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Research Article

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Psychometric Properties of the Turkish Version of the Algorithmic Media Content Awareness (AMCA) Scale

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Abstract

Given the rapid technological advancements, there is an increasing need for users to acquire new skills, particularly in the realm of algorithmic awareness. This study aims to adapt and validate the Algorithmic Media Content Awareness Scale (AMCA), developed by Zarouali et al. (2021), to the Turkish context and to test its validity and reliability. The original scale is a 5-point Likert type measure consisting of 13 items with four factors in English. Participants included 414 undergraduate students from various faculties of a state university in Türkiye, selected through convenience sampling during the spring term of 2022-2023. The study employed confirmatory factor analysis (CFA) to assess the scale's construct validity and utilized Cronbach's alpha to examine reliability. The CFA results revealed a good model fit for the proposed four-factor structure ($\chi2/df$ = 2.902, CFI = .95, GFI = .939, TLI =.93, RMR = .035, SRMR = .047, RMSEA = .068). Reliability coefficients ranged from .74 to. 81 across the factors, with an overall alpha of .90, indicating high reliability. The item-total correlation analysis revealed that all items significantly contributed to the measure. Additionally, both convergent and discriminant validity were found to be satisfactory. Consequently, all evidence suggests that the Turkish version of the AMCA scale is a valid and reliable tool for assessing algorithmic literacy among undergraduate students, contributing significantly to the field of media literacy research.

Keywords: Algorithms, algorithmic awareness, Scale adaptation, Scale validation

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Algoritmik Medya İçerik Farkındalık (AMİF) Ölçeğinin Türkçe Versiyonunun Psikometrik Özellikleri

Özet

Hızlı teknolojik gelişmelerle birlikte, kullanıcıların özellikle algoritmik farkındalık alanında yeni beceriler kazanmalarına duyulan ihtiyaç giderek artmaktadır. Bu çalışma, Zarouali ve arkadaşlarının (2021) geliştirdiği Algoritmik Medya İçerik Farkındalık Ölçeği'nin (AMİF) Türkçeye uyarlanmasını ve geçerlik ile güvenirliğinin test edilmesini hedeflemektedir. Orijinal ölçek, İngilizce olarak 13 madde ve dört faktör içeren 5'li Likert tipi bir ölçektir. Araştırmaya, 2022-2023 bahar döneminde, kolay örnekleme yöntemiyle seçilen bir devlet üniversitesinin çeşitli fakültelerinden 414 lisans öğrencisi katılmıştır. Ölçeğin yapısal geçerliliğini belirlemek için doğrulayıcı faktör analizi (DFA) kullanılmış, güvenilirliğini test etmek için ise Cronbach alfa değerleri kontrol edilmiştir. DFA sonuçları, dört faktörlü yapının iyi bir model uyumu sergilediğini göstermiştir ($\chi2/df = 2.902$, CFI = .95, GFI = .939, TLI = .93, RMR = .035, SRMR = .047, RMSEA = .068). Güvenilirlik katsayıları, faktörlerde .74 ile .81 arasında değişirken, genel alpha .90 olarak yüksek bir güvenilirlik göstermiştir. Madde-toplam korelasyon analizi, tüm maddelerin ölçeğe önemli bir katkıda bulunduğunu göstermiştir. Ayrıca hem yakınsak hem de ayırıcı geçerlilik yeterli düzeydedir. Sonuç olarak, Türkçe AMİF ölçeği, lisans öğrencilerinin algoritmik okuryazarlığını ölçmede geçerli ve güvenilir bir araçtır ve medya okuryazarlığı araştırmalarına da katkı sunma potansiyeli vardır.

Anahtar Kelimeler: Algoritmalar, Algoritmik farkındalık, Ölçek uyarlama, Ölçek doğrulama

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1. Introduction

Rapid developments in technology have provided numerous advantages, accompanied by new challenges that demand the acquisition of novel skills by users. In this era, individuals must be aware of various literacies, such as new media literacy, digital literacy, technology literacy, digital competencies, and many more. The prevalence of social network sites and recent developments have elevated the role of algorithms in our lives, influencing how we interact, consume information, and make decisions (Wilson, 2019). Algorithms are everywhere, influencing every facet of life domains, and their impact is contingent on decisions made in their social use. When anticipating our actions or preferences, algorithmic inferences can be remarkably accurate to the extent that they occasionally appear to possess a deeper understanding of us than we have of ourselves, or even before we realize certain aspects (Krassman, 2020). In this current digital age, we are constantly exposed to algorithmically selected content, including social media feeds, recommendations, and personalized search results. Algorithms make decisions influenced by user behavior and impact knowledge building as they confine individuals with algorithmic filtering. Given their pivotal role in personalization and content curation (Gillespie, 2014), individuals must improve their understanding of how algorithms operate, including interpreting algorithmic outputs or adapting to technological changes (Shin et al., 2022).

