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Smartphone Addiction Assessment Using Pythagorean Fuzzy CRITIC-TOPSIS

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Abstract: Addiction to smartphones, particularly among adolescents, has reached alarming proportions, rivaling or perhaps exceeding internet addiction as the most widespread kind of dependence in modern culture. Evaluating the degree of problematic smartphone use habits by experts and identifying the vulnerable ones to steer to the right treatment program has become a critical issue. Since such a task may involve an abundance of criteria and candidates, as well as the inherent subjectivity of multiple decision experts participating in the process, the assessment of smartphone addiction can be framed as an uncertain multi-criteria decision-making (MCDM) problem. As an extension of intuitionistic fuzzy sets, Pythagorean fuzzy sets can be used to efficiently manage ambiguity and uncertainty during decision-making. This study provides an integrated fuzzy MCDM methodology based on Pythagorean fuzzy sets for evaluating the smartphone addiction level of adolescents. The Criteria Importance Through Inter-criteria Correlation (CRITIC) method is used to determine the importance levels of criteria in an objective manner, and smartphone addiction levels of the selected candidates are ranked using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach. A sensitivity analysis is conducted to examine the variations in candidate rankings caused by changes to the criteria and weights of the decision experts. Moreover, in the context of comparative analysis, the Evaluation based on Distance from Average Solution (EDAS) approach is used to validate the acquired findings.

Keywords: smartphone addiction; Pythagorean fuzzy; CRITIC; TOPSIS; MCDM

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1. Introduction

Smartphones have become an integral part of our daily lives due to their ever-increasing mobility, access, and availability. Apart from their benefits, smartphones are also being attributed to addictive behaviors across all ages [1–3]. Smartphone addiction, which is also known as problematic smartphone usage, has come to such a point that it has become the most prevalent addiction type, even more than internet addiction [4,5] due to smartphones' peculiar characteristics and widespread adoption rate reported in various countries [6–8]. This is especially true for adolescents, as they are particularly more vulnerable as compared to their elder counterparts [9,10]. Therefore, this study focuses specifically on adolescents in the assessment and treatment of problematic smartphone usage. The global COVID-19 pandemic has further complicated the problem, as adolescents have difficulty physically interacting with each other due to the restrictions in many countries across the world [11].

On the other hand, it is argued that technology addiction in general and smartphone addiction in particular are architected phenomena designed by digital platforms [10,12,13]. Digital businesses are alleged to perform such practices in order to maximize the time spent and thereby the profit generated in an ecosystem characterized as the "attention economy" [14]. In this economy, be it YouTube, Instagram or WhatsApp, the consumers do not pay for the usage of the digital platforms. Such platforms have a rather indirect monetization model owing to the advertising companies seeking to obtain consumers' attention.

The main objective of this study is to develop a new method to provide a quick preliminary assessment of problematic smartphone usage patterns in adolescents by experts (i.e., clinical psychologists). As such, this tool could serve as a means for easily identifying problematic smartphone usage severity levels and readily directing them to the appropriate treatment program.

Multi-criteria decision-making (MCDM) approaches are frequently used for ranking the alternatives among numerous possible candidates pursuant to a set of criteria, and prioritizing the candidates in terms of their degrees of addiction to smartphones can be regarded as a MCDM kind of problem. On the other hand, such problems reflect the nature of the actual world, which includes uncertainty. Since the criteria in these sorts of problems are often qualitative in nature, decision experts may feel uncertain and be limited to evaluating them using linguistic terms. Fuzzy systems, in this context, provide useful methods to manage the uncertainty and convert the verbal assessments of decision-makers to a numerical form.

1.1. Conceptual Background

Addiction, in general, is defined as "a syndrome in which a reward-seeking behavior has become out of control" [15]. In the context of behavioral addictions, reward-seeking behavior is a key concept that deserves attention. Technology addiction, and more specifically smartphone addiction, could be classified as behavioral addictions, which have similar psychological and behavioral symptoms to other addictions, such as addiction to alcohol. It has evolved into a disease that requires treatment. The common symptoms are loss of control, preoccupation, withdrawal, orientation toward cyberspace to manage moods, and conflict or negative consequences [16–18].

Many studies conducted in the field of technology addiction regarded the phenomenon as a mental health problem [19,20]. Spending too much time on online activities performed with the use of technology has been shown to cause depressive symptoms [21]. Behavioral addictions are generally difficult to define because they are related not only to physical factors, but also to social and psychological factors [22]. Behavioral addictions typically incorporate engagement in a behavior pattern in spite of their negative effects [23]. Smartphone addiction can be described as a specific type of behavioral addiction that could be regarded as the overuse of smartphones to the extent that it disturbs users' daily lives [24].

The concept of reward represents an approach that has been used for years to shape behaviors in many fields. The variable reward mechanism is frequently adapted to various applications by digital platforms with its reinforcing function, which inevitably results in technology addiction. Experiments on animals in the 1950s are of great importance in order to understand the critical importance of variable rewards in the habituation process of the brain [25]. Stimulation of the amygdala region, which is the reward region of the brain, with variable rewards causes the routine to enter into an endless habit loop in anticipation of greater rewards. The same mechanism is also seen in the behaviors of individuals, which become a continuous cycle when, for instance, people wonder how many people will like their posts on social media (variable reward). As such, it is accepted that the habit cycle phenomenon plays a critical role in relation to technology addiction [26].

The habit loop is a very important mechanism that explains the role of the brain in the formation of behavioral patterns that occur on autopilot. Since the early nineties, various neurological and anatomical studies have brought about important findings about habitual behavior. In those studies, it has been demonstrated that subcortical loops affect behaviors and habits through the study of synaptic connections, through different neurons activated by dopamine [27,28].

The cycle begins when a cue triggers. As the routine is finished, if the brain senses a reward, the dopamine hormone is released. The uninterrupted repetition of this process brings the routine into a habit loop. The extant literature suggests that as teenagers are exposed to new types of media, they may acquire more habitual usage problems than adults [29].

Problematic smartphone usage has been linked to significant problems such as difficulty socializing with peers, depression, and insomnia among adolescents. A study of American youth [30] found a 40% decrease in the frequency of young people meeting with their friends on a daily basis between 2000 and 2015. Adolescents who heavily use social media have also seen a 27% increase in the prevalence of depression. The same study also identified a 57% increase in behavior that leads to less than the recommended minimum of 7 h of sleep per night due to technology use. There are four features that are found on digital platforms and exacerbate technology addiction, but not on platforms such as television, books, and magazines; these are the absence of a stop sign, fear of missing out (FOMO), variable rewards, and the habit loop.

1.1.1. Absence of a Stop Sign

The concept of a stopping signal underlies the fact that many activities do not create addiction. Completing a watched film or finishing a book is a natural stopping signal for the conclusion of the relevant activity. The stopping signal informs the individual that the activity has ended. Removing the stopping signal or creating content presentation without an end result leads to increased consumption. Social media pages and mobile applications have the feature of infinite scrolling. The page is updated as it is scrolled down, that is, new content is presented. Video platforms such as YouTube and Netflix automatically start the next video without the need to press any button. These and similar applications are typical examples of a digital world without a stopping signal.

1.1.2. Fear of Missing Out

Fear of Missing Out (FOMO) is a phenomenon that is particularly evident in social media use and refers to the anxiety of missing out on developments that everyone else has learned about. The desire to quickly access information about friends, surroundings, or things of interest, such as people, teams, etc., and the fear of being left behind, leads to the constant keeping of mobile devices open and checking them compulsively [31]. FOMO is defined as an individual's fear of missing out on something that others are already doing, knowing, or owning without being aware of it, in a way that is disturbing or takes up all of one's time. Research on the subject shows that three out of four young consumers experience this anxiety.

