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Development and Validation of a Multidimensional Perceived Distance Scale in Open and Distance Learning: A Transactional Distance Theory-Based Approach

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Abstract: This study aimed to develop and validate a multidimensional scale for measuring perceived distance among learners in open and distance learning (ODL) environments, grounded in Transactional Distance (TD) Theory. Perceived distance was operationalized across seven sub-dimensions: physical distance, temporal distance, psychological distance, technological distance, experience, bias, and learning facilitation. An exploratory sequential mixed-methods design was employed. In the qualitative phase, a systematic literature review, document analysis, and structured expert consultation involving 24 ODL specialists were conducted to generate and content-validate an initial item pool using the Lawshe technique, yielding a 34-item draft scale. In the quantitative phase, data were collected from 545 active open and distance learners enrolled in the Faculty of Open Education at Anadolu University (Türkiye) via an online survey administered through the institutional LMS. The dataset was randomly split; Exploratory Factor Analysis (EFA) was performed on the first subsample and Confirmatory Factor Analysis (CFA) on the second. EFA confirmed a seven-factor structure accounting for 64.82% of total variance. CFA supported this structure with acceptable goodness-of-fit indices (χ^2/df = 2.909, CFI = .902, SRMR = .051, RMSEA = .059). Internal consistency coefficients (Cronbach's α) ranged from .715 to .913 across sub-dimensions. The results indicate that the scale is a valid and reliable instrument for measuring perceived distance in ODL environments. The scale is anticipated to provide practitioners and policymakers with evidence-based diagnostic data for identifying learners at risk of dropout and informing the design of more effective ODL interventions.

Keywords: *Learner dropout, open and distance learning, perceived distance, scale development, transactional distance theory.*

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Introduction

It is important for educational programs that students choose open and distance learning (ODL) programs, actively engage in the teaching and learning process, and complete their programs. Therefore, dropping out of a course or school is an issue that requires careful examination in both distance learning and face-to-face education systems.

Dropout behavior in ODL environments represents one of the most persistent challenges facing higher education institutions. Arce et al. (2015) have stated that dropout rates in higher education are seen as a significant problem because education authorities use them as quality indicators and because they affect resource allocation. Recent studies indicate that dropout rates in distance education are significantly higher than in traditional education (Grau-Valldosera et al., 2019); According to the South Korean government's Public Disclosure Information on Higher Education in Korea, as of 2022, the dropout rate in these universities is notably higher at 16.41%, compared to 5.97% at offline universities (Seo et al., 2024).

Even if educational programmers and instructional designers design instruction in accordance with program development methodologies, the learning environment the designer intends to create may not align with the learner's expectations. In such a situation, we might expect the learner to adopt different attitudes and approaches towards the content, the method employed, the technological environment provided, or the style of assessment. According to the Theory of Planned Behavior (Ajzen, 1991), when individuals develop a positive attitude, an increase is observed in their intention to use that technology. In addition, when individuals perceive themselves as competent in using a technology and believe that they possess the necessary resources, their intention to use that technology is further strengthened. In

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a study examining the factors affecting science teachers' instructional practices during the distance education process, Öz et al. (2025) found that individuals' intentions were most strongly and positively associated with their attitudes. An individual's attitude towards distance education and its technologies can be directly linked to their learning. Negative attitudes may also affect individuals' ability to adapt to learning environments, their academic achievement, and their likelihood of dropping out of school. Understanding what individuals know, think, and feel is therefore necessary to develop their attitudes towards ODL technologies and environments (Smidt et al., 2014).

Interaction is one of the key variables in the design of ODL systems. A review of the literature shows that research on the Transactional Distance (TD) theory and its components for designing and implementing distance education usually focuses on reducing the perception of distance. Whilst studies in the field of TD theory focus on numerous aspects, they generally address the readiness levels of distance education students (Davis, 2006; Fogerson, 2005; Gunawardena & Duphorne, 2001), their perceptions of self-efficacy (Horzum et al., 2015), learning approaches (Horzum, 2011) and the relationship between structure and dialogue the foundations of the TD theory (Y.-J. Chen, 1997; Demir Kaymak & Horzum, 2013; Saba & Shearer, 1994). Recent studies continue to examine the effects of TD theory on learning engagement, social presence, and autonomous motivation (Akram & Li, 2024; L. Chen, 2023). However, it has been noted that the relevant studies do not directly address dropping out of school or a course. From this point, we consider it a significant academic gap that studies on both TD in ODL and school dropout have been examined independently of one another.

The school dropout is a highly complex phenomenon shaped by numerous interacting factors. Individuals who are capable of taking responsibility for their own learning, yet are often distanced from their teachers, may exhibit behavior that disengages them from the learning process in many respects. Many researchers have also presented multidimensional frameworks to explain this phenomenon.

In their systematic review of 110 articles, Rahmani et al. (2024) categorized the factors influencing school dropout behavior into five main categories: demographic, subject-related, technology-related, motivational, and support-related. They observed that these categories exert a dual influence on school dropout rates, with both positive and negative implications. Similarly, Elibol and Bozkurt (2023) conducted a social network analysis and text mining of 164 publications on school dropout in ODL. Their findings revealed a lack of precise definitions of the school dropout term as well as insufficient use of non-human analytical approaches to describing dropout in ODL. Furthermore, they put forward recommendations to reduce dropout rates in distance learning by improving learner motivation, satisfaction, and autonomy. The joint consideration of TD and the term 'school or course dropout' will contribute to the literature.

The COVID-19 pandemic triggered a sudden and compulsory shift to distance learning at all levels of education worldwide. While courses were moved online in higher education in response to the suspension of face-to-face teaching, this rapid transition did not yield the same results across all regions and sectors of society. During the pandemic, distance learning has become a multidimensional experience involving issues such as digital access, economic hardship, loss of motivation, and psychosocial vulnerability (Ortakaya, 2026). This situation necessitates a more in-depth examination of the pedagogical, psychological, and sociological aspects of distance learning. We view the sense of distance perceived by learners in ODL environments as a multi-layered phenomenon encompassing psychological (Garrison, 2000; Moore, 1993), social, and pedagogical dimensions.

Moore's (1993) TD theory, based on the concepts of autonomy, dialogue, and structure, defines the psychological and communicative distance between the learner and the teacher. Unlike physical distance, it also encompasses feelings experienced by learners, such as loneliness, disconnection, or a lack of belonging (Moore & Kearsley, 2011). A lack of perceived sense of community, motivation, familiarity with technology (Song et al., 2004), the type of teaching model, the level of learning materials and activities, the teaching environment, autonomy, prior experience, and technology skills (Usta, 2016) can directly influence the level of participation in lessons and learner success. These explanations show that TD goes beyond physical distance. It is shaped by a complex interplay of psychological, social, and technological factors.

With education moving online, there is less social interaction between the instructors and the learners. This can make learners feel less connected to their school and lead to them not paying as much attention (Anderson & Dron, 2011). It is also considered that learners' technological competencies will have an impact on their interactions with online learning environments and their self-regulated learning skills (Tinmaz et al., 2023). Recent studies have demonstrated a direct positive effect correlation between digital literacy and learners' academic achievement, with the learning engagement and online self-regulated learning serving as mediating factors (Chaw & Tang, 2024; F. Chen, 2025). Given the evolving characteristics of learners and the continually advancing technology, we believe that TD theory will be a central framework in the context of 21st-century open, distance, and digital education, as evidenced by research by Xiao (2025) and Achuthan et al. (2024).

Although the concept of distance is generally addressed within the TD framework in the literature, we believe that it should be evaluated more broadly. The perception of distance is not limited solely to a lack of interaction with the instructor. However, it can also be linked to factors such as the connection established with the content, the accessibility of the learning environment, the level of social interaction, and technical support (Bolliger & Inan, 2012;

Wei et al., 2015). Learners' preconceptions about distance education, issues they encounter with the technological infrastructure, or the inadequacy of their previous learning experiences can be considered factors that reinforce the perception of distance (Arbaugh, 2000; Shea et al., 2006). Recent studies conducted in hybrid learning environments have shown that online learners experience higher TD due to a lack of dialogue (Nussli & Oh, 2025).