Recent educational research emphasizes how software not only gathers information about human behavior but also predicts our actions (Perrotta & Selwyn, 2020), necessitating an awareness of algorithms. The term "algorithmic awareness" is described as "knowing that a dynamic system is in place that can personalize and customize the information that a user sees or hears" (Hargittai et al., 2020, p. 771). The literature highlights several concerns related to algorithms, which may be the main reason that requires users to be algorithmically aware. The first issue is that algorithms have the power to limit our access to knowledge, necessitating individuals to develop proactive skills to effectively navigate algorithms. This limitation is related to the content filtering mechanism, which directly affects user inputs to offer personalized recommendations or newsfeed. Being aware of filtering has been a critical element that shapes users' actions on online platforms (Bucher, 2017). The second concern is associated with privacy issues, as algorithms utilize enormous amounts of personal data to collect information and present relevant content to users (Araujo et al., 2020; Thurman et al., 2018).

Some individuals perceive this in a negative way and develop a more negative attitude toward technology. Furthermore, another concern exists related to the digital divide, which encompasses varying levels of algorithmic awareness (Gran et al., 2021; Just & Latzer, 2017). With these concerns, it can be inferred that algorithms restrict our exposure to diverse information, potentially resulting in biased algorithmic decision-making. Thus, our decision mechanism is unintentionally affected and limited by channels that are beyond our control.

The concerns outlined above have necessitated the need for research studies to enhance individuals' understanding of algorithms, a crucial element of internet infrastructure, and their profound impact on users' online search experiences (Beer, 2017; García-Orosa et al., 2023; Kitchin, 2017; Latzer & Festic, 2019). One group of those studies has investigated individuals' algorithmic awareness, aiming to understand whether people know that the digital content they access is algorithmically filtered or not (Eslami et al., 2015; Klawitter & Hargittai, 2018; Proferes, 2017; Swart, 2021; Zarouali et al., 2021). The other group of studies focused on educational interventions aimed at enhancing users' algorithmic awareness (Jacques et al., 2020; Swart, 2021). A notable contribution to the literature comes from the study conducted by Eslami et al. (2015), who observed users' reactions upon discovering the algorithmic management of their Facebook news feed. The findings of the study showed that participants feel surprised or frustrated when updates from their friends or families are omitted from the feed. On the other hand, most of them are unaware of the fact that their Facebook's news feed is curated by an algorithm. In another study, interviews with entrepreneurs were conducted to understand their understanding of algorithms impacting sales (Klawitter & Hargittai, 2018). The results revealed varied levels of algorithmic skills among participants, emphasizing the necessity for algorithmic awareness. Despite being aware of the impact of algorithms on online viability, only a few of them have implemented strategies to optimize their content to reach potential customers.

Existing studies show that there is a pervasive lack of algorithmic awareness among several groups of people, including students, workers, and others, despite the high number of social media or Internet usage rates. Additionally, these studies collectively contribute to the growing body of knowledge in terms of algorithmic awareness that shapes human digital experiences. There is a need to explore the functionality of algorithms and how they impact the overall experience of individuals. It can be concluded that algorithmic awareness is a critical aspect that should be gained by individuals. Recognizing its critical importance, researchers have found it necessary to explore algorithmic media context awareness on a valid and reliable scale.