1.1.3. Variable Reward

The concept of reward has been used for many years to shape behavior in various fields. The reward element is often adapted to various applications by digital platforms due to its consistently influential role in the development of smartphone addiction. The stimulation of the amygdala region, which is the brain's reward region, with variable rewards leads to the formation of a never-ending habit cycle with the expectation of a larger reward. The same mechanism is also observed in behaviors that become a continuous cycle due to the curiosity of how many people will like the shares made on social media (variable reward). It is therefore considered that the habit cycle plays a critical role in technology addiction [26].

1.1.4. The Habit Loop

The Habit Loop is a highly significant mechanism that explains the role of the brain in the formation of automatic behavior patterns. The cycle begins with the brain being triggered by a cue, after which a specific routine is carried out, and if the brain senses a reward at the end of the routine, the hormone dopamine is released. The continuous repetition of this process leads to the routine becoming an addictive one. Eyal [32], taking the power of habits and variable rewards as a starting point, has developed a method of designing digital products that will turn the experience into a habit and therefore create addiction, by adding a fourth element to the three-step addiction cycle. The "Hook" method, consisting of trigger, action, variable reward, and investment steps, aims to create a cycle that is addictive.

1.2. Motivation and Contribution

Regarding smartphone addiction evaluation, there are no studies except one undertaken by [33]. In contrast to the existing study, our suggested study handles the problem in a MCDM setting, includes a more comprehensive fuzzy set for capturing the uncertainty in the problem, sensitivity analyses for criterion and decision expert weights, a comparative study, and the calculation of criterion weights in an objective manner.

The primary motivation for this study can be seen from two perspectives. The first objective is to present a novel methodology that is not currently available in the literature, and the second objective is to apply the proposed method by addressing a current and critical issue. In this context, Pythagorean fuzzy CRITIC-TOPSIS is established and smartphone addiction levels of adolescents are evaluated with the proposed approach.

In order to determine criterion weights, rank the candidates, and simulate the uncertainty inherent in the nature of the problem, we integrate the CRITIC and TOPSIS approaches in a Pythagorean fuzzy environment in order to maximize their respective advantages. The main motivation for employing the CRITIC approach in this study is as follows: In MCDM problems, the assigning of weights is an important stage in the whole decision-making process. In certain cases involving decision-making, the extraction of subjective preferences is either difficult or undesirable. A separate criterion weight assignment is not required by the CRITIC technique, which might increase the reliance of the results on the subjective judgments of the decision-makers. The CRITIC method obtains these weights objectively from the contrast intensity measurement and the conflicting character of the assessment criteria. In conclusion, CRITIC enables the user to objectively determine the weights of criteria. TOPSIS [34], on the other hand, is a MCDM method for determining solutions from a set of criteria and alternatives. The fundamental premise is that the selected alternative must be closest to the ideal positive ideal solution and farthest from the negative ideal solution. The following are the main motivations for selecting the TOPSIS method for ranking the candidates: It is simple over many other decision-making methods, it can account for any form of subjective and objective criteria, it adheres to a reasonable logic and is simple for practitioners to comprehend, and the mathematical procedure is quite straightforward [35]. In the proposed methodology, the decision matrix is constructed using the acquired weights obtained with Pythagorean fuzzy CRITIC, and the candidates are then prioritized using the Pythagorean fuzzy TOPSIS approach. The key contributions of this study, which may also be seen as its innovative features or advantages, are as follows:

- A CRITIC-integrated TOPSIS technique is used for the first time in a Pythagorean fuzzy environment.
- The evaluation of adolescent smartphone addiction is addressed for the first time within a comprehensive fuzzy MCDM framework.
- The proposed approach addresses the demand for objective criterion weighting in addition to providing a quick and accurate ranking of candidates. The proposed technique does not need a separate criterion weight assignment, which may make the results more reliant on the decision expert's subjective evaluations.
- Through this research, we want to enlighten practitioners about the state of the art in this field and call attention to the importance of MCDM application in identifying the highest-risk candidates with regards to their smartphone addiction. Additionally, the set of criteria that can be applied to the assessment of smartphone addiction offered within the study's purview, together with their relative weights, can be seen as a useful manual for academics and professionals working in this area.
- To evaluate the consistency of our approach, a sensitivity analysis for criteria and decision-maker weights is conducted. In addition, a comparative study is provided to validate the methodology.

This study seeks to address the following research question: What is the effectiveness of using a Pythagorean fuzzy CRITIC-TOPSIS model for the ranking of smartphone addiction in adolescents while calculating the criteria weights in an objective manner, and how does the proposed methodology behave against different criteria and decision expert weight distribution scenarios, and how consistent are the results obtained with other accepted MCDM methods?

The rest of the paper is organized as follows: Section 3 summarizes the related work. Section 3 presents the methodology by providing the preliminaries of Pythagorean fuzzy sets and explaining the detailed steps of the proposed Pythagorean fuzzy CRITIC-TOPSIS. Section 4 is concerned with the application. Descriptions of the criteria, the numerical solution of the problem, sensitivity and comparative analyses are included in this section. Section 5 finalizes the paper with the limitations and future research avenues.

2. Literature Review

MCDM models are used in a variety of problems, e.g., the prioritization of renewable energy projects [36], assessment of information system governance [37], selection of ideal structural systems [38], evaluation of seismic strengths of educational and hospital buildings [39,40], performance ranking of brands [41], logistics quality analyses [42] and even pandemic readiness analyses [43].

Pythagorean fuzzy sets [44] are an efficient and significant extension of the intuitionistic fuzzy sets, with a broader space than the intuitionistic fuzzy sets, and therefore provide a more comprehensive method for modeling the uncertainty and vagueness of real-life applications [45,46]. Pythagorean fuzzy sets have drawn the interest of many academics due to their relaxed fuzziness modeling environment and have been frequently used for a variety of MCDM problems. Ayyildiz and Taskin Gumus [47] developed a Pythagorean fuzzy AHP-based risk assessment framework for transporting hazardous materials. Zeng et al. [48] used averaging operators of Pythagorean fuzzy sets and developed a MCDM framework for ranking unmanned vehicles. On the other hand, Liu et al. [49] suggested a Pythagorean fuzzy CoCoSo and handled a technology evaluation problem for the treatment of medical waste. Rani et al. [50] provided a Pythagorean fuzzy SWARA VIKOR for assessing solar panels, and Akram et al. [51] developed a Pythagorean fuzzy ELECTRE and addressed a problem in risk assessment for the healthcare industry.

Moreover, Bulut and Özcan [52] proposed an AHP TOPSIS in a Pythagorean fuzzy atmosphere and prioritized advertising goals. Mishra et al. [53] evaluated agriculture crop patterns based on a Pythagorean fuzzy CRITIC-VIKOR methodology. Liu et al. [54] suggested a Pythagorean fuzzy EDAS technique for manufacturing supplier selection. Molla et al. [55] suggested a Pythagorean fuzzy PROMETHEE and illustrated it through a medical diagnosis problem, and Zhao et al. [56] extended TODIM with Pythagorean fuzzy sets and handled a technology-related problem.

In MCDM applications, the allocation of weights is an important stage in the whole decision-making process, and in some cases, the extraction of subjective preferences for assigning criterion weights is either difficult or undesirable. Based on the measurement of contrast intensity and the conflicting character of evaluation criteria, the CRITIC [57] approach generates these weights objectively. The CRITIC method has been incorporated into MCDM applications in several domains, and some of the notable ones are as follows: by providing a triangular fuzzy CRITIC approach, Mitrović Simić et al. [58] built a decision-making model for assessing the safety of roads. Mishra et al. [59] presented a Fermatean fuzzy MCDM framework for choosing logistics suppliers and utilized CRITIC to calculate the attribute weights. Kamali Saraji et al. [60] used a Fermatean fuzzy-based strategy to investigate the barriers to the adoption of Industry 4.0 and claimed that their method lessens subjectivity by using the CRITIC technique.