Existing Scales and Gaps in the Literature

Upon examining the scale instruments developed in the context of ODL in the literature, it becomes apparent that these instruments can be classified according to three key criteria: (1) the nature of the construct they measure (attitude, satisfaction, readiness or distance), (2) the target participant group (student, teacher, trainee teacher) and (3) their level of specificity to the ODL context. According to this classification, a comprehensive scale for the perception of distance has not yet been developed.

It has been determined that satisfaction-focused measurement tools are the most widely developed scales for the construct they measure. The ODESS scale, developed by Durak et al. (2026), measures students' satisfaction with online distance education through seven factors and 39 items; it focuses on dimensions such as instructor support, course materials, and student-student interaction. Kafes and Yıldırım (2021), and Hwang and Kim (2022) have similarly developed tools centered on satisfaction. Upon examining these two scales, although they measure the extent to which students derive satisfaction from the system, they do not directly address the underlying psychological perception of distance.

Meanwhile, attitude scales constitute the second largest group. Gülleroğlu and Coşkun (2023), Çıplak et al. (2023), Çelik and Uzunboylu (2022), Koç et al. (2024), Eşkil and Yarım (2023), Zorlutuna and Erilli (2022), and Demir and Çetin (2022) measure general attitudes towards distance learning, i.e., positive or negative tendencies. Considering the years in which these tools were developed, we argue that these tools were designed in response to the specific conditions of the pandemic period and were developed primarily for teachers or trainee teachers. Deniz and Bağçeci (2022) also developed a two-dimensional attitude scale titled 'Perceived Benefits and Limitations of Distance Education'. We contend that whilst attitude scales can reveal how a student evaluates a given situation, they may not adequately reflect the dynamic and multidimensional nature of distance perception.

Tools based on TD theory, however, are quite scarce. Tria (2024) developed a 30-item instrument based on Moore's three core components (structure, learner autonomy, and dialogue); Yandi (2025), meanwhile, adapted a scale developed by Weidlich and Bastiaens (2018) to Turkish culture. We consider these two scale development studies to be the most conceptually close to our research.

On the whole, we believe that these scales, developed based on satisfaction, attitude, and TD, fall short within the framework we have defined as the perception of distance. It appears that there is currently no valid, reliable, and original Turkish scale that assesses learners' perceived distance in an ODL environment across sub-dimensions such as prior experiences, technological distance, preconceptions about ODL, and whether ODL actually facilitates learning. This situation forms the fundamental rationale for our research.

The planned scale for development differs from existing scales in several ways. Firstly, unlike many scales developed with a focus on specific student groups or academic disciplines, it is designed to apply to all higher education students, taking into account the diverse needs and experiences of those with different academic backgrounds.

Secondly, the scale development process involved students from diverse demographic backgrounds who were studying at a university that was implementing fully remote education. Among the scale development studies examined, only Hwang and Kim (2022) worked with learners who had e-learning experience. In other studies, the study groups consisted of undergraduate students receiving face-to-face education and teacher. We believe that this approach will produce reliable results in terms of sensitivity to students from diverse demographic backgrounds.

Thirdly, the scale items were formulated within the context of distance education theories and related theories, without being tied to a specific disaster, emergency, or situation requiring a transition to distance learning. When assessing its usability, we believe practitioners can use this scale to measure learners' perceived distance in any distance-learning experience across varied institutional contexts and delivery modes.

Finally, scale development studies were considered, and it was determined that no equivalent scale incorporates psychological distance, bias toward distance learning, perceived learning, and prior experience.

We argue that developing a comprehensive scale to determine the perceived distance experienced by learners in ODL environments would meet an important need in both practice and theory. At this scale, educational designers, instructors, and policymakers could develop strategies to make distance learning processes more interactive, inclusive, and learner-friendly.

In the course or program development phase of distance education, priority should be given to intrinsic motivations (Park & Choi, 2009). Identifying an internal state, such as perceived distance, has the potential to reduce dropout rates, increase student engagement, and improve the quality of learning.

Relationship With Theory

In this study, the perception of distance is examined as a single dimension, but through interrelated sub-dimensions. These sub-dimensions have been evaluated in the light of TD theory and the relevant literature.

In Moore's theory, the concept of distance is explained by three variables: dialogue, structure, and autonomy. He refers to the psychological and communicative gap created by the mutual influence of these three structures as TD (Moore & Kearsley, 1996). Structure and dialogue are generally explained by the characteristics of the communication environment, the emotional and philosophical characteristics of teachers, the personalities of learners and teachers, and the content determined by educational institutions (Usta, 2016).

Dialogue is generally influenced by factors such as pre-process educational philosophy, process design, the personalities of teachers and students, learning styles, teacher selection and training, lesson design format, the communication environment, class size, the emotional environment, the quality of reinforcement and feedback provided for activities, and language differences (Moore & Kearsley, 1996).

By 'structure', what is meant is the degree to which an educational program responds to and serves student needs (Moore, 1993). Moore defines structure as the flexibility or rigidity of an educational program's objectives, teaching strategies, and assessment methods, as well as its ability to meet learners' individual needs (Moore & Kearsley, 1996).

Regarding the physical distance dimension, Moore states that in any distance learning context, the physical distance between the instructor and the student is less significant than TD and suggests that success in distance education can be achieved not by reducing the physical distance between the student and the instructor, but by reducing the psychological distance (Moore & Kearsley, 1996).

Indeed, Saba and Shearer (1994) noted that whilst physical distance is a determining factor in distance education, it is not a significant predictor on its own.

TD theory explains the psychological and communicative distance that emerges between learners and the instructor, course content, and learning environment. When dialogue is insufficient, when course structure does not align with learners' needs, or when learners struggle to manage their own learning, this sense of distance tends to increase over time. It is assumed that the perception of such distance plays a decisive role in learners' active participation in the learning process. If not identified in a timely manner, this perceived distance may lead learners to disengage from the learning process.

Within the scope of this study, the perceived distance scale developed on the theoretical foundation of TD is expected to render this process, namely, how learners' perceived distance transforms into disengagement, more visible and measurable.

When examining the dimension of temporal distance within the TD theory framework, whether the learning and teaching process is conducted synchronously or asynchronously is a matter that requires careful consideration. According to Moore (1993), synchronous interaction and the provision of immediate feedback strengthen the dialogue dimension, thereby reducing TD. However, in asynchronous interaction, although learners have greater autonomy in such environments, dialogue may diminish in groups where learners do not take full responsibility for their learning. This situation is similar to Hrastinski's (2008) finding that synchronous communication encourages individual participation more effectively, but asynchronous communication encourages cognitive participation more effectively.

In this study, we will examine the experience dimension in terms of the quality and adequacy of the learners' prior ODL experiences. Moore and Kearsley (2011) examined the concept of learner autonomy, emphasizing that learners' past educational experiences directly determine their capacity for independent learning. Tinmaz et al. (2023) have also demonstrated that digital literacy and prior online learning experiences reinforce each other. If we define experience as the individual's positive or negative experiences, we can state that the level of ODL experience may influence the learners' perception of distance from the system.

The technological distance dimension captures the perceived distance that arises from learners' difficulties in using digital tools and ODL platforms effectively. Although the underlying construct draws on the concept of technological distance, the dimension is framed as distance rather than ability, consistent with the scale's overarching focus on perceived barriers rather than skill levels per se. In TD theory, the dialogue component indicates the quality of communication between the educator and the student. However, this communication is only possible through the effective use of technology. Both F. Chen (2025) and Chaw and Tang (2024) demonstrate that digital competence directly influences online learning. Given this direct influence, we might consider that the nature of the learner's relationship with technology could directly affect both the effective use of dialogue and structural components, and consequently influence the perceived level of distance.

