	3.45 (.66)	-.34	-.38	1.60	4.7	.85
Reading to do well in other realms	4	3.26 (.66)	-.21	.39	1.25	5	.55
Reading for recognition	3	3.09 (.86)	-.44	-.35	1	5	.70
Reading efficacy	4	3.06 (.61)	.20	-.44	1.50	4.5	.31

The composite reliability (CR) and average variance extracted (AVE) of the construct were respectively calculated based on the estimates in (Table 6) using formulae in (Netemeyer et al., 2003) and originally by Fornell and Larcker (1981).

Table 6 Obtained convergent validity (composite reliability and average variance extracted) of ARMS factors

Model	Composite reliability	Average variance extracted
Reading as part of self	.861	.390
Reading to do well in other realms	.683	.372
Reading for recognition	.805	.580
Reading efficacy	.589	.270

Inter-construct correlation was performed and discriminant validity on the other hand was calculated using the commonly used Fornell-Larcker (1981) criterion as adapted from (Henseler et al., 2015).

Table 7 Discriminant validity of the four Self-esteem factors

Factor 1	Factor 2	Φ	$Φ^2$	AVE 1	AVE 2	Decision
RAPS	RTWOR	.494	.244	.390	.372	Established
RAPS	RFR	.179	.032	.390	.580	Established
RAPS	RE	.556	.309	.390	.270	Unestablished
RFR	RTWOR	.294	.086	.580	.372	Established
RFR	RE	-.533	.284	.580	.270	Unestablished
RE	RTWOR	.184	.034	.270	.372	Established

Note. RAPS: Reading as part of self; RTWOR: Reading to do well in other realms; RFR: Reading for recognition; RE: Reading efficacy; Φ: inter-construct correlation coefficient

Lastly, a considerably more sophisticated method for calculating discriminant validity is based on the Hetero-trait mono-method (HTMT) ratio which was developed by Henseler et al. (2015). The results using the HTMT ratio for the four factors were calculated. Pairwise HTMT ratios appear in Table 8.

Table 8 HTMT ratio for the four ARMS factors

Factor	1	2	3	4
Reading as part of self	-			
Reading to do well in other realms	.528	-		
Reading for recognition	.193	.342	-	
Reading efficacy	.399	.132	.513	-

Further, Table 9 summarizes of the overlap between the ARMS's original factors' items and its Morocco-tested counterpart.

Table 9 Comparative distribution of items across the original and the Morocco-tested ARMS versions

Original factors		Obtained factors		Shared factors
Label	Items	Label	Items	Corresponding items
Reading as part of self	8	Reading as part of self	10	6
Reading for doing well	6	Reading for doing well	4	4
Reading for recognition	3	Reading for recognition	3	3
Reading efficacy	4	Reading efficacy	4	3

5. Discussion

We proceeded with data preparation consisting of missing data analysis, multivariate outlier identification and processing, multicollinearity and multivariate normality tests. Then we conducted PCA to examine the structure of the RM scale before assessing its reliability, and evaluating both its convergent and discriminant validity. As part of the requirements for performing factor analysis, an acceptable sample size, univariate and multivariate normality, in addition to the absence of outliers in the dataset and low or no multi-collinearity between variables are fundamental assumptions that have to be met (Yong & Pearce, 2013).

With respect to the sample issue, there is no general consensus about what constitutes an adequate sample size despite the fact that opinions about it tend not to markedly diverge (Williams et al., 2010). However, for our purposes, it was sufficient that researchers reported that 200 records constitute a fair sample size (MacCallum et al., 1999; Pett et al., 2003; Tabachnick & Fidell, 2013). While many researchers adhere to the latter view, Hair et al. (1995) stated that a sample size exceeding 100 is acceptable. Therefore, we were able to confidently move to subsequent steps.