On the other hand, Yang et al. [61] used an integrated q-Rung orthopair fuzzy MCDM approach to handle a problem in the manufacturing industry and used CRITIC to estimate the weights of the criteria. Peng et al. [62] evaluated a smart healthcare management system based on a fuzzy soft decision-making technique in which the CRITIC objectively determines the weights of the criteria. Furthermore, Naik et al. [63] developed a classical EDAS model for a contractor prequalification review and determined the weights of the criteria using the CRITIC method. Biswas et al. [64] selected passenger autos, determined the relative importance of several factors for selecting vehicles using the CRITIC method, and ranked the candidates using the CoCoSo technique. Finally, using the CRITIC technique, Pan et al. [65] assessed the operational characteristics of junctions under high traffic.

3. Methodology

In this section, the proposed methodology is presented. In Section 3.1, the basic operators of Pythagorean fuzzy sets are summarized, and in Section 3.2, the flowchart and details of the suggested methodology are provided.

3.1. Preliminaries of Pythagorean Fuzzy Sets

Zadeh [66] introduced the fuzzy set that is characterized by a membership function that gives each target a membership value ranging from 0 to 1 in order to dispose of ambiguous or unclear information while making decisions. Intuitionistic fuzzy sets [67], on the other hand, are associated with not only a membership function, but also a non-membership function whose sum is less than or equal to one. Therefore, it is more precise and decisive than a fuzzy set. In some actual situations, however, the total of the membership degree and nonmembership degree of an element meeting an expert's given characteristic may be greater than one, but their square sum may be less than or equal to one. Therefore, intuitionistic fuzzy sets cannot handle such a circumstance. Therefore, Yager [44] proposed a new fuzzy set known as the Pythagorean fuzzy set. In comparison to intuitionistic fuzzy sets, Pythagorean fuzzy sets can characterize uncertain information more extensively and effectively.

The definition, basic operators, aggregation operator and defuzzification operator developed for Pythagorean fuzzy sets [44,68] are given below:

Definition [44,68]. A Pyhtagorean fuzzy set $\tilde{X}_P$ of the universe of discourse $\cup$ is given in Equation (1).

$$\tilde{X}_P = \{u, \mu_{\tilde{X}_P}(u), \nu_{\tilde{X}_P}(u) \mid u \in \cup\} \tag{1}$$

where $\mu_{\tilde{X}_P}$(u): $\cup \rightarrow$ [0,1], $\nu_{\tilde{X}_P}$(u): $\cup \rightarrow$ [0,1], and

$$0 \leq \mu^2_{\tilde{X}_P}(u) + \nu^2_{\tilde{X}_P}(u) \leq 1 \mid \forall u \in \cup \tag{2}$$

where $\mu_{\tilde{X}_P}$(u) and $\nu_{\tilde{X}_P}$(u) are the degrees of membership and non-membership.

$\pi_{\tilde{X}_P}$(u) is the hesitancy of u to $\tilde{X}_P$.

$$\pi_{\tilde{X}_P}(u) = (1 - \mu^2_{\tilde{X}_P}(u) - \nu^2_{\tilde{X}_P}(u))^{1/2} \tag{3}$$

Addition [68]. Addition of two Pythagorean fuzzy numbers is given in Equation (4).

$$\tilde{X}_P \oplus \tilde{Y}_P = \{(\mu^2_{\tilde{X}_P} + \mu^2_{\tilde{Y}_P} - \mu^2_{\tilde{X}_P}\mu^2_{\tilde{Y}_P})^{1/2}, \nu^2_{\tilde{X}_P}\nu^2_{\tilde{Y}_P}\} \tag{4}$$

Multiplication [68]. Multiplication of two Pythagorean fuzzy numbers is given in Equation (5).

$$\tilde{X}_P \otimes \tilde{Y}_P = \mu_{\tilde{X}_P}\mu_{\tilde{Y}_P}, (\nu^2_{\tilde{X}_P} + \nu^2_{\tilde{Y}_P} - \nu^2_{\tilde{X}_P}\nu^2_{\tilde{Y}_P})^{1/2}\} \tag{5}$$

Multiplication by a scalar. ($\lambda > 0$) [68]. Multiplication of a Pythagorean fuzzy number by a scalar ($\lambda > 0$) is given in Equation (6).

$$\lambda \cdot \tilde{X_P} = \{(1-(1-\mu^2_{\tilde{X_P}})^{\lambda})^{1/2}, \nu^{\lambda}_{\tilde{X_P}}\} \tag{6}$$

Power of $\tilde{X_P}$. ($\lambda > 0$) [44].

$$\tilde{X_P}^{\lambda} = \{\mu^{\lambda}_{\tilde{X_P}}, (1-(1-\nu^2_{\tilde{X_P}})^{\lambda})^{1/2}\} \tag{7}$$

Pythagorean weighted geometric mean operator [44].

$$\begin{aligned} PWGM_w(\tilde{X_{P1}}, \ldots, \tilde{X_{Pn}}) &= \tilde{X_{P1}}^{w1} + \tilde{X_{P2}}^{w2} + \ldots + \\ \tilde{X_{Pn}}^{w_n} &= \{\prod_{i=1}^{n} \mu^{w_i}_{\tilde{X_{Pi}}}, \prod_{i=1}^{n} \nu^{w_i}_{\tilde{X_{Pi}}}\} \end{aligned} \tag{8}$$

where $w = (w_1, w_2, \ldots, w_n); w_i \in [0,1]; \sum_{i=1}^{n} w_i = 1$

Defuzzification operator, i.e., score function [69].

$$S(\tilde{X_P}) = \mu^2_{\tilde{X_P}} - \nu^2_{\tilde{X_P}} \tag{9}$$

Normalized Euclidean distance [70].

$$D(\tilde{X_P}, \tilde{Y_P}) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}(\mu_{\tilde{X_P}} - \mu_{\tilde{Y_P}})^2 + (\nu_{\tilde{X_P}} - \nu_{\tilde{Y_P}})^2 + (\pi_{\tilde{X_P}} - \pi_{\tilde{Y_P}})^2} \tag{10}$$

3.2. Proposed Methodology

Prior to describing the proposed methodology in detail, the flowchart of the proposed methodology is given in Figure 1 to provide the reader with a general notion of the study.

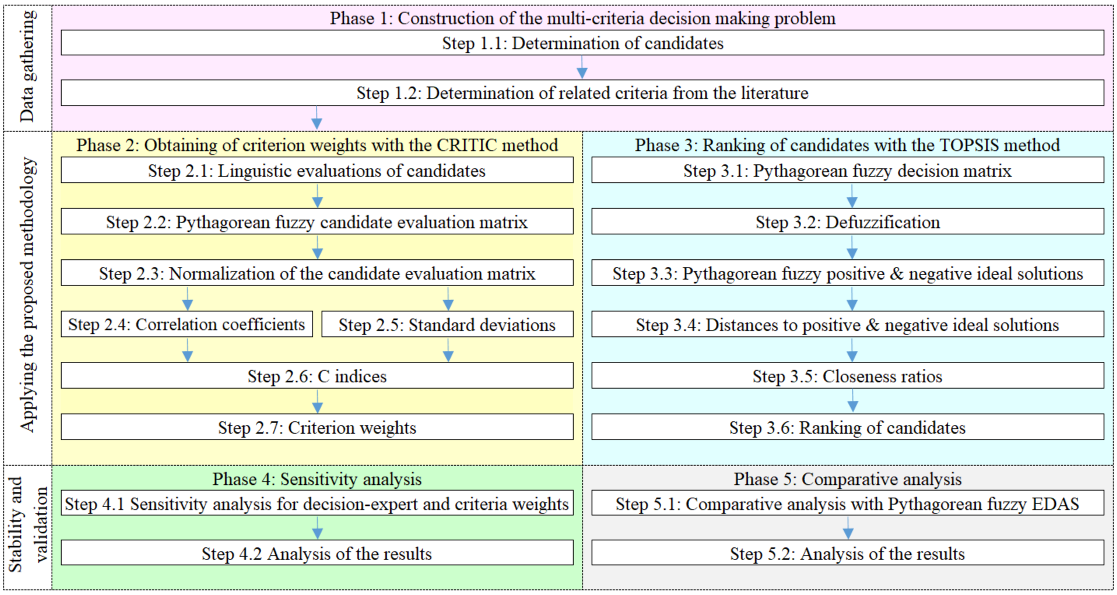

Figure 1. Flowchart of the proposed methodology.