Zarouali et al. (2021) introduced the Algorithmic Media Content Awareness Scale (AMCA-scale) to systematically measure algorithmic awareness. This scale, validated with strong psychometric properties, measures users' awareness across four dimensions, which are content filtering, automated decision-making, human-algorithm interplay, and ethical considerations. The AMCA-scale emerges as a valuable contribution, providing scholars with a reliable tool to investigate algorithmic awareness in online platforms. The current study aimed to adapt the scale developed by Zarouali et al. (2021) to the Turkish context and establish a valid and reliable measurement tool, given the significance of possessing algorithmic readiness and the absence of such a scale in Turkish literature. Within the growing prevalence of social media and the Internet, this study introduces a scale designed to measure users' algorithmic media content awareness. In today's digital age, where communication is predominantly conducted online, the importance of this scale is heightened due to its numerous benefits. By using this scale, researchers can measure users' algorithmic awareness, fostering a deeper understanding of the complex interaction between individuals and the algorithms shaping their online experiences. This valuable information not only contributes to the academic discourse but also has practical implications for digital literacy initiatives and media literacy education. Comprehensive research initiatives can be started to enhance users' conscious social media and Internet use and equip them with a thorough understanding of algorithmic media content awareness. Thus, users can improve their skills and knowledge necessary for navigating the digital landscape. Based on its purpose, the current study is guided by the following research question:

- How valid and reliable are the psychometric properties of the Turkish version of the AMCA scale?

2. Method

This study employs a descriptive and cross-sectional design.

2.1. Participants and Procedure

The data collection period spanned from February to September 2023, and it involved undergraduate students from a state university in Türkiye. The surveys for the study were created using Google Forms and shared with participants through convenience sampling.

Unlike random or stratified sampling methods, convenience sampling does not allow for comprehensive generalizations about a population (Creswell, 2012). Participants were notified that they had the option to withdraw from the study at any point while completing the online questionnaire. To maintain data quality, the electronic questionnaire was set to accept only complete submissions, limiting one response per student. Of the 419 collected responses, 5 were excluded due to lack of consent, resulting in a final sample of 414 participants for the analysis. Approvals to carry out the study were obtained from the relevant university's Research and Ethics Committee (February 3, 2023; Approval no. 571441).

2.2. Measures

2.2.1. Personal information

The questionnaire comprised demographic information such as gender, age, Grade Point Average (GPA), grade level, and faculty. It also contained questions about students' previous education in computer and technology-related courses, daily Internet use, and Internet Use Patterns categorized into academic, social, and recreational Internet use hours.

2.2.2. Algorithmic media content awareness scale

The original scale, developed by Zarouali et al. (2021), aims to measure people's awareness of how algorithms influence media content on digital platforms. Zarouali et al. (2021) suggest that this scale has the potential to evaluate a groups' "algorithmic literacy"- an individual's understanding of algorithms' roles and outcomes in media. The AMCA scale includes 13 items with four dimensions. Each dimension, along with explanations and sample items, is provided in Table1.

Table 1.

Dimensions, Explanations, and Sample Items of the AMCA scale

Dimensions – no. of items	Explanation	Sample item
Content filtering (FIL/ 4-item)	It reflects the users' recognition that algorithms tailor media content based on individual online data.	"Algorithms are used to show someone else sees different [media content] than I get to see on [platform name]".
Automated decision-making (ADM/ 3-item)	Awareness that algorithms autonomously decide the media content displayed.	Algorithms do not require human judgments in deciding which [media content] to show me on [platform name].
Human-algorithm interplay (HAI/ 3-item)	Understanding that user behavior influences algorithmic content suggestions made by the algorithms.	The [media content] that algorithms recommend to me on [platform name] depend on my online behavioral data.
Ethical considerations (ETC/ 3-item)	Recognizing potential biases and ethical dilemmas in algorithm-recommended content.	The [media content] that algorithms recommend to me on [platform name] can be subjected to human biases such as prejudices and stereotypes.

The AMCA scale uses a 5-point Likert scale ranging from 1 (not at all aware) to 5 (completely aware). Cronbach alpha values of four dimensions indicate a good internal consistency. The reliability coefficients lie between .89 and .92. This research focuses on adapting this scale into Turkish context.