At first, all records in the dataset were judged to be valid for analysis since no missing data was observed. The next step was outlier identification and processing. Using the Mahalanobis distance (Mahalanobis, 1936) for multivariate normality testing, we identified one outlier that was subsequently removed, to remain with one hundred and seventy nine records. In addition to the previous step, the dataset was checked for multicollinearity, as it is vital to make sure there is no multicollinearity between the variables (Field, 2013). As far as our dataset is concerned, the highest multicollinearity indicator value using the variance inflation factor (VIF) was 2.485, well below the threshold of 10 (Hair et al., 2010; Pallant, 2010). We concluded that no significant multicollinearity was found. Afterwards, standardized scores for RM were calculated. RM scores were found to follow a normal distribution pattern ($W(179) = .988$, $p = .154$) using the Shapiro-Wilk test.

At this point, there were three fundamental questions with regard to factor analysis: is data factorizable? If yes, how many factors to retain? What rotation method to use? As important as these questions were, the relevant literature indicates no conclusive answers. There are nevertheless good arguments in support of each position, as each step undertaken has to be justified. The following discussion proceeds in accordance with these questions.

With regards to factor structure, data factorizability is the first step. The two indexes are the Kaiser Meyer Olkin (KMO) measure of sampling adequacy and the Bartlett's test of sphericity (Bartlett, 1950, 1951). Upon examining the relevant literature, there was clear indication that when it comes to the KMO measure, a value of .60 is considered acceptable (Kaiser, 1974), which comparatively made the reported KMO result of .774 for the RM construct (see Table 1) satisfactory. Furthermore, Bartlett's test of sphericity was statistically significant with a p value less than five per cent (χ^2 (120) = 1112.051, $p < .001$). This showed that data can be confidently factorizable.

The next step was factor extraction. But prior to that, it is noteworthy to mention upfront that multiple methods of factor analysis may not necessarily strongly converge or yield conclusive results. In fact, classical methods often yield results different than those obtained from their competing robust counterparts. This pertains to the classical question of the number of factors to retain (Matsunaga, 2010; Velicer & Jackson, 1990). In response to this question, the literature encourages the use of robust methods. Paradoxically, the most common practice is to use the Kaiser-Guttman criterion which stipulates retaining a number of factors corresponding to the number of generated eigenvalues superior to one, and so does the second method of Scree plot (Cattell, 1936), which graphically shows the number of components occurring above and below an eigenvalues threshold of one. Nevertheless, both methods suffer from weaknesses as they tend to overestimate the number of components (Zwick & Velicer, 1986). Ultimately, two of the most compelling alternative methods employed in our methodology were Horn's (1965) parallel analysis and Velicer's (1976) minimum average partial test. The MAP test is considerably more reliable than the Kaiser-Guttman rule and the Scree test and is only superseded by PA and other equally sophisticated approaches (Courtney & Gordon, 2013; Ledesma & Valero-Mora, 2007).

After performing the tests, PCA results (See Table 2) and the scree plot (See Figure 1) yielded an unparsimonious seven-factor solution based on the corresponding eigenvalues, while the MAP test yielded a three-factor solution and PA a four-factor solution (See Table 1 and Figure 2). We opted for a four-factor solution for multiple reasons. First, unequivocally the most reliable statistical factor analytical test we deployed in comparison with its competing cited counterparts is by far PA (Courtney & Gordon, 2013). In this case, PA yielded a four-factor solution as previously mentioned. Second, the four-factor structure has previous theoretical support. Third, we took into account the insufficiency of loadings of multiple items in the alternative three-factor and seven-factor structures and multiple cross-loadings in the alternative five-factor structure. These alternative configurations pose serious interpretation difficulty with regards to subsequent factors below and beyond four factors.

At this stage, there remained the factor rotation method question. As far as this procedure is concerned, there are two distinct methods and each method subsumes multiple configurations (Browne, 2001). One fundamental difference however is that oblique rotation assumes that factors are correlated while their orthogonal counterparts assume that they are uncorrelated (Vogt, 1993). Gorsuch (1983) gave a clear answer to navigate one's way to a factor rotation choice as he briefly says: "If the simple structure is clear, any of the more popular procedures can be expected to lead to the same interpretations" (p. 205). In this context, Tabachnick and Fiddell (2007) give a practical answer to the rotation method question as they explain:

> Perhaps the best way to decide between orthogonal and oblique rotation is to request oblique rotation with the desired number of factors and look at the correlations among factors...if factor correlations are not driven by the data, the solution remains nearly orthogonal. Look at the factor correlation matrix for correlations around .32 and above. If correlations exceed .32, then there is 10% (or more) overlap in variance among factors, enough variance to warrant oblique rotation unless there are compelling reasons for orthogonal rotation. (p. 646)

In a similar vein, Kim and Mueller (1978) state that "If identification of the basic structuring of variables into theoretically meaningful sub-dimensions is the primary concern of the researcher, as is often the case in an exploratory factor analysis, almost any readily available method of rotation will do the job" (p. 50). Then they go on to give a concise and straight-forward recommendation stating that "we advise that beginners choose one of the commonly available methods of rotation, such as Varimax if orthogonal rotation is sought or Direct Oblimin if oblique rotation is sought" (p. 50).

In light of these recommendations and other commonly recommended practices in factor analysis (Worthington & Whittaker, 2006), it was deemed judicious to perform factor analysis using an oblique rotation through examining the component correlation matrix with a threshold of ±0.32 correlation coefficient before taking any further steps. Results showed weak correlation between RM factors except for one pair of two significantly correlating factors (.39) (see Table 3). Since the afore-mentioned conditions to use the oblique rotation were not, we then performed orthogonal rotation based on the previously concluded configuration (see Table 4).

PCA using orthogonal rotation with Kaiser normalization resulted in ten items loading onto the first factor “Reading as part of self,” four items making up the second factor “Reading to do well in other realms,” three items in the third factor “Reading for recognition,” and four items loading into “Reading efficacy.” We observed that some items loaded weakly particularly on the second factor. Incidentally, while doing EFA, it is recommended that very low loading items be removed provided that they do not significantly correlate with any of the factors (generally less than .30) (Beavers et al., 2013). Very low-loading items explained the low consistency level of factors two and four. We chose to keep all items as they figure in the original scale (Schutte & Malouff, 2007)

Out of the original 50-item pool, twenty one items were selected to make up the final scale in the original study. The items that loaded up onto the four factors in our analysis largely but not fully corresponded to those obtained by Schutte and Malouff (2007) in terms of factor loadings. In fact, sixteen out of twenty one items loaded onto the same factors as in the original scale. Sixteen items corresponded to those making up the original extracted factors (see Table 9).

As far as internal consistency is concerned, when adopting the classical Cronbach’s alpha method, the reliability cut-off of .70 is commonly accepted by researchers for internal consistency (Gefen et al., 2000), and while .60 is rare, it is a tolerable minimum (Nunnally & Bernstein, 1994). In fact, it is even suggested that a .50 arguably suffices in certain contexts of exploratory research (Peter, 1979). Based on the values obtained, two out of four factors namely, “Reading as part of self” and “Reading to do well in other realms,” showed acceptable to good consistency while the third factor, “Reading for recognition,” is barely consistent even with the most favorable and liberal estimation, and the forth factor, “Reading efficacy,” shows insufficient consistency.

Although Cronbach’s alpha is indisputably the most commonly used reliability measure, a more compelling and substantially more robust alternative is composite reliability (Peterson & Kim, 2013). For CR, it is not uncommon to use a .70 cutoff value (Aguirre-Urreta et al., 2013; Gefen et al., 2000;). However, a .60 value is considered acceptable in exploratory research (Hair et al., 2011) and even slightly less than .60, as could for instance be explained by measurement error (Fornell & Larcker, 1981). The CR for the factors was calculated: “Reading as part of self” (*CR* = .86), “Reading to do well in other realms” (*CR* = .68), “Reading for recognition” (*CR* = .80) and “Reading efficacy” (*CR* = .59). Alternatively, it turned out that the four factors on the whole demonstrate variably acceptable consistency.

With regards to convergent validity, which indicates that “the items that are indicators of a specific construct should converge or share a high proportion of variance in common” (Hair et al., 2019, p. 675), there is evidence that the average variance extracted (AVE) should be higher than .50 to establish convergent validity, and if the AVE is less than .50, "the construct is questionable" (Fornell & Larcker, 1981, p. 46). Using the aforementioned threshold, the convergent validity for three out of four constructs proved to be problematic indeed ("Reading as part of self": AVE = .390; "Reading to do well in other realms" = .372; "Reading efficacy": .270) with the exception of "Reading for recognition" (AVE = .580).