The bias dimension encompasses the learners' pre-existing negative beliefs and attitudes towards ODL and distance learning technologies. Assuming there is a congruence between an attitude towards a specific behavior and that behavior, certain factors lead individuals to develop an attitude towards it, influencing their decision to perform or

refrain from performing it (Ajzen, 1991). In their empirical studies examining the theory of planned behavior, Bentler and Speckart (1979) found that attitudes significantly influenced behavior. They also claimed that intention didn't mediate the relationship between attitude and behavior. Therefore, we might conclude that prejudice towards the ODL environment could reinforce the perception of distance by weakening the student's participation in the system, their communication with the educator, and the overall learning process. Arbaugh (2000) and Shea et al. (2006) have also demonstrated that pre-existing negative attitudes delay students' adaptation to online environments. Consequently, the bias dimension represents the cognitive and emotional roots of the perception of distance.

The facilitation of learning dimension encompasses all the environments encountered by students during the ODL process. Bolliger and Inan (2012) and Wei et al. (2015) have demonstrated that the perception of distance extends beyond interactions with the instructor to encompass connections with the content, accessibility, technical support, and learning theories. Anderson and Dron (2011) note that constructivist and connectivist approaches can also be explained by access to learning materials. They state that the effectiveness of resources such as websites, books, and videos is directly related to the extent to which they support learning. The learning facilitation dimension represents the holistic effect of these external factors on the perception of distance, directly corresponding to the structure component of TD theory.

This study aims to develop an original scale based on TD theory and the phenomenon of school dropout to identify the dimensions of perceived distance among open and distance learners. The objective is to enable decision-makers and educators to define the perceived distance experienced by open and distance learners in a multidimensional manner and, consequently, to improve teaching practices. It is anticipated that adjustments based on the scale's results will help reduce prejudice toward ODL programs, increase students' motivation to learn, inform the development of policies to address dropout behavior, and guide the design of more effective teaching programs.

Methodology

Research Design

This study employs an exploratory sequential design, a type of mixed-methods research design (Creswell & Plano Clark, 2011). An exploratory design is a research design that combines qualitative and quantitative methods, using qualitative data to guide the quantitative data collection phase (Büyüköztürk, 2014). This design is typically used in the development and testing of a survey or assessment scale (Fraenkel et al., 2012). Since this study aims to determine the perception of distance in open and distance education and to develop a measurement tool, it is necessary to base the study on qualitative findings and to guide the quantitative data accordingly.

In an exploratory sequential mixed-methods design, the qualitative phase precedes and directly informs the quantitative phase (Creswell & Plano Clark, 2011). In the present study, the qualitative phase comprised three interrelated procedures: (1) a systematic literature review of national and international studies on perceived distance, TD theory, and learner dropout in ODL environments, through which the conceptual boundaries of each sub-dimension were established; (2) document analysis of existing scale instruments developed within ODL contexts, which informed decisions about item formulation and factor structure; and (3) structured expert consultation with 24 academics specializing in ODL, conducted using the Lawshe (1975) technique, through which items were evaluated, revised, or eliminated based on content validity ratios. Together, these three procedures constituted the qualitative strand of the study, generating the conceptual and empirical basis from which the initial item pool was derived. The outcomes of this qualitative phase, specifically a theoretically grounded factor structure and a content-validated 34-item draft scale, then served as the direct input for the quantitative phase, in which EFA and CFA were conducted to assess construct validity. In this context, following the steps outlined in Figure 1 to develop the scale is expected to contribute positively to the research process.

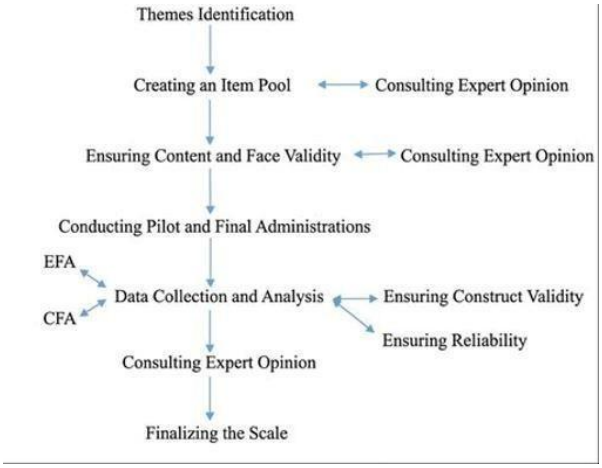


Figure 1. Scale Development Procedural Steps (Özen, 2022)

Scale Development Process

In this study, the scale was developed to measure learners' experiences and satisfaction with the platform by following the scale development steps proposed by DeVellis (2012), Hinkin et al. (1997), Netemeyer et al. (2003), and Germain (2006). Accordingly, the process aimed to produce a measurement tool with a strong theoretical foundation that is valid and reliable in an applied context.

In the first phase, the literature on distance learning, platform usage, and learner experience was comprehensively reviewed. The basic framework of the measurement tool was established in line with the TD Theory; an item and factor pool was created based on the distance dimensions and learner characteristics indicated by the theory. In this context, the scale was structured around the factors of physical distance, time distance, psychological distance, technological distance, experience, and learning facilitation. The suitability of the identified Factors for the platform context were evaluated by soliciting the opinions of four academics with experience in ODL, and content validity was ensured in accordance with these expert opinions. Factors that did not align with the research context were excluded from the process.

Development of the Item Pool

After the purpose and theoretical boundaries were established, a draft item pool representing the dimensions identified within the framework of TD theory was created, and relevant national and international scales were reviewed to form a pool of 58 items. To ensure content validity, the opinions of 24 academics specializing in ODL were sought. In this study, to ensure content validity, the expert opinions obtained according to the Lawshe (1975) technique (updated by Wilson et al. (2012) and Ayre and Scally (2014)) are examined sequentially for each item. Within the scope of this technique, to determine the content validity of the items to be included in the scale, qualitative data obtained through a detailed literature review, document analysis, and expert opinions are converted into quantitative data by calculating the Content Validity Ratio (CVR) and Content Validity Index (CVI). In this conversion process, the CVR was calculated first, followed by the CVI.

To apply the Lawshe technique, a group of 5 to 40 experts is required (Yurdugül & Bayrak, 2012). In calculating the scale's content validity ratios, items were scored as "Appropriate" (3), "Appropriate but Needs Revision" (2), and "Should Be Removed" (1). In this context, opinions regarding the scale items presented to the experts were collected, and content validity ratios were determined. Subsequently, the CVR ratios were calculated as the difference between the number of experts indicating an "Appropriate" opinion for any given scale item and half the total number of experts who expressed an opinion on that item, minus 1. If the CVR values are negative or 0, remove these items first. Items with positive CVR values, on the other hand, can be described as requiring certain statistical procedures. In this context, to facilitate the calculation of content validity ratios, the minimum values were converted into a table at the α=0.05 significance level, and the CVR was determined.

Table 1. Minimum/Critical Values of CVR at the α=.05 Significance Level (CVRcritical) (Ayre & Scally, 2014)

Number of Experts	Minimum Value	Number of Experts	Minimum Value
5	1.000	23	.391
6	1.000	24	.417
7	1.000	25	.440
8	.750	26	.385
9	.778	27	.407
10	.800	28	.357
11	.636	29	.379
12	.667	30	.333
13	.538	31	.355
14	.571	32	.375
15	.600	33	.333
16	.500	34	.353
17	.529	35	.314
18	.444	36	.333
19	.474	37	.297
20	.500	38	.316
21	.429	39	.333
22	.455	40	.300

For this reason, items that failed to achieve full consensus and scored below .440 were removed from the scale; items with sufficient representativeness were retained; and some items were revised for linguistic simplification and contextual adaptation. At the conclusion of this content validity process, a 34-item draft scale was obtained.