2.3. Translation Procedure

We began translating the scale with a thorough assessment of the items for cultural suitability, guided by Merenda's (2006) framework. Accordingly, three steps were followed to achieve item and test equivalence. The initial step involves a comprehensive review of the AMCA items and response scales, assessing them from emic (culture-specific) and etic (universal) perspectives. This preliminary analysis is crucial for identifying any culturally bound content that may not translate directly across cultures. Following this, two translators with proficiency in both the original and target languages translated the scale into Turkish. They were followed by a pair of translators who back translated this Turkish version into the source language. We compared the back-translation to the original to ensure accuracy in the final Turkish version. During the translation of the scale, discrepancies in the equivalence of translations for idioms such as "human judgments" (item 6), and "prejudices and stereotypes" (item 12) were identified. This aligns with Merenda's observation that certain items may not seamlessly transfer across cultural contexts without undergoing necessary adjustments or even replacement. To navigate this issue, three expert reviewers—a linguist and two measurement specialists—carefully evaluated these idioms, thereby ensuring a more accurate translation. The consensus among these experts confirmed the items' content validity as well. After the final step, Merenda (2006) emphasizes the significance of language equivalence and references Sireci (2005), who recommends testing both language versions with bilingual subjects proficient in both languages to mitigate 'language group' effects. However, as mentioned by Cha et al. (2007), there is no gold standard, meaning a universally preferred method, for scale translation due to variations in research contexts, such as the accessibility and availability of bilingual participants. Given these constraints, our study faced challenges in implementing this specific aspect of the process, primarily due to difficulties in finding bilingual participants for our sample. In addition, before finalizing the instrument, cognitive interviews were carried out with an expert in computer science and seven students across various faculties to assess the face validity of the scale. The objective was to uncover potential errors in responses and to delve into the reasons behind these errors on the scale (Willis, 2004). Based on these findings, the researchers implemented minor adjustments to several items.

2.4. Data Analysis

Descriptive statistical methods were employed to outline the attributes of the entire sample. The validity of the study was verified through three distinct approaches: construct, convergent, and discriminant validity. For evaluating construct validity, Confirmatory Factor Analysis (CFA) was applied. Before conducting CFA, certain assumptions such as sample size adequacy, normality, and outlier detection were thoroughly examined. By checking univariate and multivariate outliers, a total of six outliers were identified and subsequently excluded from the analysis. The sample size was deemed adequate for the analysis, substantially meeting the 1:10 thumb rule with 13 items and 408 participants. This size falls within the suggested range of 260 to 420 participants, based on the guideline that the sample size should be 10 to 20 times the number of survey items (Andrew et al., 2010; Kline, 2015).

Univariate normality was confirmed through the assessment of skewness and kurtosis values, alongside visual inspection of histogram and Q-Q plots. A second-order CFA was performed, as in the original research, where the four factors can operate both as distinct scales and collectively as a comprehensive overarching meaningful scale. CFA was carried out utilizing the maximum likelihood estimation method. The reliability of the Turkish version of the AMCA scale was evaluated through Cronbach' alpha coefficient. Item-total correlations were observed to assess item homogeneity. All statistical analyses were conducted using IBM SPSS 28 and IBM AMOS 20.

3. Result

3.1. Descriptive Statistics

The sample consisted of 414 undergraduate students from various faculties at a public university in Türkiye, representing all grade levels. Among them, 306 (73.9%) of them were female and 108 of them (26.1%) were male. The mean age of the total sample was 21.50 (SD= 5.14), ranging from 18 to 65. The largest group within the sample was the juniors, with 157 students (37.9%), followed by sophomores and freshmen, with 97 (23.4%) and 88 (21.3%) respectively. Seniors accounted for 72 students (17.4%). GPA of the students, excluding freshmen who did not yet have a GPA, exhibited a mean value of 3.02 (SD = .37), with a range from 1.72 to 3.81. The mean of daily Internet use was found to be 5.31 (SD = 2.73) ranging from a minimum of 0.6 hour to a maximum of 20 hours. In relation to Internet usage patterns among participants, the data revealed varying trends across different purposes. The academic-related Internet usage had a mean of 2.29 hours (SD = 1.67), spanning a range from no usage to 9 hours. Social Internet use had a slightly higher mean of 3.30 hours (SD = 2.27), with the range also varying from no usage to a high of 20 hours. Lastly, recreational Internet use showed a mean of 1.94 hours (SD = 1.55), extending from no usage to 13 hours. The survey also explored students' previous education in computer and technology-related courses, with a majority (259) indicating no prior courses, while 155 affirmed having taken such courses. Of those who had taken relevant courses, 95 reported these were part of the university curriculum, 39 had taken extracurricular private courses outside the university, and 21 participated in both types of courses. This demographic and academic profile provides a detailed snapshot of the students' engagement with digital technologies and their educational backgrounds in computing and technology, shown in Table 2.

Table 2.