The last aspect to examine was discriminant validity. Discriminant validity is "the extent to which a construct or variable is truly distinct from other constructs or variables." (Hair et al., 2019, p. 676). There are several methods to establish discriminant validity (Henseler et al., 2015). One common and widely used proposes that "the AVE of each latent construct should be higher than the construct's highest squared correlation with any other latent construct" (Hair et al., 2011, p.154). Based on this approach, three subconstructs, that is, "Reading as part of self," "Reading to do well in other realms," and "Reading for recognition," showed acceptable discriminant validity, but "Reading efficacy" did not. This said, through a demonstrably more reliable substitute, namely, the Heterotrait mono-trait (HTMT) ratio, which is "an alternative procedure for assessing discriminant validity" and which "estimates the true correlation between two constructs if they were perfectly measured" (Hair et al., 2019, p. 761), we were able to obtain encouraging and more positive results. All pairwise HTMT ratios (Table 8) met the standards according to Henseler et al., (2015) since a ratio below .90 means well-established discriminant validity (Hair et al., 2019).

6. Conclusions and limitations

Factor analysis was conducted using PCA to study the structure of the ARMS in the Moroccan context. In line with the existing literature, the results demonstrated a four-factor structure of the measure using the MAP test and PA. Using some of the most reliable if not the most reliable tools for construct validity (convergent and discriminant validity), the ARMS subconstructs demonstrated acceptable internal consistency and discriminant validity despite insufficient convergent validity. In summary, we are very optimistic about future use of the ARMS in, to the best of our knowledge, the hitherto untested and novel context of Morocco, as we were able to show that the ARMS is readily deployable therein in the four-factor configuration that was evaluated.

A posteriori, we would like to suggest several paths for future improvement and inquiry. One important limitation of the present study as previously mentioned is the small sample size. In order to remedy this shortcoming, it is proposed that researchers include considerably larger samples especially in factor analytical research (Tabachnick & Fidell, 2013). One strategy is to maximize the sample size to a larger extent and, if possible, arrange for a sample where one can ensure probability random selection for generalizability purposes. This would in principle allow for better results based on increased statistical power that are likely to lead to improved convergent validity. Another recommendation is to extend the sample to equally include non-students and to geographically be more integrating in the sense that more samples from other non-sampled universities can be included, preferably in a randomly selected fashion from a larger pool of participants. Relatedly, it is similarly advised to dedicate separate databases respectively for exploratory and for confirmatory factor analysis. Additionally, it is recommended that the conduct of a confirmatory factor analysis in the Moroccan context be conducted both a posteriori and separately based on data different from the same context. This will allow researchers to use other factor extraction techniques such as maximum likelihood or principal axis factoring in order to evaluate the fit of both the four-factor and other potentially competing models. Furthermore, in terms of face, content and construct validity, just as we proposed on a previous occasion when adapting the *Rosenberg Self-Esteem Scale* to at least one of the local Moroccan languages and to standard Arabic (Bouih et al., 2022), we recommend developing the translational and cultural adaptation of the ARMS to Arabic and the local languages in Morocco. The last limitation pertains to the lack of previous research on the ARMS using factor analysis in Morocco. Since, based on our overview of the literature, the present work breaks new ground in this context, drawing conclusions based on existing results from previous studies was not possible.

References

Aarnoutse, C., & Schellings, G. (2003). Learning reading strategies by triggering reading motivation. *Educational Studies*, *29*(4), 387-409. https://doi.org/10.1080/03055690320001596688

Aguirre-Urreta, M. I., Marakas, G. M., & Ellis, M. E. (2013). Measurement of composite reliability in research using partial least squares: some issues and an alternative approach. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *44*(4), 11-43. https://doi.org/10.1145/2544415.2544417

Beavers, A. S., Lounsbury, J. W., Richards, J. K., & Huck, S. W. (2013). Practical considerations for using exploratory factor analysis in educational research. *Practical Assessment, Research, and Evaluation*, *18*(1), 6. https://doi.org/10.7275/qv2q-rk76