3.2.1. Evaluate Criterion Weights with Pythagorean Fuzzy CRITIC

Step 2.1

The decision experts evaluate the candidates with respect to the criteria by utilizing the linguistic terms [50] that are given in Table 1.

Table 1. Linguistic scale for Pythagorean fuzzy numbers.

Linguistic Term	Pythagorean Fuzzy Number (μ, ν)
Extremely Low (EL)	(0.15, 0.95)
Very Low (VL)	(0.25, 0.90)
Low (L)	(0.30, 0.85)
Medium Low (ML)	(0.35, 0.75)
Medium (M)	(0.45, 0.65)
Medium High (MH)	(0.60, 0.50)
High (H)	(0.70, 0.35)
Very High (VH)	(0.80, 0.30)

Step 2.2

Linguistic evaluations of decision experts are converted to Pythagorean fuzzy numbers through Table 1. Then, all the matrices are aggregated to obtain one unique collective matrix, which we call Pythagorean fuzzy candidate assessment matrix $\tilde{M}$. The structure of $\tilde{M}$ is given in Equation (11).

$$\tilde{M}_{mxn} = \begin{bmatrix} \tilde{r}_{11} & \tilde{r}_{12} & \dots & \tilde{r}_{1n} \\ \tilde{r}_{21} & \tilde{r}_{22} & \dots & \tilde{r}_{2n} \\ \dots & \dots & \dots & \\ \tilde{r}_{m1} & \tilde{r}_{m2} & \dots & \tilde{r}_{mn} \end{bmatrix} \tag{11}$$

where $\tilde{r}_{ij} = \mu_{ij}, \nu_{ij}$ are the elements of $\tilde{M}$; the evaluation of candidate $X_i(i = 1, 2, \dots, m)$ with respect to criterion $C_j(j = 1, 2, \dots, n)$ is donated by $\tilde{M} = C_j(X_i)_{mxn}$ and μ_{ij} and ν_{ij} are the membership and non-membership degrees for the ith candidate and jth criterion.

Step 2.3

$\tilde{M}$ is normalized by utilizing Equations (12) and (13) for the positive and negative attributes, respectively.

$$x_{ij} = \frac{\tilde{r}_{ij} - \tilde{r}_i^-}{\tilde{r}_i^+ - \tilde{r}_i^-}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{12}$$

$$x_{ij} = \frac{\tilde{r}_{ij} - \tilde{r}_i^+}{\tilde{r}_i^- - \tilde{r}_i^+}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{13}$$

where x_{ij} is the normalized value of r_{ij}; $r_i^+ = max(r_1, r_2, \dots, r_m)$; $r_i^- = min(r_1, r_2, \dots, r_m)$.

r_i^+ and r_i^- are obtained based on the defuzzified values by utilizing Equation (9).

The normalized Euclidean distance that is given in Equation (10) is used to obtained the nominator and denominator parts of the above equations.

Step 2.4

The correlation coefficient ρ between each attribute pair is calculated by utilizing Equation (14).

$$\rho_{jk} = \frac{\sum_{i=1}^{m}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)}{\sqrt{\sum_{i=1}^{m}(x_{ij} - \bar{x}_j)^2 \sum_{i=1}^{m}(x_{ik} - \bar{x}_k)^2}} \tag{14}$$

where $\bar{x}_j$ and $\bar{x}_k$ are the mean values of jth and kth attributes, and $\bar{x}_j$ is obtained by utilizing Equation (15). $\bar{x}_k$ is also obtained in the same way.

$$\bar{x}_j = \frac{1}{n} \sum_{j=1}^{n} x_{ij}, i = 1, 2, \dots, m \tag{15}$$

Step 2.5

The standard deviation of each criterion is calculated as given in Equation (16).

$$\sigma_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}(x_{ij} - \bar{x}_j)^2}, i = 1, 2, \ldots, m \tag{16}$$

Step 2.6

The C index of each criterion is calculated as given in Equation (17).

$$C_j = \sigma_j \sum_{k=1}^{n}(1 - \rho_{jk}), j = 1, 2, \ldots, n \tag{17}$$

Step 2.7

The criterion weights w_j are obtained as given in Equation (18).

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{18}$$

3.2.2. Rank the Candidates with Pythagorean Fuzzy TOPSIS

Step 3.1

Pythagorean fuzzy decision matrix $\tilde{D}$ is obtained by multiplying $\tilde{M}$ by the criterion weights w_j calculated with the CRITIC approach in the previous phase. Pythagorean fuzzy multiplication by a scalar function that is given in Equation (6) is used for this task.

Step 3.2

$\tilde{D}$ is defuzzified for calculating positive X^+ and negative ideal X^- solutions. Since the crisp form of fuzzy numbers can be used for ranking fuzzy numbers, it is also convenient to obtain positive and negative ideal solutions. $\tilde{X}^+$ has the highest score values for each criterion, and $\tilde{X}^-$ has the lowest. The defuzzification operator that is given in Equation (9) is used to calculate crisp values.

Step 3.3

Pythagorean fuzzy positive $\tilde{X}^+$ and negative ideal solutions X^- are determined based on the defuzzified values calculated in the previous step. $\tilde{X}^+$ and $\tilde{X}^+$ are defined as in Equations (19) and (20), respectively.

$$\tilde{X}^+ = C_j, max < S(C_j(\tilde{X}_i) > | j = 1, 2, \ldots, n \tag{19}$$

$$\tilde{X}^- = C_j, min < S(C_j(\tilde{X}_i) > | j = 1, 2, \ldots, n \tag{20}$$

Step 3.4

Calculate the distance of each candidate to $\tilde{X}_j^+$ and $\tilde{X}_j^-$ as in Equations (21) and (22), which are adapted from Equation (10). Note that the theory of the TOPSIS technique suggests that the best candidate is the one that is close to the $\tilde{X}^+$ and far from the $\tilde{X}^-$.

$$d(\tilde{X}_i, \tilde{X}^+) = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}(a_{ij} - a_j^+)^2 + (b_{ij} - b_j^+)^2 + (c_{ij} - c_j^+)^2} \tag{21}$$

$$d(\tilde{X}_i, \tilde{X}^-) = \sqrt{\frac{1}{2n}\sum_{j=1}^{n}(a_{ij} - a_j^-)^2 + (b_{ij} - b_j^-)^2 + (c_{ij} - c_j^-)^2} \quad (22)$$

where a_i, b_i and c_i are the membership, non-membership and hesitancy degrees for the ith candidate and jth criterion; n is the number of criteria, and a_j^+, b_j^+ and c_j^+ are the parameters of $\tilde{X}^+$. In the same way, a_j^-, b_j^- and c_j^- are the parameters $\tilde{X}^-$.

Step 3.5

Closeness ratio CR, i.e., the appraisal score for each candidate is obtained as in Equation (23). We rank all candidates according to the descending values of their appraisal scores. The candidate with the highest appraisal score is the most critical.

$$CR = \frac{d(\tilde{X}_i, \tilde{X}_j^-)}{d(\tilde{X}_i, \tilde{X}_j^-) + d(\tilde{X}_i, \tilde{X}_j^+)} \quad (23)$$

Step 3.6

The candidates are ranked according to their appraisal scores. The one with highest appraisal score is the most critical.