Characteristics of the Sample (N = 414)

Variable	f		%	
Gender				
Female	306		73.9	
Male	108		26.1	
Study Year				
Freshman	88		21.3	
Sophomore	97		23.4	
Junior	157		37.9	
Senior	72		17.4	
Have you received any courses on computers, various technologies, or software before?				
Yes	155		37.4	
No	259		62.6	
If yes, these courses were…				
Within university	95		22.9	
Outside the university	39		9.4	
Both of them	21		5.1	
	M	**SD**	**Min**	**Max**
Age	21.5024	5.137	18.0	65.0
GPA (excluding freshman n = 326)	3.0161	.37047	1.72	3.81
Daily Internet Use	5.3138	2.72656	0.6	20.0
Internet Use Patterns				
Academic Internet Use	2.2783	1.67143	0.0	9.0
Social Internet Use	3.3007	2.27381	0.0	20.0
Recreational Internet Use	1.9372	1.54602	0.0	13.0

Note. f: Frequency, %: Percentage, M: Mean; SD: Standard Deviation; Min: Minimum; Max: Maximum

3.2. Validity and Reliability

3.2.1. Construct validity – Confirmatory factor analysis

CFA was conducted on the AMCA scale using the remaining data, comprising 408 students, to validate the proposed four-factor structure. The selected fit indices for evaluating the measurement model included the chi-squared divided by the degree of freedom ($\chi2/df$), the comparative fit index (CFI), the goodness of fit index (GFI), the Tucker–Lewis index (TLI), the root mean square residual (RMR), the standardized root mean squared residual (SRMR) and the root mean squared error of approximation (RMSEA). As seen in Table 3, the fit indices revealed a good fit to the data ($\chi2/df$ = 2.902, CFI = .95, GFI = .944, TLI = .939, RMR = .033, SRMR

= .0466, RMSEA = .068) with no modifications made to the model. The CFI, GFI, and TLI indices should possess a value of at least .90, which is considered acceptable, and .95 and above is considered a perfect fit (Hu & Bentler, 1999). Furthermore, RMSEA, RMR, and SRMR values less than .05 indicate an excellent fit, while values ranging from .05 to .08 are good and acceptable (Browne & Cudeck, 1993). Values of χ^2/df less than 3 are typically seen as indicative of a good fit, while those less than 5 are deemed acceptable (Kline, 2011).

Table 3.