Brittain, M. M. (1970). Inflectional performance and early reading achievement. *Reading Research Quarterly*, *6*(1), 34-48. https://doi.org/10.2307/747047

Bouih, A., Benattabou, D., Nadif, B., Benhima, M., & Benfilali, I. (2022). The Rosenberg self-esteem scale: a confirmatory factor analysis study. *European Journal of Psychology and Educational Research, 5*(2), 143-160. https://doi.org/10.12973/ejper.5.2.143

Browne, M. W. (2001) An overview of analytic rotation in exploratory factor analysis. *Multivariate Behavioral Research, 36*(1), 111-150. https://doi.org/10.1207/S15327906MBR3601_05

Cain, K., & Oakhill, J. (2011). Matthew effects in young readers: Reading comprehension and reading experience aid vocabulary development. *Journal of Learning Disabilities*, *44*(5), 431-443. https://doi.org/10.1177/0022219411410042

Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate Behavioral Research*, *1*(2), 245-276. https://doi.org/10.1207/s15327906mbr0102_10

Chua, S. P. (2008). The effects of the sustained silent reading program on cultivating students' habits and attitudes in reading books for leisure. *The Clearing House: A Journal of Educational Strategies, Issues and Ideas*, *81*(4), 180-184. https://doi.org/10.3200/TCHS.81.4.180-184

Courtney, M., & Gordon, R. (2013). Determining the number of factors to retain in EFA: using the SPSS r-menu v2 0 to make more judicious estimations. *Practical Assessment, Research, and Evaluation*, *18*(1), 8. https://doi.org/10.7275/9cf5-2m72

Cunningham, A. E., & Stanovich, K. E. (1991). Tracking the unique effects of print exposure in children: associations with vocabulary, general knowledge, and spelling. *Journal of Educational Psychology*, *83*(2), 264-274. https://doi.org/10.1037/0022-0663.83.2.264

Cunningham, A. E., & Stanovich, K. E. (1997). Early reading acquisition and its relation to reading experience and ability 10 years later. *Developmental Psychology*, *33*(6), 934-945. https://doi.org/10.1037/0012-1649.33.6.934

Davis, M. H., Tonks, S. M., Hock, M., Wang, W., & Rodriguez, A. (2018). A review of reading motivation scales. *Reading Psychology*, *39*(2), 121-187. https://doi.org/10.1080/02702711.2017.1400482

Dhanapala, K. V., & Hirakawa, Y. (2015). L2 reading motivation among Sri Lankan university students. *Reading Psychology*, *37(2)*, 202-229. https://doi.org/10.1080/02702711.2015.1025163

Echols, L. D., West, R. F., Stanovich, K. E., & Zehr, K. S. (1996). Using children's literacy activities to predict growth in verbal cognitive skills: A longitudinal investigation. *Journal of Educational Psychology*, *88*(2), 296-304. https://doi.org/10.1037/0022-0663.88.2.296

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. Sage.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.1177/002224378101800l

Gambrell, L. B., Palmer, B. M., Codling, R. M., & Mazzoni, S. A. (1996). Assessing motivation to read. *The Reading Teacher*, *49*(7), 518-533.

Gefen, D., Straub, D., & Boudreau, M. C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, *4*(1), 7. https://doi.org/10.17705/1CAIS.00407

Gorsuch, R. (1983). *Factor analysis* (2nd ed.). Lawrence Erlbaum.

Griffin, R. A., Farran, L. K., & Mindrila, D. (2020). Reading motivation in bi/multilingual Latino adolescents: An exploratory structural equation model. *Reading Psychology, 41.* 856-862. https://doi.org/10.1080/02702711.2020.1801540

Guthrie, J. T., Hoa, A. L. W., Wigfield, A., Tonks, S. M., Humenick, N. M., & Littles, E. (2007). Reading motivation and reading comprehension growth in the later elementary years. *Contemporary Educational Psychology*, *32*(3), 282-313. https://doi.org/10.1016/j.cedpsych.2006.05.004