Following these revisions, the draft scale was reviewed in the second phase of scale development by five academics specializing in measurement and evaluation, with a focus on language, clarity, and measurability. In line with the experts' recommendations, some statements were restructured, and items containing technical terms or with ambiguous meanings were simplified. In the final stage, interviews were conducted with learners who actively use the platform; learners were asked to read the items aloud and identify any statements they did not understand or were unsure about. The final form of the scale was developed based on these evaluations.

The items in the scale are presented as statement sentences, and participants expressed their opinions using a 5-point Likert-type scale. Participants rated each item on a scale ranging from 1 = "Strongly disagree" to 5 = "Strongly agree."

Data Collection Process

The study population comprises all open and distance learners enrolled in the Faculty of Open Education at Anadolu University during the spring semester of the 2025–2026 academic year. Purposive sampling, a non-probability sampling method, was used to select the sample. Participants were required to meet the following criteria: (1) active enrollment in the Faculty of Open Education at Anadolu University during the spring semester of the 2025–2026 academic year; (2) a minimum of one full semester of prior experience with the Anadolu LMS platform, ensuring that responses reflected actual engagement with the ODL environment rather than initial impressions; (3) current active use of the platform, defined as having logged in and completed at least one assessed activity during the current semester; and (4) voluntary participation, with informed awareness that the data would be used solely for scientific purposes. These criteria were designed to ensure that participants possessed sufficient experiential grounding to respond meaningfully to items measuring perceived distance across all seven sub-dimensions of the scale. In accordance with the recommended principle of "at least 10 times the number of items" (DeVellis, 2012; Tabachnick & Fidell, 2013) in scale development, the goal was to reach at least 340 participants for a 34-item scale.

The data collection process was conducted via an online survey administered through the Anadolu LMS platform. Participants were informed of the study's purpose, that participation was voluntary, and that data would be used anonymously solely for scientific purposes. Data collection was carried out over 20 days among 650 students who had experience with the platform and volunteered to participate. After excluding incomplete responses, incorrect answers to control questions, or response patterns that compromised data integrity (such as providing the same answer to all items), analyses were conducted based on 545 valid responses. The final sample size (n = 545) exceeds the targeted minimum sample size (n = 340).

Data Analysis

During the data analysis, preliminary examinations of the scale items were conducted first. In this context, descriptive statistics were calculated, and skewness and kurtosis values were examined to assess the assumption of normality. Additionally, item-total correlation coefficients were calculated to evaluate the items' discriminant validity and their ability to represent factor cohesion.

Subsequently, following Fabrigar et al. (1999), the dataset was randomly split into two parts. Exploratory Factor Analysis (EFA) was performed on the first dataset, and Confirmatory Factor Analysis (CFA) was conducted on the second dataset. In the final stage, Cronbach's alpha (α) internal consistency coefficient was calculated for the entire dataset to assess the scale's reliability.

Study Group

When determining the study group, purposive sampling, one of the sampling methods, is preferred. The pilot applications of the scale developed in the study were conducted with students at the Anadolu University Open Education Faculty during the 2025-2026 academic year. The developed scale items were sent to the learners at the relevant institution, and they were asked to respond in accordance with the existing guidelines. There are different opinions regarding sample adequacy and size for the pilot study. While Evci and Aylar (2017) recommend conducting a pilot study by reaching approximately 5% of the target population, Şeker and Gençdoğan (2014) state that selecting 30-50 participants who represent the target population is sufficient. Within the scope of the pilot application of this study, a group of 50 participants was reached. The pilot study yielded several actionable findings. Item-total correlation coefficients were examined for all 34 items; items falling below the conventional threshold of .30 were flagged for review (Nunnally, 1978). Based on this analysis, two items were identified as linguistically ambiguous within the Psychological Distance sub-dimension. These items were revised in consultation with two measurement specialists prior to the final data collection phase; specifically, both items were simplified to reduce double-barreled phrasing that had caused interpretive difficulty among pilot participants. No items were eliminated at this stage, as all retained items demonstrated acceptable corrected item-total correlations following revision. The final 34-item scale was thus confirmed as ready for administration in the main study.

The final applications of the scale developed in the study were conducted with open and distance learners at Anadolu University during the 2025-2026 academic year. The developed scale items were sent to the learners at the relevant

institution, and they were asked to respond in accordance with the existing guidelines. When the relevant literature on sample size for the final application is examined, it is recommended that the sample size in Likert-type scale development studies should preferably be at least 300 or more; there are also views advocating that a sample size between 5 and 10 times the number of items is sufficient (Çokluk et al., 2016; Kline, 1994; Nunnally, 1978; Şencan, 2005; Turan, 2019).

Findings/Results

Data was collected from 650 participants in the study. In the preliminary review conducted, it was observed that none of the participants provided repetitive or inconsistent answers to the survey questions. Following this process, analyses were conducted to determine whether the data collected in the study met the assumption of normality for the statistical tests to be performed. To test for a univariate normal distribution, the principle of a sample size of n > 300 was applied, and it was required that the absolute skewness of the scale items not exceed 2.0 and the absolute kurtosis not exceed 7.0. As a result, none of the items exceeded these threshold values (Kim, 2013). To test for multivariate normal distribution, the Mahalanobis distances of the items were calculated. Responses from 10 participants who exceeded the critical chi-square threshold at the $p < .001$ significance level were removed from the dataset as outliers. Using the remaining 545 data points, it was assessed that the dataset met both the univariate and multivariate normality criteria (Arifin, 2015).

Validity and Reliability

To ensure the validity and reliability of the study, EFA, CFA, and Cronbach's Alpha reliability analysis were employed, respectively. The findings were organized and presented according to each subheading and interpreted accordingly.

Common Method Bias

Since the data were collected via a single self-report survey administered at a single time point (n=545), we assessed common method bias using Harman's single-factor test and a common latent factor (CLF) analysis (Podsakoff et al., 2003). Seven factors exhibited eigenvalues greater than 1, and the largest proportion of variance explained by a single factor was 29.07%. In addition, the CLF assessment indicated that standardized regression weights differed by less than .20 between the measurement model with and without the CLF. Taken together, these results suggest that common method bias is unlikely to materially affect the study findings (Fuller et al., 2016; Harman, 1976).

Exploratory Factor Analysis (EFA)

To ensure the validity of the study's scale, EFA was applied as the first step. The approach proposed by Nunnally (1978) was used to determine whether the constructs in the study's scale were theoretically unidimensional or multidimensional. In this context, EFA was applied. This condition, deemed necessary for testing the validity of constructs measured quantitatively, was met for all constructs. Additionally, in the EFA analyses, the Principal Component Analysis (PCA) extraction method and the Varimax rotation method were used. PCA aims to group a large number of variables under a smaller number of factors by ensuring that each factor captures as much variance as possible from the dataset. Varimax is one of the orthogonal rotation methods; it rotates the factors by 90 degrees without changing their axis positions, thereby maximizing variance in the factor columns (Çokluk et al., 2016). As a result, the KMO and Bartlett's Sphericity Test results indicated an acceptable to good level of distribution and were statistically significant (Hair et al., 2019). These findings are presented in Table 2.

Table 2. Bartlett's Test of Sphericity and KMO Sampling Adequacy Test Results

Scale	Bartlett's Test of Sphericity			KMO Sampling Adequacy Test
	x^2	df	*p*	
Perceived Distance (34 items)	10146.958	561	< .001	.928

Note. Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy are computed for the full item correlation matrix and yield a single value for the scale as a whole, not separate values per sub-dimension. The $\chi^2(561) = 10146.958$, $p < .001$ result confirms that the correlation matrix is significantly different from an identity matrix, and the KMO value of .928 indicates excellent sampling adequacy (Kaiser, 1974), supporting the appropriateness of factor analysis for the present dataset.