4. Application

In this section, the applicability of the suggested methodology is illustrated through a smartphone addiction evaluation problem. To this end, four candidates, X_1, X_2, X_3, and X_4, are evaluated based on seven critical criteria obtained from the literature. Three of the decision experts are clinical psychologists with equivalent experience, thus their judgments have equal weight (1/3). Note that the proposed methodology is adaptable to any number of decision-makers and candidates; four candidates and three experts are employed in this study for demonstration purposes only. This section is organized as follows: In Section 4.1, the details of the criteria are described. In Section 4.2, the numerical solution of the problem is given. Section 4.3 provides sensitivity analysis for criteria and decision expert weights, in Section 4.4 a comparative analysis is performed, and Section 4.5 provides the managerial implications.

4.1. Criteria for the MCDM Problem: Smartphone Addiction Symptoms and Scales

The smartphone addiction phenomenon has been demonstrated by Lin et al. [71] to share several traits with DSM-5 substance-related disorders, such as obsessive behavior, functional impairment, withdrawal, and tolerance. The authors have also proposed a number of diagnostic criteria for smartphone addiction. The Korean National Institute of Addiction (NIA) has developed a scale specific to adolescents. The scale is composed of four sub-dimensions for orientation toward loss of control, withdrawal, and negative consequences. In yet another study, Kwon et al. [24] has identified smartphone addiction symptoms similar to the aforementioned, including craving, withdrawal, tolerance, daily-life disturbance, and preference of cyberspace-oriented relationships, which were confirmed through the diagnosis. Based on [24], Demirci et al. [72] have developed the Turkish Version of the Smartphone Addiction Scale (TSAS). TSAS is a 6-point Likert-type scale including thirty-three items and seven sub-scales that identifies seven distinct symptoms to assess smartphone addiction level, which constitute the basic criteria set of this study. The aforementioned symptoms are disturbing daily life and tolerance, withdrawal symptoms, positive anticipation, cyberspace-oriented relationships, overuse, social network dependence, and physical symptoms.

- *C1. Positive anticipation.* Becoming excited and having a feel of relief from stress when using a smartphone, and feeling empty without a smartphone [24,72,73].

- *C2. Withdrawal symptoms.* Being impatient and unbearable without a smartphone, constantly thinking about it when it is absent [24].
- *C3. Social network dependence.* Problematic dependence of individuals on social networking sites (SNSs) to such an extent that it negatively affects their lives due to social factors, impulsiveness, etc. [74]. It is argued that this phenomenon is a typical consequence of habitual behavior formation [75]. Social network dependence is also attributed to diminished impulse control in individuals [76] and dysfunctional use. Dysfunctional use reflects uncontrolled behavior that involves consequences in the user's daily life [77]. These effects could be overuse, financial problems, sleep disturbances or dangerous use [77,78].
- *C4. Overuse.* An individual's use of their smartphone in an uncontrollable manner (i.e., preferring to search for an answer using a smartphone instead of asking for help from others) and feeling an urge to use a smartphone again immediately after using it [24].
- *C5. Physical symptoms.* Physical symptoms such as headaches, back pain, wrist pain and shoulder pain [79].
- *C6. Disturbing daily life and tolerance.* Missing planned work and having difficulty concentrating in work or class and having unsuccessful attempts limiting oneself [24].
- *C7. Cyberspace-oriented relationships.* An individual's finding cyberspace-oriented relationships as more intimate than those with real life friends and family [24,72,73].

4.2. Numerical Solution of the Problem

4.2.1. Criterion Weights with Pythagorean Fuzzy CRITIC

The linguistic evaluations of four candidates ($X1, \ldots, X4$) with respect to seven criteria ($C1, \ldots, C7$) by three decision experts ($DE1, \ldots, DE3$) are obtained as in Table 2.

Table 2. Linguistic evaluations of candidates.

Decision Expert	Candidate	C1	C2	C3	C4	C5	C6	C7
DE1	X1	H	VL	ML	M	EL	VL	ML
	X2	EL	VH	H	ML	H	MH	H
	X3	ML	M	EL	EL	ML	M	EL
	X4	VL	ML	L	MH	MH	M	L
DE1	X1	M	ML	VL	VH	L	ML	M
	X2	VL	H	VH	L	MH	L	VH
	X3	L	VL	L	H	EL	MH	L
	X4	MH	L	EL	VL	MH	M	L
DE3	X1	M	L	H	M	VL	H	VL
	X2	L	MH	MH	VL	M	EL	M
	X3	EL	ML	ML	ML	L	MH	ML
	X4	VH	VL	VL	MH	M	ML	EL

Linguistic expressions of three decision experts are converted to Pythagorean fuzzy numbers and aggregated as in Table 3.

Table 3. Pythagorean fuzzy candidate assessment matrix $\tilde{M}$.

Candidate	C1	C2	C3	C4	C5	C6	C7
X1	(0.45; 0.65; 0.61)	(0.30; 0.85; 0.43)	(0.70; 0.35; 0.62)	(0.45 ;0.65; 0.61)	(0.25; 0.90; 0.36)	(0.70; 0.35; 0.62)	(0.25; 0.90; 0.36)
X2	(0.30; 0.85; 0.43)	(0.60; 0.50; 0.62)	(0.60; 0.50; 0.62)	(0.25; 0.90; 0.36)	(0.45; 0.65; 0.61)	(0.15; 0.95; 0.27)	(0.45; 0.65; 0.61)
X3	(0.15; 0.95; 0.27)	(0.35; 0.75; 0.56)	(0.35; 0.75; 0.56)	(0.35; 0.75; 0.56)	(0.30; 0.85; 0.43)	(0.60; 0.50; 0.62)	(0.35; 0.75; 0.56)
X4	(0.80; 0.30; 0.52)	(0.25; 0.90; 0.36)	(0.25; 0.90; 0.36)	(0.60; 0.50; 0.62)	(0.45; 0.65; 0.61)	(0.35; 0.75; 0.56)	(0.15; 0.95; 0.27)

Correlation coefficients are calculated as in Table 4.

Standard deviation σ_j, C index and criterion weights w_j are calculated as in Table 5.

According to the findings, the smartphone assessment factors in decreasing order of significance are as follows: C6. Disturbing daily life and tolerance; C1. Positive Anticipation; C5. Physical Symptoms; C4. Overuse; C2. Withdrawal; C7. Cyberspace oriented relationships and C3. Social network dependence.

Table 4. Correlation coefficients.

	C1	C2	C3	C4	C5	C6	C7
C1	1.000	−0.725	−0.425	0.979	−0.353	−0.001	−0.469
C2	−0.725	1.000	0.915	−0.686	0.566	−0.687	0.940
C3	−0.425	0.915	1.000	−0.344	0.377	−0.871	0.997
C4	0.979	−0.686	−0.344	1.000	−0.494	−0.027	−0.400
C5	−0.353	0.566	0.377	−0.494	1.000	−0.484	0.438
C6	−0.001	−0.687	−0.871	−0.027	−0.484	1.000	−0.863
C7	−0.469	0.940	0.997	−0.400	0.438	−0.863	1.000

Table 5. Standard deviation σ_j, C index and criterion weights w_j.

	C1	C2	C3	C4	C5	C6	C7
σ_j	0.473	0.481	0.453	0.448	0.531	0.422	0.460
C index	3.308	2.732	2.426	3.123	3.162	3.772	2.464
w_j	0.158	0.130	0.116	0.149	0.151	0.180	0.117

4.2.2. Candidate Rankings with Pythagorean Fuzzy TOPSIS

Pythagorean fuzzy decision matrix $\tilde{D}$ and Pythagorean fuzzy positive $\tilde{X}^+$ and negative ideal $\tilde{X}^-$ solutions are obtained as in Table 6.

Table 6. Pythagorean fuzzy decision matrix $\tilde{D}$ and Pythagorean fuzzy positive $\tilde{X}^+$ and negative ideal $\tilde{X}^-$ solutions.