Guthrie, J. T., Wigfield, A., Humenick, N. M., Perencevich, K. C., Taboada, A., & Barbosa, P. (2006). Influences of stimulating tasks on reading motivation and comprehension. *The Journal of Educational Research*, *99*(4), 232-246. https://doi.org/10.3200/JOER.99.4.232-246

Guthrie, J. T., Wigfield, A., Metsala, J. L., & Cox, K. E. (1999). Motivational and cognitive predictors of text comprehension and reading amount. *Scientific Studies of Reading*, *3*(3), 231-256. https://doi.org/10.1207/s1532799xssr0303_3

Hair Jr, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2010). SEM: An introduction. *Multivariate data analysis: A global perspective*, *5*(6), 629-686.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis*. Cengage Learning.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1995). *Multivariate data analysis*. Prentice-Hall.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

Henk, W. A., Marinak, B. A., & Melnick, S. A. (2012). Measuring the reader self-perceptions of adolescents: Introducing the RSPS 2. *Journal of Adolescent & Adult Literacy*, *56*(4), 311-320. https://doi.org/10.1002/JAAL.00144

Henk, W. A., & Melnick, S. A. (1995). The Reader Self-Perception Scale (RSPS): A new tool for measuring how children feel about themselves as readers. *The Reading Teacher*, *48*(6), 470-482.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179-185. https://doi.org/10.1007/BF02289447

Hughes-Hassell, S., & Rodge, P. (2007). The leisure reading habits of urban adolescents. *Journal of Adolescent & Adult Literacy*, *51*(1), 22-33. https://doi.org/10.1598/JAAL.51.1.3

Katrancı, M. (2015). Book reading motivation scale: Reliability and validity study. *Educational Research and Reviews*, *10*(3), 300-307. https://doi.org/10.5897/ERR2014.1998

Krashen, S. D. (1993). The case for free voluntary reading. *Canadian Modern Language Review*, *50*(1), 72-82. https://doi.org/10.3138/cmlr.50.1.72

Kim, J. O., & Mueller, C. W. (1978). *Factor analysis: Statistical methods and practical issues*. Sage.

Kim, K. J. (2011). Reading motivation in two languages: An examination of EFL college students in Korea. *Reading and Writing*, *24*(8), 861-881. https://doi.org/10.1007/s11145-010-9229-z

Lau, K. L., & Chan, D. W. (2003). Reading strategy use and motivation among Chinese good and poor readers in Hong Kong. *Journal of Research in Reading*, *26*(2), 177-190. https://doi.org/10.1111/1467-9817.00195

Ledesma, R. D., & Valero-Mora, P. (2007). Determining the number of factors to retain in EFA: An easy-to-use computer program for carrying out parallel analysis. *Practical assessment, research, and evaluation*, *12*(1), 2. https://doi.org/10.7275/wjnc-nm63

Leppänen, U., Aunola, K., & Nurmi, J. E. (2005). Beginning readers' reading performance and reading habits. *Journal of Research in Reading*, *28*(4), 383-399. https://doi.org/10.1111/j.1467-9817.2005.00281.x

Lin, D., Wong, K. K., & McBride-Chang, C. (2012). Reading motivation and reading comprehension in Chinese and English among bilingual students. *Reading and Writing*, *25*(3), 717-737. https://doi.org/10.1007/s11145-011-9297-8

MacCallum, R. C., Widaman, K. F., Zhang, S., & Hong, S. (1999). Sample size in factor analysis*. Psychological Methods, 4*(1), 84-99*.* https://doi.org/10.1037/1082-989X.4.1.84

Mahalanobis, P. C. (1936). *On the generalized distance in statistics*. National Institute of Science of India.