A factor loading is a value that indicates the degree to which items on a scale are related to the factor being measured by that scale. For a factor loading to be considered significant, it must be at least .50 (Hair et al., 2019). Factor loading thresholds are not absolute; Hair et al. (2019) indicate that the minimum acceptable factor loading varies as a function of sample size. For samples of approximately 200, a loading of .45 is sufficient, whereas for samples exceeding 350, a loading of .40 is considered statistically acceptable. Given the present study's sample size (n = 545), a minimum factor loading of .40 was adopted as the threshold criterion. Accordingly, the factor loadings obtained in the EFA range from

.828 to .406, and all items, including I25 (λ = .406), meet this criterion. However, in social science studies, it is also stated that for a factor to be considered meaningful, the explained total variance must be 50% or higher, and the eigenvalue must be greater than 1.0 (Seçer, 2015). The factor loadings, total variance explained, and eigenvalues from the EFA results are presented in Table 3.

Table 3. EFA Results

Factor	Item (I)	Factor Loading	Total Variance Explained	Eigenvalue
Physical Distance (PhyD)	I 2	.810	29.076	9.886
	I 1	.809		
	I 3	.784		
	I 4	.740		
	I 6	.672		
	I 8	.660		
	I 5	.634		
	I 9	.616		
Experience (ExpD)	I 39	.828	16.037	5.45
	I 35	.802		
	I 37	.799		
	I 36	.793		
	I 40	.786		
	I 34	.763		
	I 38	.734		
Bias (BiaD)	I 47	.807	4.870	1.66
	I 48	.754		
	I 46	.732		
	I 45	.677		
	I 44	.640		
Learning Facilitation (LF)	I 50	.819	4.503	1.53
	I 52	.738		
	I 51	.707		
	I 53	.664		
Psychological Distance (PsyD)	I 19	.574	3.813	1.30
	I 17	.557		
	I 20	.544		
Technological Distance (TechD)	I 26	.729	3.454	1.17
	I 29	.674		
	I 31	.625		
	I 25	.406		
Temporal Distance (TimeD)	I 14	.687	3.068	1.04
	I 15	.686		
	I 16	.606		

In Table 3, the item loadings on the factors range from .828 to .406. In this context, it can be concluded that the loadings for all factors in the scale are adequate. It is also noteworthy that the total variance explained was 64.821 and that the eigenvalues exceeded 1.0. In summary, the EFA findings indicate that all values are at an adequate level (Hair et al., 2017; Seçer, 2015).

To assess whether the scale's theoretically determined factor structure, finalized based on field experts' opinions, was consistent, parallel analysis was used to determine the number of factors by comparing eigenvalues from random data sets with those of the actual data set (DeVellis, 2012). To determine the appropriate number of factors, we conducted a parallel analysis comparing the observed eigenvalues with those from randomly generated datasets of the same size. The first seven observed eigenvalues exceeded the corresponding random eigenvalues, while the eighth and subsequent observed eigenvalues did not. Figure 1 presents the observed and random eigenvalues and the scree pattern, providing transparent evidence supporting the seven-factor solution. This finding demonstrates that the scale's seven-factor structure has been validated both theoretically and statistically and is quantitatively supported through parallel analysis.

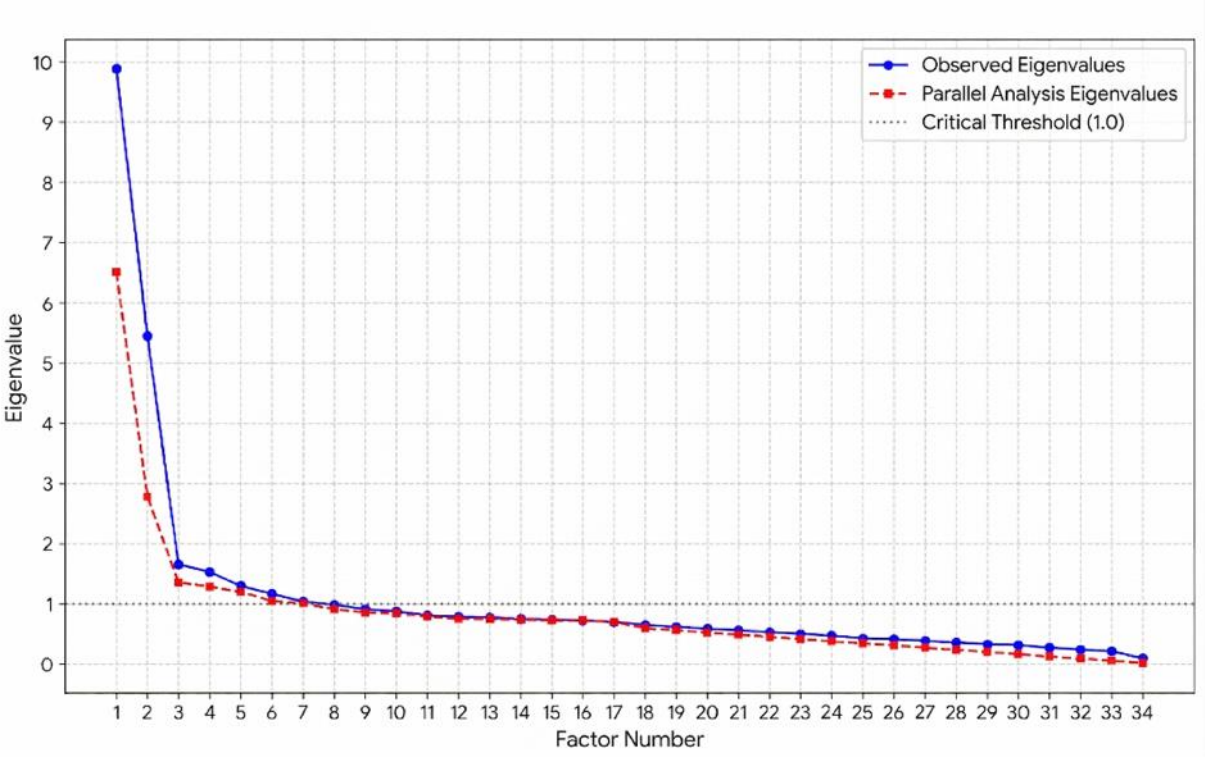


Figure 2. Scree-Plot Graphic of Parallel Analysis

Confirmatory Factor Analysis (CFA)

Based on the findings from the EFA analyses, CFA was employed to confirm the scale's seven-factor structure and to establish its construct validity. In the two-stage CFA procedure, the factor structure identified through EFA was first tested for fit, followed by structural validity assessments including convergent and discriminant validity. CFA is a statistical method used to evaluate whether the factor structure of a scale conforms to a theoretically and empirically predefined model, thereby assessing how accurately the scale measures the construct it is intended to capture (Hair et al., 2017). In the present study, CFA serves its primary function as a scale development tool, enabling the empirical verification of the seven-factor perceived distance structure prior to its recommended use in applied ODL contexts.

Structural validity is used to determine how accurately a scale measures the trait it is intended to measure. This type of validity is divided into two subcategories: convergent validity and discriminant validity. Convergent validity indicates the extent to which the items in a scale are related to the factor they belong to. To ensure this validity, it is expected that the scale's construct reliability (CR) values will be greater than .70 and the average variance explained (AVE) values will be greater than .50. On the other hand, discriminant validity refers to the extent to which items targeting specific factors are less related to other factors than they are to their own factor (Hair et al., 2019).

To validate the scale's factors used in the study, a CFA was conducted following the EFA results. In examining the cutoff values for fit indices, the work of Hu and Bentler (1999) was used for the CFI, and that of Tabachnick and Fidell (2013) for the RMSEA and SRMR. The CFA factor loadings, fit indices, and validity assessments are presented in the following tables.