Results of the Selected Fit Indices for the Model Based on CFA

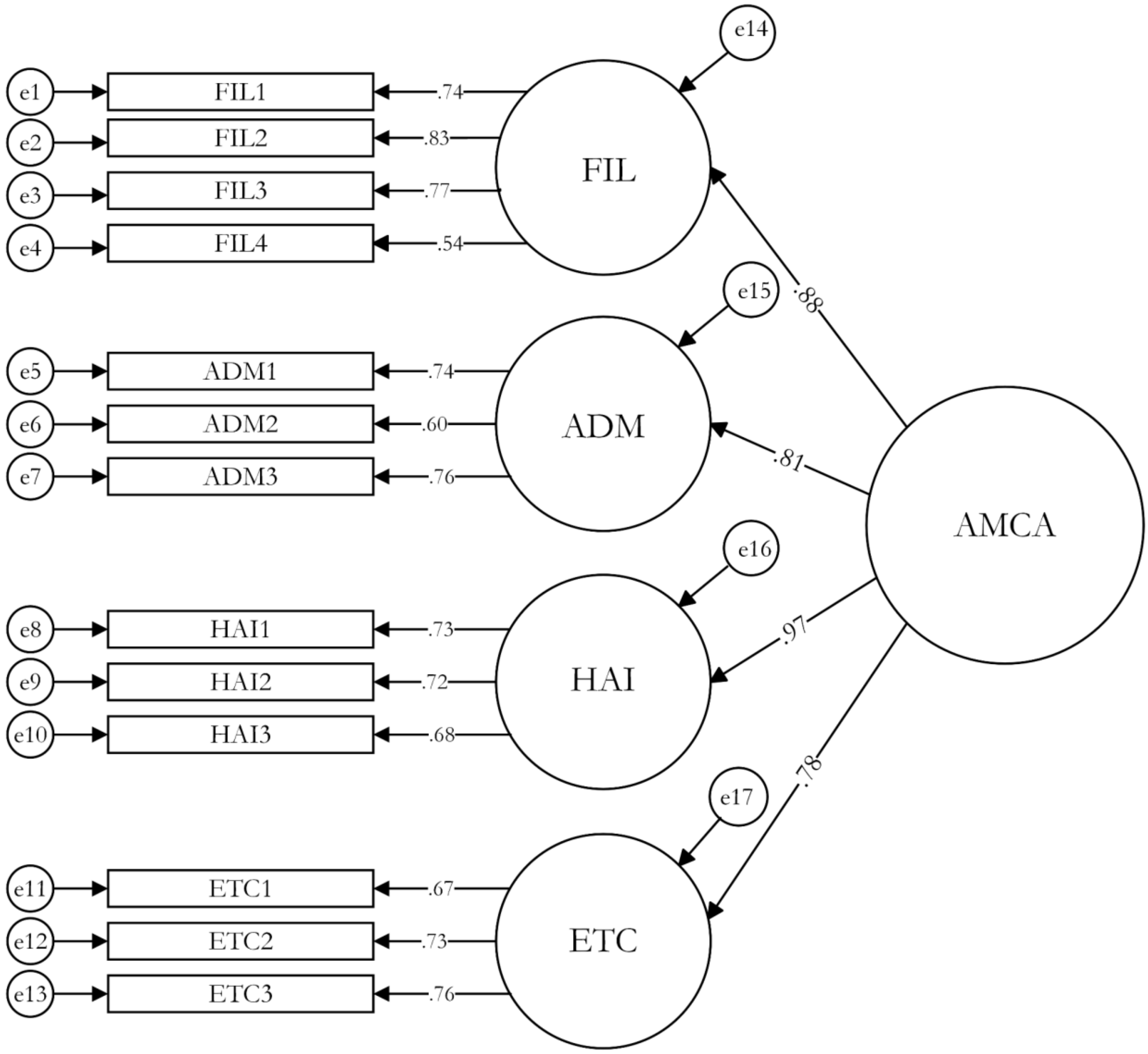
	$\chi 2/df$	CFI	GFI	TLI	RMR	SRMR	RMSEA
AMCA	2.902	.95	.939	.933	.035	.0466	.068
Decision	*Good*	*Perfect*	*Good*	*Good*	*Perfect*	*Perfect*	*Good*

Note. $\chi 2$: Chi-squared; df: Degree of freedom; CFI: Comparative fit index; GF: Goodness of fit index; TLI: Tucker–Lewis's index; RMR: Root mean square residual; SRMR: Standardized root mean squared residual (SRMR); RMSEA: Root Mean squared error of approximation

The factor loadings of the items ranged between .54 and .83, which are greater than .40 as recommended by Stevens (2002). The Figure 1 showed a second-order CFA model of the translated version of the AMCA scale below.

Fig. 1

Second-order measurement model of the Turkish version of AMCA-scale



3.2.2. Convergent and discriminant validity

Convergent validity: All standardized loadings should surpass .5, proving good reliability (Hair et al., 2010), and average variance extracted (AVE) should be above .5, demonstrating sufficient convergent validity (Fornell & Larcker, 1981). The findings from the present study corroborated the convergent validity as all factor loadings and AVE values surpassed the .5 benchmark.

Table 4.

Measurement Model

Construct	***L* Interval**	**AVE**	**CR**	***α***
FIL	.54 – .83	.61	.82	.81
ADM	.60 – .76	.50	.74	.74
HAI	.68 – .73	.51	.75	.76
ETC	.67 - .76	.52	.76	.77

Note. L: Factor Loadings; AVE: Average Variance Extracted; CR: Composite Reliability; α: Cronbach's alpha

Discriminant validity: The square root of AVE should exceed the inter-construct correlations to ascertain a satisfactory level of discriminant validity and should also be higher than .5 (Fornell & Larcker, 1981). As illustrated in Table 5, the square root of AVE values for each construct were higher than the correlation coefficients and the threshold of .5, thereby validating the discriminant validity.

Table 5.

Discriminant Validity for the Measurement Model

	FIL	ADM	HAI	ETC
FIL	**(.787)**	-	-	-
ADM	.602	**(.683)**	-	-
HAI	.669	.577	**(.704)**	-
ETC	.520	.491	.581	**(.718)**

Note. **The values in parentheses are the square roots of AVE*

3.2.3. Reliability and item homogeneity

Fornell and Larcker (1981) established that a Cronbach's Alpha (α) value above .7 indicates good reliability, and a Composite Reliability (CR) score above .7 suggests acceptable internal consistency. For the Turkish version of the AMCA scale, α values across various dimensions ranged from .74 to .81, with the overall α value reaching .90, as detailed in Table 6. Additionally, CR values for each dimension surpassed the .7 threshold, confirming adequate reliability of the constructs, as shown in Table 4.