Malloy, J. A., Marinak, B. A., Gambrell, L. B., & Mazzoni, S. A. (2013). Assessing motivation to read: The motivation to read profile–revised. *The Reading Teacher*, *67*(4), 273-282. https://doi.org/10.1002/trtr.1215

Matsunaga, M. (2010). How to Factor-Analyze Your Data Right: Do's, Don'ts, and How-To's. *International Journal of Psychological Research*, *3*(1), 97-110. https://doi.org/10.21500/20112084.854

McGeown, S. P., Duncan, L. G., Griffiths, Y. M., & Stothard, S. E. (2015). Exploring the relationship between adolescent's reading skills, reading motivation and reading habits. *Reading and Writing*, *28*(4), 545-569. https://doi.org/10.1007/s11145-014-9537-9

Mokhtari, K., & Sheorey, R. (1994). Reading habits of university ESL students at different levels of English proficiency and education. *Journal of Research in Reading*, *17*(1), 46-61. https://doi.org/10.1111/j.1467-9817.1994.tb00051.x

Netemeyer, R. G., Bearden, W. O., & Sharma, S. (2003). *Scaling procedures: Issues and applications*. Sage Publications.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Pallant, J. (2020). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS*. Routledge.

Pecjak, S., & Peklaj, C. (2006). Dimensions of reading motivation and reading achievement in 3rd and 7th grade students. *Studia Psychologica*, *48*(1), 11.

Peter, J. P. (1979). Reliability: A review of psychometric basics and recent marketing practices. *Journal of Marketing Research*, *16*(1), 6-17. https://doi.org/10.1177/002224377901600102

Peterson, R. A., & Kim, Y. (2013). On the relationship between coefficient alpha and composite reliability. *Journal of Applied Psychology*, *98*(1), 194-198. https://doi.org/10.1037/a0030767

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making sense of factor analysis: The use of factor analysis for instrument development in health care research*. sage.

Schiefele, U., & Schaffner, E. (2016). Factorial and construct validity of a new instrument for the assessment of reading motivation. *Reading Research Quarterly*, *51*(2), 221-237. https://doi.org/10.1002/rrq.134

Schiefele, U., Schaffner, E., Möller, J., & Wigfield, A. (2012). Dimensions of reading motivation and their relation to reading behavior and competence. *Reading Research Quarterly*, *47*(4), 427-463. https://doi.org/10.1002/RRQ.030

Schutte, N. S., & Malouff, J. M. (2007). Dimensions of reading motivation: Development of an adult reading motivation scale. *Reading Psychology*, *28*(5), 469-489. https://doi.org/10.1080/02702710701568991

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Allyn & Bacon/Pearson Education

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics*. (6th ed.). Pearson.

Vallerand, R. J., Pelletier, L. G., Blais, M. R., Briere, N. M., Senecal, C., & Vallieres, E. F. (1992). The Academic Motivation Scale: A measure of intrinsic, extrinsic, and amotivation in education. *Educational and Psychological Measurement*, *52*(4), 1003-1017. https://doi.org/10.1177/0013164492052004025

Velicer, W. F. (1976). Determining the number of components from the matrix of partial correlations. *Psychometrika*, *41*(3), 321-327. https://doi.org/10.1007/BF02293557

Velicer, W. F., & Jackson, D. N. (1990). Component analysis versus common factor analysis: Some issues in selecting an appropriate procedure. *Multivariate behavioral research*, *25*(1), 1-28. https://doi.org/10.1207/s15327906mbr2501_1

Vogt, W. P. (1993). *Dictionary of statistics and methodology: A nontechnical guide for the social sciences.* Sage.

Watkins, M. W., & Coffey, D. Y. (2004). Reading motivation: Multidimensional and indeterminate. *Journal of Educational Psychology*, *96*(1), 110-118. https://doi.org/10.1037/0022-0663.96.1.110

Williams, B., Onsman, A., & Brown, T. (2010). Exploratory factor analysis: A five-step guide for novices. *Australasian Journal of Paramedicine*, *8*(3), 1-13. https://doi.org/10.33151/ajp.8.3.93

Wilson, K. M., & Trainin, G. (2007). First-grade students' motivation and achievement for reading, writing, and spelling. *Reading Psychology*, *28*(3), 257-282. https://doi.org/10.1080/02702710601186464

Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, *34*(6), 806-838. https://doi.org/10.1177/0011000006288127

Yong, A. G., & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in Quantitative Methods for Psychology*, *9*(2), 79-94. https://doi.org/10.20982/tqmp.09.2.p079

Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin*, *99*(3), 432-442. https://doi.org/10.1037/0033-2909.99.3.432