Table 4. Factor Loadings From CFA

Factor / Item	Factor Loading
PhyD	
PhyD 1	.839
PhyD 2	.843
PhyD 3	.805
PhyD 4	.719
PhyD 5	.569
PhyD 6	.691
PhyD 7	.711
PhyD 8	.680

Table 4. Continued

Factor / Item	Factor Loading
TimeD	
TimeD 1	.670
TimeD 2	.603
TimeD 3	.771
PsyD	
PsyD 1	.813
PsyD 2	.852
PsyD 3	.817
ExpD	
ExpD 1	.686
ExpD 2	.627
ExpD 3	.696
ExpD 4	.666
TechD	
TechD 1	.816
TechD 2	.858
TechD 3	.840
TechD 4	.793
TechD 5	.664
TechD 6	.784
TechD 7	.680
BiaD	
BiaD 1	.635
BiaD 2	.715
BiaD 3	.712
BiaD 4	.845
BiaD 5	.765
LF	
LF1	.779
LF2	.755
LF3	.735
LF4	.676

In Table 4, the factor loadings range from .569 to .858. The factor loadings obtained from confirmatory factor analysis (CFA), that is, the standardized loading estimates, should be evaluated in relation to sample size. While loadings of .40 and above may be considered acceptable depending on sample size and research context, standardized loadings are generally expected to be at least .50 and ideally .70 (Hair et al., 2017). In this respect, it can be stated that the factor loadings are adequate.

Table 5. Goodness-of-Fit Values for the Scale

Scale	x^2/df	CFI	SRMR	RMSEA
Perceived Distance	2.909	.902	.051	.059
Good Fit	<3	≥.95	≤.05	<.05
Acceptable Fit	<5	≥.9	≤.08	<.1

The fit indices in Table 5 fall within the acceptable-to-good range recommended in the literature (Hu & Bentler, 1999; Tabachnick & Fidell, 2013). These fit indices indicate no issues with the scale's fit in the model validation. The construct validity assessment conducted for the scale is presented in Table 6.

Table 6. Construct Validity Evaluation of the Scale

Construct	CR	AVE	1	2	3	4	5	6	7
1. PhyD	.903	.543	**.853**						
2. TimeD	.724	.537	.47	**.804**					
3. PsyD	.864	.679	.74	.52	**.907**				
4. ExpD	.764	.538	.45	.35	.43	**.807**			
5. TechD	.915	.607	-.23	-.10	-.25	.11	**.852**		
6. BiasD	.855	.544	.60	.38	.65	.36	-.18	**.897**	
7. LF	.826	.543	-.11	-.12	-.16	.17	.51	-.10	**.830**

Bold values on the diagonal are the square roots of AVE values.

In the context of construct validity, convergent and discriminant validity were examined. To assess convergent validity, the CR and AVE values were examined. It was noted that these values were well above the thresholds recommended in the literature (.70 for CR and .50 for AVE). In this context, the findings indicated that convergent validity had been established. On the other hand, for divergent validity, the square roots of the AVE values were calculated and compared with the correlations between constructs. Consequently, the aforementioned square root values remained higher than the inter-construct correlation values. Therefore, it was concluded that discriminant validity was established. As both convergent and discriminant validity were established, it was concluded that the scale's construct validity was established (Hair et al., 2019).

We conducted additional checks to probe discriminant validity (Table 7) further. First, the Heterotrait-Monotrait ratio (HTMT) values ranged from .12 to .71, remaining below the stricter 0.85 threshold and well below 0.90, thereby supporting discriminant validity (Hanseler et al., 2015; Sarstedt et al., 2022). Second, we tested an alternative collapsed-factor (single-factor) measurement model that combines conceptually proximate constructs. This alternative model showed poor fit (χ^2/df = 6.470, CFI = .690, SRMR = .209, RMSEA = .259), whereas the correlated seven-factor model demonstrated good fit (χ^2/df = 2.909, CFI = .902, SRMR = .051, RMSEA = .059). Overall, the results favor retaining the seven distinct factors as the more plausible representation (Franke & Sarstedt, 2019; Hanseler et al., 2015). Therefore, since both convergent and discriminant validity were met, the developed scale demonstrated construct validity (Hair et al., 2019).

Table 7. HTMT Values

Factors	**1**	**2**	**3**	**4**	**5**	**6**	**7**
PhyD	-	.39	.71	.42	.22	.55	.17
TimeD		-	.53	.36	.17	.3	.13
PsyD			-	.41	.22	.57	.18
ExpD				-	.12	.37	.14
TechD					-	.19	.5
BiaD						-	.14
LF							-

Reliability Analyses

Cronbach's alpha (α) coefficient was employed to assess the reliability of the scales used in the study. The criterion applied was that the alpha coefficient obtained from the analysis should exceed .70 (Hair et al., 2019). The findings from the assessments carried out in this context are presented in Table 8, indicating that the α coefficients for the scale's factors exceed the .70 threshold, suggesting that the factors are reliable (Hair et al., 2019).

Table 8. Reliability Analysis Results

Scale	**Factor**	**Number of Items**	**α**
Perceived Distance	PhyD	8	.891
	TimeD	3	.715
	PsyD	3	.866
	ExpD	4	.723
	TechD	7	.913
	BiaD	5	.851
	LF	4	.801

Descriptive Statistics

Once the validity and reliability of the scale used in the study had been established, descriptive statistics for the scale were calculated. These statistics are presented in Table 9.

Table 9. Descriptive Statistics of the Scale

Factor	Item		*M*	*SD*	*ITC*
PhyD	PhyD 1		2.71	1.36	.777
	PhyD 2		2.54	1.33	.776
	PhyD 3		2.70	1.42	.744
	PhyD 4		2.90	1.44	.688
	PhyD 5		3.46	1.37	.526
	PhyD 6		2.72	1.35	.659
	PhyD 7		2.54	1.46	.676
	PhyD 8		3.21	1.53	.646
		Mean	2.85	1.08	-
TimeD	TimeD 1		2.88	1.31	.497
	TimeD 2		2.90	1.41	.455
	TimeD 3		2.66	1.33	.466
		Mean	2.81	1.00	-
PsyD	PsyD 1		2.62	1.44	.714
	PsyD 2		2.59	1.38	.765
	PsyD 3		2.70	1.47	.756
		Mean	2.64	1.27	-
ExpD	ExpD 1		3.77	1.14	.430
	ExpD 2		3.45	1.35	.517
	ExpD 3		3.32	1.34	.489
	ExpD 4		3.03	1.35	.486
		Mean	3.39	0.89	-
TechD	TechD 1		3.89	1.09	.745
	TechD 2		4.00	1.03	.780
	TechD 3		4.04	1.01	.772
	TechD 4		3.94	1.02	.756
	TechD 5		3.60	1.26	.658
	TechD 6		3.92	1.08	.780
	TechD 7		3.79	1.10	.684
		Mean	3.88	0.88	-
BiaD	BiaD 1		2.77	1.46	.586
	BiaD 2		2.44	1.34	.663
	BiaD 3		2.80	1.53	.660
	BiaD 4		3.00	1.39	.756
	BiaD 5		3.11	1.44	.653
		Mean	2.82	1.13	-
LF	LF1		4.01	1.09	.695
	LF2		3.88	1.17	.629
	LF3		3.90	1.13	.636
	LF4		4.28	1.02	.506
		Mean	4.02	0.83	-

(1 = Strongly Disagree; 5 = Strongly Agree). ITC = Item-Total Correlation Value.