Table 6.

Item Homogeneity of Each Item of the Turkish Version of AMCA Scale

Factors	Item	Correlation coefficient of item-subscale	Alpha coefficient if item deleted	Alpha coefficient
Content filtering	1	.633	.737	.81
	2	.709	.702	
	3	.671	.723	
	4	.463	.826	
Automated decision-making	5	.594	.617	.74
	6	.511	.716	
	7	.591	.625	
Human-algorithm interplay	8	.538	.720	.76
	9	.603	.620	
	10	.587	.676	
Ethical considerations	11	.585	.700	.77
	12	.626	.653	
	13	.582	.702	
Overall score				.90

Item homogeneity, which measures the consistency among items within a subscale by calculating the Pearson correlation coefficient between each item and its subscale, was analyzed. Mason et al. (2021) notes that a correlation coefficient above .30 denotes item homogeneity, leading to the exclusion of items with coefficients below this value. Our item-total correlation analysis revealed that all items had correlation coefficients greater than .30, ensuring their sufficient contribution to the overall measure, as indicated in Table 6.

4. Discussion

This current study presents a valid and reliable scale that can be implemented in studies to measure the algorithmic awareness of users. Within the study, the Algorithmic Media Content Awareness Scale, originally developed by Zarouali et al. (2021), was adapted into Turkish. This scale can be used to determine the algorithmic literacy of users, which is related to their understanding of algorithms. The scale has 13 items and four dimensions: content filtering, automated decision-making, human-algorithm interplay, and ethical considerations. Considering the increasing rates of online environments and social media tools in every aspect of life, this scale has a contribution to the field, both in an academic context and in other social contexts. The Cronbach alpha values of the dimensions range between .89 and .92, indicating a good value (Cortina, 1993). The study showed that the construct validity of the scale was ensured, and based on the results, AMCA was found to be linguistically equivalent, valid, and reliable for measuring the algorithmic awareness of Turkish users. Although initially designed for use at the undergraduate level, the scale can be applied to individuals irrespective of their academic standing.

The studies in the literature point to the increasing importance of users' algorithmic awareness, as algorithms have the capability to shape users' behaviors in online environments and impact their decisions (Cohen, 2018; Gran et al., 2021; Shin et al., 2022). The first factor, content filtering, consists of 4 items and is associated with users' recognition of algorithms customizing media content based on individual online data. Recent research has concentrated on algorithmic filtering, elucidating its societal impact on users, and also examining how the collection of personal information influences their experiences on online platforms (de Groot et al., 2023; Light et al., 2016). Additionally, studies indicate that users are unaware online platforms employ filtering for their newsfeeds (Eslami et al., 2015; Smith, 2018).

The second factor, automated decision-making, comprises 3 items and is linked to users' awareness that algorithms independently determine the displayed media content. As emphasized in the literature, understanding how online platforms make automated decisions is a crucial aspect (Shin et al., 2022). This issue is becoming more prevalent and automated with the increasing use of online platforms, involving aspects like creating personalized advertisements and recommendations. Studies have shown that users still may not comprehend that online platforms like Netflix, Facebook, and Instagram utilize algorithms to provide suggestions (Gran et al., 2021).

The third factor, human-algorithm interplay, comprises 3 items and is associated with users' comprehension of their behaviors that influence algorithmic content suggestions. As explored in the literature, the content presented to users and the aspects of content filtering are not solely linked to algorithmic logic but are also shaped by users' behaviors (Wilson, 2019). Understanding this issue is crucial for algorithmic awareness, as it enables users to consciously make choices while using online platforms and anticipate content based on their actions (Gillespie, 2014).

The fourth factor, ethical considerations, comprises 3 items related to recognizing potential biases and ethical dilemmas in algorithm-recommended content. The literature highlights various ethical considerations arising from content curated by algorithms, such as privacy risks (Araujo et al., 2020; Thurman et al., 2018), a lack of transparency (Zerilli et al., 2019), or biased algorithmic decision-making (Zarsky, 2016). Being algorithmically literate is also associated with being aware of these concerns that are closely related to ethical issues. Users should understand that algorithmic content may carry potential bias and cannot be classified as neutral (Zarouali et al., 2021). To address these concerns, individuals should understand that algorithms shape our access to information, and we should be aware of the potential impact of algorithmic filtering.