	C1	C2	C3	C4	C5	C6	C7
X1	(0.22; 0.92; 0.33)	(0.11; 0.98; 0.18)	(0.14; 0.97; 0.20)	(0.23; 0.92; 0.32)	(0.09; 0.99; 0.14)	(0.17; 0.95; 0.25)	(0.12; 0.97; 0.19)
X2	(0.09; 0.99; 0.15)	(0.29; 0.89; 0.36)	(0.27; 0.90; 0.35)	(0.12; 0.98; 0.19)	(0.24; 0.91; 0.34)	(0.13; 0.97; 0.20)	(0.24; 0.92; 0.32)
X3	(0.10; 0.98; 0.17)	(0.13; 0.97; 0.20)	(0.09; 0.99; 0.15)	(0.13; 0.97; 0.20)	(0.10; 0.98; 0.17)	(0.25; 0.90; 0.36)	(0.09; 0.98; 0.15)
X4	(0.21; 0.95; 0.25)	(0.11; 0.98; 0.18)	(0.08; 0.99; 0.13)	(0.18; 0.95; 0.24)	(0.23; 0.92; 0.33)	(0.18; 0.94; 0.30)	(0.08; 0.99; 0.14)
$\tilde{X}^+$	(0.22; 0.92; 0.33)	(0.29; 0.89; 0.36)	(0.27; 0.90; 0.35)	(0.23; 0.92; 0.32)	(0.24; 0.91; 0.34)	(0.25; 0.90; 0.36)	(0.24; 0.92; 0.32)
$\tilde{X}^-$	(0.09; 0.99; 0.15)	(0.11; 0.98; 0.18)	(0.08; 0.99; 0.13)	(0.12; 0.98; 0.19)	(0.09; 0.99; 0.14)	(0.13; 0.00; 0.99)	(0.08; 0.99; 0.14

Appraisal scores and final rankings of the candidates are obtained as in Table 7.

Table 7. Appraisal scores and final rankings of the candidates.

Candidate	Distance to $\tilde{X}^+$	Distance to $\tilde{X}^+$	Appraisal Score	Final Ranking
X1	0.131	0.334	0.718	2
X2	0.097	0.366	0.790	1
X3	0.151	0.297	0.662	4
X4	0.136	0.321	0.703	3

4.3. Sensitivity Analysis

Sensitivity analysis is often used to evaluate the effectiveness of a MCDM procedure by measuring the output in response to varying inputs [80]. In the sensitivity analysis, the effect of the changes in both the criterion and decision maker weights on the output of the proposed method is examined. In the CRITIC method, the criterion weights are objectively derived from the alternative evaluation matrix as a whole. Instead of individually modifying the weight of each individual criterion in the sensitivity analysis, it is preferable to approach the entire set of criteria as a whole and maintain the integrity of the weights of the criteria. In this context, the sensitivity analysis for criterion weights is carried out by generating different scenarios based on the original scenario. For this purpose, the initial scenario $w1$ is systematically shifted, and six other scenarios, $w2$, $w3$, $w4$, $w6$, and $w7$, are generated, as shown in Table 8.

Table 8. Criterion weight distribution scenarios.

Scenario	C1	C2	C3	C4	C5	C6	C7
w1	0.158	0.130	0.116	0.149	0.151	0.180	**0.117**
w2	0.130	0.116	0.149	0.151	0.180	**0.117**	0.158
w3	0.116	0.149	0.151	0.180	**0.117**	0.158	0.130
w4	0.149	0.151	0.180	**0.117**	0.158	0.130	0.116
w5	0.151	0.180	**0.117**	0.158	0.130	0.116	0.149
w6	0.180	**0.117**	0.158	0.130	0.116	0.149	0.151
w7	**0.117**	0.158	0.130	0.116	0.149	0.151	0.180

Based on these criterion weight distribution scenarios, the appraisal scores and final rankings of the candidates are obtained as in Table 9.

Table 9. Appraisal scores and final rankings of candidates for different criterion weight distribution scenarios.

	w1	w2	w3	w4	w5	w6	w7
X1	0.718 (2)	0.716 (2)	0.716 (2)	0.711 (2)	0.717 (2)	0.723 (2)	0.707 (2)
X2	0.790 (1)	0.811 (1)	0.801 (1)	0.809 (1)	0.805 (1)	0.795 (1)	0.812 (1)
X3	0.662 (4)	0.662 (4)	0.660 (4)	0.658 (4)	0.666 (4)	0.659 (4)	0.657 (4)
X4	0.703 (3)	0.699 (3)	0.688 (3)	0.690 (3)	0.696 (3)	0.691 (3)	0.686 (3)

In Table 9, the numbers in parentheses next to the appraisal scores represent the ranking value. When the results are analyzed, it can be said that the appraisal score values vary in various criterion weight distribution scenarios, but the ranks remain the same, and the suggested methodology yields balanced outcomes in response to the criterion weight changes.

Furthermore, for a more extensive sensitivity analysis, the impact of changing decision expert weight distributions on the outcomes is examined. In this setting, 10 different weight distribution scenarios are generated as shown in Table 10.

Table 10. Decision expert (DE) weight distribution scenarios.

	1	2	3	4	5	6	7	8	9	10
(DE1; DE2; DE3)	(0.33; 0.33; 0.33)	(0.20; 0.20; 0.40)	(0.20; 0.40; 0.20)	(0.40; 0.20; 0.20)	(0.25; 0.25; 0.50)	(0.25; 0.50; 0.25)	(0.50; 0.25; 0.25)	(0.15; 0.15; 0.70)	(0.15; 0.70; 0.15)	(0.70; 0.15; 0.15)

The criterion weights calculated by the CRITIC phase of the methodology in this manner are shown in Figure 2.

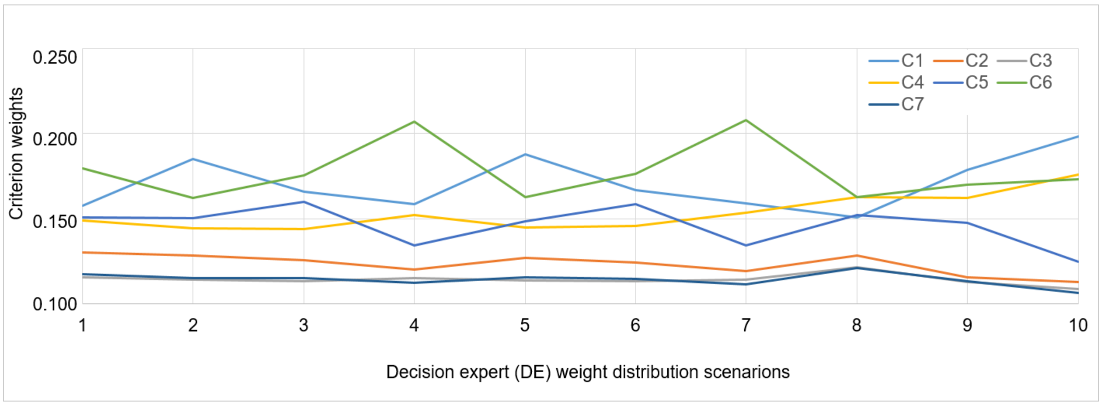

Figure 2. Criterion weights for different decision expert weight distribution scenarios.

Appraisal scores and final rankings of candidates for different decision expert weight distribution scenarios obtained in the TOPSIS phase of the methodology are given in Table 11.

Table 11. Appraisal scores and final rankings of candidates for different decision expert weight distribution scenarios.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
X1	0.718	0.745	0.715	0.710	0.743	0.712	0.709	0.759	0.709	0.707
X2	0.790	0.788	0.787	0.790	0.786	0.785	0.789	0.774	0.770	0.774
X3	0.662	0.692	0.656	0.651	0.688	0.653	0.649	0.707	0.644	0.642
X4	0.703	0.723	0.692	0.699	0.722	0.690	0.698	0.733	0.670	0.692

4.4. Comparative Analysis

A comparative study is also conducted to demonstrate the applicability and validate the established methodology. In order to accomplish this, the same problem is solved using Pythagorean fuzzy EDAS [81] and Pythagorean fuzzy WASPAS [82] methods by employing the criterion weights determined with the CRITIC approach. The appraisal scores and final rankings of the candidates are given in Table 12.