Table 9 presents the descriptive statistics of the scale. According to these statistics, the factor with the highest mean is the LF factor (*M* = 4.02; *SD* = 0.83), whilst the factor with the lowest mean is the PsyD factor (*M* = 2.64; *SD* = 1.27). Item-total correlations (ITC) were calculated to assess the consistency of the scale's items with the scale as a whole. The literature indicates that values of 0.40 and above signify that the items possess sufficient discriminatory power (Hair et al., 2019). In this study, the ITC values for all items ranged from .43 to .78, indicating performance clearly above the threshold.

Discussion

The primary aim of this study is to develop a valid and reliable scale to measure the perception of distance experienced by students in ODL environments. According to TD theory, perceived distance is defined by the seven following dimensions: physical distance (PhyD), temporal distance (TimeD), psychological distance (PsyD), technological distance (TechD), experience (ExpD), bias (BiaD), and learning facilitation (LF). The findings of this research indicate that the scale is a valid and reliable instrument for measuring perceived distance.

It is observed that scales developed for ODL environments have predominantly focused on measuring attitudes (Çelik & Uzunboylu, 2022; Demir & Çetin, 2022; Deniz & Bağçeci, 2022; Durak et al., 2026; Eşkil & Yarım, 2023; Gülleroğlu & Coşkun, 2023; Koç et al., 2024), satisfaction (Çıplak et al., 2023; Hwang & Kim, 2022; Kafes & Yıldırım, 2021; Zorlutuna & Erilli, 2022), or specific components of transactional distance (Tria, 2024; Yandi, 2025). This scale development study distinguishes itself from existing instruments by addressing perceived distance within a multidimensional framework incorporating interactive sub-dimensions, such as experience, technological distance, bias, and learning context, within a single scale.

Xiao (2025) and Achuthan et al. (2024) have emphasized the importance of re-evaluating TD theory in the context of 21st-century digital education. TD served as the fundamental theoretical framework in the development of this scale.

Beyond its psychometric contributions, this study provides a significant theoretical expansion of TD. TD, which is grounded in the variables of structure, dialogue, and learner autonomy (Moore & Kearsley, 1996), has been examined in the literature primarily in relation to interaction elements associated with program development and instructional design. Psychological and experiential factors on the learner side have not been elaborated upon (Achuthan et al., 2024; Xiao, 2025). The scale developed here will help to address this psychological and experiential gap in TD.

First, by including the dimensions of ExpD and BiaD as separate sub-dimensions, the model incorporates the underlying structures that shape how learners enter and interpret the ODL environment before any instructional interaction takes place. Second, technological distance is addressed in the scale as a perceived barrier structure. Learner-technology interaction is reconceptualized within the framework of TD Theory. Accordingly, technology is identified not merely as a tool through which dialogue and structure operate, but also as an independent source of perceived distance in its own right. Third, although previously discussed theoretically (Elibol & Bozkurt, 2023; Rahmani et al., 2024), directly linking this scale, as a diagnostic assessment tool, to the risk of school dropout could help TD provide operational recommendations regarding the concept of dropout. By centering TD, it reveals that the structure, dialogue, and autonomy components are shaped by biographical, attitudinal, and technological factors that prioritize and mediate learners' interaction with the ODL system, constituting a multidimensional psychological state.

It is important for ODL to define the perceived psychological distance by learners during the learning process. Within the scope of this study, the low mean scores (M = 2.64, SD = 1.27) observed for the PsyD dimension warrant discussion. At the item level, the means range from 2.59 to 2.70. This pattern should be interpreted in light of the characteristics specific to the study sample. Firstly, the participants are students enrolled in a faculty that exclusively offers ODL. It can be assumed that these individuals have become accustomed to the dynamics of a technology-intensive learning environment over time. This adaptation may have led learners to internalize asynchronous communication norms and self-regulated learning strategies, thereby gradually reducing their perception of psychological distance. The literature also suggests that perceptions of loneliness and distance decrease with ODL experience (Shin, 2003; Wengrowicz & Offir, 2013). For ODL systems, it is essential that learners do not feel isolated, that they develop a sense of belonging to the learning environment and that their engagement with distance education is consequently enhanced. Instructional designers and practitioners can achieve this by creating course designs that increase opportunities for interaction and strengthen the sense of social belonging. This enables learners to see themselves as integral parts of the system rather than isolated individuals, thereby reducing perceived distance.

It is important for ODL to define the temporal distance by learners during the learning process. Within the scope of this study, the low item-total correlations (ITC) in the Temporal Distance (TimeD) subscale are another issue that warrants careful consideration. The ITC values for the three items in this subscale were calculated as .497, .455, and .466, respectively. Although these values do not technically violate acceptable psychometric thresholds, they indicate that the items share variance with the scale's current structure only to a limited extent. There are several possible reasons that could explain this situation. First, the small number of items in the TimeD subscale (n = 3) may have negatively affected internal consistency. Especially when dealing with multidimensional structures, small item pools tend to produce low ITC estimates. Second, unlike physical, psychological, experiential, and attitudinal distance, which are experienced in a more relational and affective manner, temporal distance encompasses objective curriculum constraints, delays in asynchronous communication, and time management in learning environments based on self-paced learning. It is expected that these characteristics will result in TimeD items having a weaker relationship with an integrated psychological distance construct and, consequently, lower correlations with the total scale score. Taking into account the results relating to the temporal distance factor, practitioners, instructional designers, and decision-makers can implement various measures or organize learner-centered activities to enhance teaching and learning. They can plan instructional interventions that do not disrupt learners' daily routines, do not require real-time dependence on the instructor, and reduce anxiety related to taking responsibility for one's own learning. In this way, perceived distance can be reduced, with the result that people feel more connected.

Assessing learners' technological literacy is another matter that warrants examination in ODL environments. In this study, an analysis of the descriptive statistics for the Technological Distance (TechD) dimension revealed a pattern of ceiling effects. This issue clearly warrants further discussion. Ceiling effects occur when the variance of scores is constrained due to a disproportionate clustering of responses at the upper end of the scale, resulting in reduced

statistical power in identifying relationships with external variables (Streiner & Norman, 2008). Item means for TechD range from 3.60 to 4.04 on a five-point scale (overall M = 3.88, SD = 0.88), while items TechD 2, TechD 3, and TechD 6 exhibit means of 4.00 or higher. This raises questions about the capacity of these items to distinguish participants in terms of their perception of technological distance. When evaluated within the context of this study's sample, we can infer that learners enrolled in ODL demonstrate familiarity with technological tools and may be experienced users. The TechD dimension may demonstrate higher measurement sensitivity and discriminant validity in groups that exhibit a more heterogeneous structure in terms of digital literacy and technological access. With regard to attitudes towards distance education, which is an inherently technology-intensive environment, Turan and Dönmez (2024) found that digital literacy is a significant positive predictor. In other words, as digital literacy levels increase, learners are more likely to continue using ODL systems. Furthermore, enhancing technological literacy, using user-friendly tools, and increasing investment in technological infrastructure (e.g., resolving internet connectivity issues and improving access) can reduce the sense of distance arising from technology-related challenges.

Understanding learners' prior experiences with ODL will provide practitioners, decision-makers, and instructional designers with insight into general perceptions. This perception may serve as the rationale for preferences regarding instructional practices throughout and after the process. It is thought that this situation may provide a foundation for creating educational and social support environments in areas such as expectations, confidence in the learning process, adaptation to new environments, and time management. These support environments can help learners remain in the system, thereby reducing perceived distance.

The identification of learners' biases regarding ODL is of considerable importance. It is particularly challenging for students to continue their education when they hold beliefs such as the following: exams do not measure real performance; ODL is inadequate for achieving personal goals; their degree lacks value; instructors do not cover topics in depth; and distance education promotes superficial learning. This is an issue that requires careful consideration. Negative preconceptions about ODL environments reduce participation in the learning process (Arbaugh, 2000; Shea et al., 2006). This reveals that attitudes towards ODL form in advance, which underscores the importance of student orientation. According to Ajzen (1991), attitudes towards a behavior influence the intention to perform that behavior, and intention in turn directly influences the behavior itself. For this reason, it is of great importance to identify learners with high levels of bias and develop orientation programs and mentoring initiatives for these students. Providing information at the beginning of the course about the factors that cause bias and encouraging students to develop shared solutions may be an effective way of reducing it.