4.1. Conclusion and Suggestions

The Algorithmic Media Content Awareness Scale was adapted to Turkish through a systematic approach, comprising 13 items and a four-factor structure. Recognizing the increasing prevalence of social media and online platforms in today's world, it becomes evident that enhancing algorithmic literacy is crucial. Developing a valid and reliable tool for determining users' algorithmic awareness in online environments is valuable. Researchers can use this scale to investigate the algorithmic literacy of individuals. Furthermore, it can also serve as a means to explore strategies for improving participants' algorithmic literacy levels.

This study has some limitations that should be noted. The current study was limited to undergraduate students from only one university. Future studies can involve users from diverse educational backgrounds and different universities, encompassing students with various cultural backgrounds. Additionally, including potential variables in comparative studies can be considered. Moreover, research can explore the associated factors that may impact users' algorithmic awareness levels. In the digital era, the effective utilization of online platforms depends on how users comprehend them. Understanding the levels of algorithmic awareness among users is critical to ensuring their effective use of online platforms.

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APPENDIX A

Table A1.

The AMCA Scale Items

Factor Name	Number of item	Original Item (EN)	Turkish Version Items
Content filtering (İçerik filtreleme)	1	Algorithms are used to recommend [media content] to me on [platform name]	1. Algoritmalar sosyal medyada bana içerik önermek için kullanılır.
	2	Algorithms are used to prioritize certain [media content] above others	2. Algoritmalar sosyal medyada belirli içerikleri ön plana çıkarmak için kullanılır.
	3	Algorithms are used to tailor certain [media content] to me on [platform name]	3. Algoritmalar sosyal medyada belirli içerikleri bana uygun/çekici hale getirmek için kullanılır.
	4	Algorithms are used to show someone else see different [media content] than I get to see on [platform name]	4. Algoritmalar sosyal medyada başkalarına benim gördüğümden farklı içerikleri göstermek için kullanılır.
Automated decision-making (Otomatik karar verme)	5	Algorithms are used to show me [media content] on [platform name] based on automated decisions	5. Algoritmalar sosyal medyada hangi içeriği göreceğim konusunda otomatik kararlar verir.
	6	Algorithms do not require human judgments in deciding which [media content] to show me on [platform name]	6. Algoritmalar sosyal medyada bana hangi içeriği göstereceğine insan müdahalesi olmaksızın karar verir.
	7	Algorithms make automated decisions on what [media content] I get to see on [platform name]	7. Algoritmalar bana sosyal medyada otomatik karara dayalı içerikleri göstermek için kullanılır.
Human-algorithm interplay (İnsan-algoritma etkileşimi)	8	The [media content] that algorithms recommend to me on [platform name] depend on my online on that platform.	8. Algoritmalar sosyal medyada -online- bulunmama bağlı olarak bana içerikler önerir.
	9	The [media content] that algorithms recommend to me on [platform name] depend on my online behavioral data	9. Algoritmalar sosyal medyada online hareketlerimden (benim sunduklarım dışında) elde ettiği verilerime bakarak bana içerikler önerir.
	10	The [media content] that algorithms recommend to me on [platform name] depend on the data that I make available online	10. Algoritmalar sosyal medyada online olarak sunduğum/paylaştığım verilerime bakarak bana içerikler önerir.
Ethical considerations	11	It is not always transparent why algorithms decide to show me certain [media content] on [platform name]	11. Algoritmalar sosyal medyada hangi içeriklerin gösterileceği konusundan her zaman şeffaf değildir.

(Etik konular)	12	The [media content] that algorithms recommend to me on [platform name] can be subjected to human biases such as prejudices and stereotypes	12. Algoritmaların sosyal medyada bana önerdiği içerikler taraflı olabilir.
	13	Algorithms use my personal data to recommend certain [media content] on [platform name], and this has consequences for my online privacy	13. Algoritmalar sosyal medyada bana belirli içerikleri önermek için kişisel verilerimi kullanır ve bu online gizliliğim/mahremiyetim açısından bazı sonuçlar doğurur.