Table 12. Comparative study results.

Candidate	**Proposed Methodology**	**Pythagorean Fuzzy EDAS**	**Pythagorean Fuzzy WASPAS**
X1	0.718 (2)	0.305 (2)	−0.894 (3)
X2	0.790 (1)	0.500 (1)	−0.826 (1)
X3	0.662 (4)	0.173 (4)	−0.902 (4)
X4	0.703 (3)	0.283 (3)	−0.874 (2)

Table 12 displays the evaluation scores and final rankings of the candidates derived by Pythagorean fuzzy EDAS [81]. According to the comparative analysis results, the rankings of the candidates are obtained as $X2 > X1 > X4 > X3$. It can be seen that the selected study gives consistent results with the proposed methodology.

4.5. Managerial Implications

Problematic smartphone usage is a topic of growing concern, as excessive smartphone use has been linked to a range of negative outcomes in adolescents, including decreased attention span, poor academic performance, and an increased risk of mental health issues. Given the negative effects of excessive smartphone use on mental health and cognitive functioning, it is important for parents, educators, and healthcare providers to be aware of this issue and to take steps to address it.

The findings of this study have important implications for the field of mental health. The use of the model to assess smartphone addiction allowed the authors to identify those at risk for negative consequences and has important implications for the field of mental health. The model provides a quick and reliable method for a preliminary assessment of smartphone addiction in this population. This can be especially useful for managers and practitioners working in the field of mental health or addiction treatment, as it allows for the efficient triaging of patients and the allocation of resources.

Additionally, the MCDM model can be used to inform the development of treatment plans for individuals with smartphone addiction. By identifying the key factors contributing to addiction and ranking their relative importance, managers and practitioners can tailor interventions to address the specific needs of each patient.

Overall, the model represents a valuable tool for managers and practitioners working to address smartphone addiction in adolescents, allowing for the efficient and effective assessment and treatment of this growing public health concern.

5. Conclusions

The portability, convenience, and widespread availability of smartphones have made them indispensable in modern life. In addition to their usefulness, smartphones have been linked to addictive patterns in people of all ages. This research aims to offer a novel methodology with the purpose of analyzing the degrees of addiction that adolescents have to their smartphones.

In light of the rising prevalence of smartphone addiction, a MCDM technique is offered in order for experts to evaluate the severity of problematic smartphone usage patterns and identify those at risk in order to direct them to the appropriate treatment program. The purpose of this paper is to use a pluralistic approach to deal with different criteria, alternatives, and the opinions of multiple experts; to translate the linguistic comments of these experts into a mathematical environment; and to give the user an idea by ranking the alternatives using a generally accepted systematic method without a separate evaluation of the criterion weights.

In this context, the smartphone addiction levels of four candidates are evaluated with respect to seven criteria derived from the literature through the suggested CRITIC-TOPSIS methodology. Since this evaluation process contains multiple experts, criteria, and candidates, the problem is structured in an MCDM setting. The suggested methodology is developed in a Pythagorean fuzzy environment to model the uncertainty and ambiguity in the decision-making process. In the CRITIC phase, objective criterion weights are obtained. According to the provided numerical example, "disturbing daily life and tolerance" is found to be the most critical criterion for assessing smartphone addiction risk levels. On the other hand, the TOPSIS phase of the methodology ranks the candidates according to their appraisal scores. This study puts forward a useful tool for practitioners for quickly assessing problematic smartphone usage levels of adolescents.

As opposed to other weighing methods, CRITIC uses statistical terminology. The statistical perspective of criterion weight assignment is provided by the use of notions such as correlation coefficient and standard deviation. It gathers all preference information included in the criterion based on the decision matrix. In other words, the information fundamental to each evaluation criterion is measured in order to calculate the objective weight. The CRITIC approach has the advantage of normalizing the decision matrix while avoiding the need for independent criteria by employing the ideal values of all the criteria concurrently.

For future studies, the provided methodology can be applied to a wide range of problems in diverse fields, including health, engineering, and management. The stability of the proposed research against rank-reversal phenomena may be analyzed by other academics using appropriate analytic methods. Other fuzzy sets, including neutrosophic sets, spherical fuzzy sets, and picture fuzzy sets, can be utilized with the CRITIC integrated EDAS approach. Other potential variations of this methodology, e.g., WASPAS or DEMATEL integrated CRITIC, can be tested against different groups (adults, etc.) with varied criteria sets. The following limitations can be noted regarding the present study. Due to the nature of the CRITIC approach, correlation coefficients are calculated. Since this calculation cannot be performed in a Pythagorean fuzzy environment, the problem is transferred to a crisp environment via normalization, which may result in information loss. On the other hand, it can be said that the study relies solely on subjective assessments and makes no use of any existing data sets. Using machine learning techniques, e.g., logistic regression, linear discriminant analysis, and decision trees, other researchers may create an MCDM model that incorporates real data.

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Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytical Hierarchy Process
CoCoSo	Combined Compromise Solution
CR	Closeness Ratio
CRITIC	Criteria Importance Through Inter-criteria Correlation
DE	Decision Expert
DEMATEL	Decision Making Trial and Evaluation Laboratory
EDAS	Evaluation based on Distance from Average Solution
ELECTRE	ELimination and Choice Translating REality
MCDM	Multi-Criteria Decision Making
PFS	Pythagorean Fuzzy Set
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
PWGM	Pythagorean Weighted Geometric Mean Operator
SWARA	StepwiseWeight Assessment Ratio Analysis
TODIM	Tomada de Decisão Iterativa Multicritério
TOPSIS	The Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	VlseKriterijuska Optimizacija I Komoromisno Resenje
WASPAS	Weighted Aggregated Sum Product Assessment