Another issue that merits examination is the learning facilitation dimension of ODL. Developing instructional strategies that are self-paced, allow learners to start with any topic of their choice, and encourage individual effort can help learners persist with the system and reduce their perceived distance from learning.

In conclusion, this study presents a valid and reliable Turkish-language scale capable of measuring perceived distance in distance learning environments within a multidimensional framework. Filling a significant gap in the field, this scale will contribute to the development of evidence-based practices aimed at making distance learning processes more interactive, inclusive, and learner-friendly for instructional designers, instructors, and policymakers. The systematic monitoring and reduction of students' perceived distance represents a critical opportunity for decreasing dropout rates and improving the quality of learning (Bağrıaçık Yılmaz & Karataş, 2022; Elibol & Bozkurt, 2023; Rahmani et al., 2024).

The Multidimensional Perceived Distance Scale in Distance Learning, which has been proven to be both valid and reliable, can be used by academics, decision-makers, and practitioners working in the ODL field. It can be used as a diagnostic assessment tool prior to the teaching-learning process, enabling the identification of students with high levels of perceived distance. By identifying the factors influencing this perception, support services can be developed. The scale can also be used to evaluate programs at the end of the teaching and learning process, providing feedback on students' perspectives regarding the scale's factors and the components of the system.

Conclusion

The theoretical foundation of this scale is based on TD theory and the dropout phenomenon. This scale was developed to determine the sense of perceived distance by open and distance learners during the learning process.

When examining the factor structures, one notable finding is that technological distance exhibits a ceiling effect in this group. First, we should note that the items that make up the TechD subdimension are negatively worded. These items reflect the barriers and stress experienced by learners in ODL settings with regard to the technological tools and environments they encounter, which are inherently technology-centered. Therefore, higher mean scores on this sub-dimension indicate greater perceived technology-related distance rather than higher technological competence. Accordingly, the relatively high mean score for TechD (M = 3.88) suggests that learners in this sample perceive barriers related to technology in their ODL experiences. This finding has important implications for institutions and instructional designers.

Another notable finding is the low mean score observed in the PsyD dimension (M = 2.64, SD = 1.27). At the item level, the means range from 2.59 to 2.70. These findings should be interpreted in light of the contextual characteristics specific to the study sample. It is particularly important to note that the participants consist of learners with prior ODL experience. This suggests that the scale is sensitive to context-specific factors within the sample, which strengthens rather than limits its applicability.

The scale incorporates and extends the original TD Theory framework, which focuses on instructional variables at a system level. It defines perceived distance as a construct influenced by past experiences, attitudes towards ODL, technological barriers, and the extent to which learning is supported. Furthermore, it shows that perceived distance is a psychological state with identifiable subfactors. This makes each factor a practical tool for diagnostic assessment and targeted intervention.

Recommendations

The findings of this study generate recommendations at two levels. These are short-term implications for practitioners and institutions, and longer-term directions for researchers.

For practitioners and institutional decision-makers, the most immediate application of the scale is diagnostic. Administering the scale at course entry allows institutions to identify which sub-dimensions of perceived distance are most salient for their specific learner population and to tailor pre-course orientation, support structures, and instructional design accordingly. Learners scoring high on BiaD warrant targeted attitude-change interventions prior to course commencement; those scoring high on TechD require accessible technical support and user-friendly platform design; those with low ExpD scores may benefit from structured peer-mentoring or scaffolded onboarding. Because the scale yields sub-dimension-level profiles rather than a single composite score, it enables precision in intervention design rather than generic support provision.

For researchers, the priority directions are as follows. First, validation studies in diverse ODL contexts, including different countries, languages, and delivery modalities, are needed to assess the scale's cross-cultural stability and identify any sub-dimensions that may require adaptation. Second, longitudinal studies tracking perceived distance across a full academic year would clarify whether and how sub-dimension scores change as learners gain experience, and whether early scores predict subsequent dropout behavior. Third, the relationship between perceived distance scores and actual dropout or persistence outcomes should be tested in predictive models; this would transform the scale from a descriptive instrument into a validated early-warning tool. Finally, as generative artificial intelligence becomes increasingly embedded in ODL environments, examining how AI-mediated interactions affect each sub-dimension of perceived distance presents a timely and theoretically productive research agenda.

Limitations

It should be noted that this study has some limitations. Since the sample consisted only of students from the Anadolu University Open Education Faculty, caution should be exercised when generalizing the findings to other ODL contexts or national/global systems. Furthermore, although this study used a self-report data collection method, future research should incorporate mixed-methods designs.

Ethics Statements

This research was conducted with the approval of the Anadolu University Social and Humanities Sciences Scientific Research Ethics Committee, dated 23.01.2025 and numbered 836034. The participants provided their written informed consent to participate in this study.

Conflict of Interest

The authors declare no conflict of interest.

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Generative AI Statement

As the authors of this study, we used an AI tool called ‘DeepL’ to translate the text, which was originally written in Turkish, into English. In addition, an AI tool called ‘Grammarly’ was used in certain sections of the research to refine wording and ensure readability and clarity. After using these AI tools, we reviewed and verified the final version of our study. As the authors, we take full responsibility for the content of our published study.

Authorship Contribution Statement

Usta: Conceptualization, design, data acquisition, data analysis, writing, critical revision of manuscript, supervision, final approval. Uğurhan: Concept and design, data acquisition, statistical analysis, critical revision of manuscript, writing. Özen: Concept and design, data acquisition, statistical analysis, critical revision of manuscript, writing

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Appendix

Table A1. Distance Perception Scale in Open and Distance Education

Factor	Scale Item
Physical Distance Factor	Being physically distant reduces my motivation toward courses. Being physically distant makes it harder for me to understand the lessons. Being physically distant reduces my participation in courses. Being physically distant reduces the quality of my communication. Being physically present in the educational environment increases my sense of belonging. Because I cannot physically reach my course instructor, I have difficulty solving my educational problems. Being physically distant causes me to prefer face-to-face education. I think that due to physical distance, I cannot have the same opportunities as face-to-face students.
Temporal Distance Factor	Synchronous sessions cause disruptions in my daily routine. When I cannot attend synchronous classes, my stress level increases. In asynchronous courses, being fully responsible for my own learning makes me anxious.
Psychological Distance Factor	Distance education makes me feel alone in the learning process. In distance education, I cannot feel that I belong to the class. The lack of social interaction reduces my interest in distance education.
Technology-Induced Distance Factor	Technological literacy level is a prerequisite for success in distance education. Internet connection problems reduce my learning motivation. Lack of access to technology in virtual classroom interactions negatively affects academic performance. Difficult-to-use technological tools make distance education stressful.
Experience Factor	My past experiences facilitate effective time management in distance education. My past experiences facilitate my adaptation to new course platforms. My past experiences increase my confidence in the learning process. My past experiences shape my expectations regarding distance education. My past experiences are determinative of my preference for distance education. My past experiences are important for a productive distance education process. My past experiences determine my perception of distance education.
Bias Factor	Exams conducted in distance education cannot measure actual performance. Distance education in reaching my personal goals is not an effective method for me. A diploma obtained through face-to-face education is more valuable than a distance education diploma. Distance education causes topics to be addressed superficially. Instructors cannot cover course content with sufficient depth in distance education.
Learning Facilitation Factor	I learn more comfortably when I study at my own pace. Starting my courses from the topic of my choice increases my academic self-confidence. I can work more independently in distance education. Individual effort is more important in distance education.