References

1. Lee, C.; Lee, S.J. Prevalence and predictors of smartphone addiction proneness among Korean adolescents. *Child. Youth Serv. Rev.* **2017**, *77*, 10–17. [CrossRef]
2. Chen, C.; Zhang, K.Z.; Gong, X.; Zhao, S.J.; Lee, M.K.; Liang, L. Examining the effects of motives and gender differences on smartphone addiction. *Comput. Hum. Behav.* **2017**, *75*, 891–902. [CrossRef]
3. Harris, B.; McCredie, M.; Fields, S. Examining the psychometric properties of the smartphone addiction scale and its short version for use with emerging adults in the US. *Comput. Hum. Behav. Rep.* **2020**, *1*, 100011. [CrossRef]
4. Samaha, M.; Hawi, N.S. Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. *Comput. Hum. Behav.* **2016**, *57*, 321–325. [CrossRef]
5. Barnes, S.J.; Pressey, A.D.; Scornavacca, E. Mobile ubiquity: Understanding the relationship between cognitive absorption, smartphone addiction and social network services. *Comput. Hum. Behav.* **2019**, *90*, 246–258. [CrossRef]
6. Haug, S.; Castro, R.P.; Kwon, M.; Filler, A.; Kowatsch, T.; Schaub, M.P. Smartphone use and smartphone addiction among young people in Switzerland. *J. Behav. Addict.* **2015**, *4*, 299–307. [CrossRef] [PubMed]
7. Randler, C.; Wolfgang, L.; Matt, K.; Demirhan, E.; Horzum, M.B.; Beşoluk, Ş. Smartphone addiction proneness in relation to sleep and morningness–eveningness in German adolescents. *J. Behav. Addict.* **2016**, *5*, 465–473. [CrossRef] [PubMed]
8. Jiang, Q.; Li, Y.; Shypenka, V. Loneliness, individualism, and smartphone addiction among international students in China. *Cyberpsychol. Behav. Soc. Netw.* **2018**, *21*, 711–718. [CrossRef]
9. Lopez-Fernandez, O.; Honrubia-Serrano, L.; Freixa-Blanxart, M.; Gibson, W. Prevalence of problematic mobile phone use in British adolescents. *Cyberpsychol. Behav. Soc. Netw.* **2014**, *17*, 91–98. [CrossRef]
10. Ertemel, A.V.; Ari, E. A marketing approach to a psychological problem: Problematic smartphone use on adolescents. *Int. J. Environ. Res. Public Health* **2020**, *17*, 2471. [CrossRef]
11. Elhai, J.D.; Yang, H.; McKay, D.; Asmundson, G.J. COVID-19 anxiety symptoms associated with problematic smartphone use severity in Chinese adults. *J. Affect. Disord.* **2020**, *274*, 576–582. [CrossRef] [PubMed]
12. Ertemel, A.V.; Aydın, G. Dijital ekonomide teknoloji bağımlılığı ve çözüm önerileri. *Addicta- Turk. J. Addict.* **2018**, *5*, 665–690. [CrossRef]
13. Ertemel, A.V. IllusionalMarketing: The Use of Storytelling User Experience and Gamification in Business. SSRN 3818520. 2021. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3818520 (accessed on 6 January 2023).
14. Beck, J.; Davenport, T. *The Attention Economy: Understanding the New Currency of Business. Harvard Business School Press Al Ries (1998)*; ACM: New York, NY, USA, 2001; Volume 22.
15. West, R.H.A. *Theory of Addiction Addiction Press Series*; Wiley: Hoboken, NJ, USA, 2006.
16. Kuss, D.J.; Griffiths, M.D.; Binder, J.F. Internet addiction in students: Prevalence and risk factors. *Comput. Hum. Behav.* **2013**, *29*, 959–966. [CrossRef]
17. Widyanto, L.; Griffiths, M. 'Internet addiction': A critical review. *Int. J. Ment. Health Addict.* **2006**, *4*, 31–51. [CrossRef]
18. Young, K.S. Internet addiction: The emergence of a new clinical disorder. *Cyberpsychol. Behav.* **2009**, *1*, 3. [CrossRef]
19. Griffiths, M. Internet addiction-time to be taken seriously? *Addict. Res.* **2000**, *8*, 413–418. [CrossRef]
20. Young, K. Internet addiction over the decade: A personal look back. *World Psychiatry* **2010**, *9*, 91. [CrossRef] [PubMed]

21. Morgan, C.; Cotten, S.R. The relationship between Internet activities and depressive symptoms in a sample of college freshmen. *Cyberpsychol. Behav.* **2003**, *6*, 133–142. [CrossRef]
22. Lee, H.; Ahn, H.; Choi, S.; Choi, W. The SAMS: Smartphone addiction management system and verification. *J. Med. Syst.* **2014**, *38*, 1–10. [CrossRef]
23. Mok, J.Y.; Choi, S.W.; Kim, D.J.; Choi, J.S.; Lee, J.; Ahn, H.; Choi, E.J.; Song, W.Y. Latent class analysis on internet and smartphone addiction in college students. *Neuropsychiatr. Dis. Treat.* **2014**, *10*, 817. https://doi/10.2147/ndt.s59293.
24. Kwon, M.; Lee, J.Y.; Won, W.Y.; Park, J.W.; Min, J.A.; Hahn, C.; Gu, X.; Choi, J.H.; Kim, D.J. Development and validation of a smartphone addiction scale (SAS). *PLoS ONE* **2013**, *8*, e56936. [CrossRef] [PubMed]
25. Dews, P.B. Studies on behavior. I. Differential sensitivity to pentobarbital of pecking performance in pigeons depending on the schedule of reward. *J. Pharmacol.* **1955**, *113*, 393–401.
26. Harris, T. How technology hijacks people's minds—from a magician and Google's design ethicist. *Medium Magazine*, 18 May 2016.
27. Graybiel, A.M. Neurotransmitters and neuromodulators in the basal ganglia. *Trends Neurosci.* **1990**, *13*, 244–254. [CrossRef] [PubMed]
28. McHaffie, J.G.; Stanford, T.R.; Stein, B.E.; Coizet, V.; Redgrave, P. Subcortical loops through the basal ganglia. *Trends Neurosci.* **2005**, *28*, 401–407. [CrossRef] [PubMed]
29. Kim, D.; Lee, Y.; Lee, J.; Kim, M.C.; Keum, C.; Nam, J.; Kang, E.; Chung, Y. New patterns in media addiction: is smartphone a substitute or a complement to the internet. *Korean J. Youth Couns.* **2012**, *20*, 71–88. https://doi/10.35151/kyci.2012.20.1.005.
30. Terrell, A. *iGen: Why Today's Super-Connected Kids Are Growing Up Less Rebellious, More Tolerant, Less Happy—and Completely Unprepared for Adulthood and What That Means for the Rest of Us*; Wiley: New York, NY, USA, 2019; p. 342. [CrossRef]
31. Przybylski, A.K.; Murayama, K.; DeHaan, C.R.; Gladwell, V. Motivational, emotional, and behavioral correlates of fear of missing out. *Comput. Hum. Behav.* **2013**, *29*, 1841–1848. [CrossRef]
32. Eyal, N. *Hooked: How to Build Habit-Forming Products*; Penguin: London, UK, 2014.
33. Sama, H.R.; Kalvakolanu, S. Novel hybrid approaches to measure smartphone addiction—application of statistical and triangular fuzzy techniques. *J. Public Aff.* **2022**, *22*, e2425. [CrossRef]
34. Hwang, C.L.; Yoon, K. Methods for multiple attribute decision making. In *Multiple Attribute Decision Making*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 58–191.
35. Sanny, L.; Simamora, B.H.; Polla, J.R.; Atipa, J.L. Business Strategy Selection Using SWOT Analysis with ANP and Fuzzy TOPSIS for Improving Competitive Advantage. *Pertanika J. Soc. Sci. Humanit.* **2018**, *26*, 1143–1158.
36. Ramezanzade, M.; Karimi, H.; Almutairi, K.; Xuan, H.A.; Saebi, J.; Mostafaeipour, A.; Techato, K. Implementing MCDM techniques for ranking renewable energy projects under fuzzy environment: A case study. *Sustainability* **2021**, *13*, 12858. [CrossRef]
37. Menekşe, A.; Camgöz Akdağ, H. Information Technology Governance Evaluation Using Spherical Fuzzy AHP ELECTRE. In *Proceedings of the International Conference on Intelligent and Fuzzy Systems*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 757–765. https://doi/10.1007/978-3-030-85577-2_89.
38. Aghazadeh, E.; Yildirim, H.; Kuruoglu, M. A Hybrid Fuzzy MCDM Methodology for Optimal Structural System Selection Compatible with Sustainable Materials in Mass-Housing Projects. *Sustainability* **2022**, *14*, 13559. [CrossRef]
39. Menekşe, A.; Camgöz Akdağ, H. Seismic Vulnerability Assessment Using Spherical Fuzzy ARAS. In *Proceedings of the International Conference on Intelligent and Fuzzy Systems*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 733–740. https://doi/10.1007/978-3-030-85577-2_86.
40. Menekşe, A.; Akdağ, H.C. Seismic Risk Analysis of Hospital Buildings: A Novel Interval-Valued Spherical Fuzzy ARAS. *J. Risk Anal. Crisis Response* **2022**, *12*, 62–76. [CrossRef]
41. Yeğin, T.; Ikram, M. Performance Evaluation of Green Furniture Brands in the Marketing 4.0 Period: An Integrated MCDM Approach. *Sustainability* **2022**, *14*, 10644. [CrossRef]
42. Stević, Ž.; Tanackov, I.; Puška, A.; Jovanov, G.; Vasiljević, J.; Lojaničić, D. Development of modified SERVQUAL–MCDM model for quality determination in reverse logistics. *Sustainability* **2021**, *13*, 5734. [CrossRef]
43. Menekse, A.; Akdag, H.C. A novel interval-valued spherical fuzzy CODAS: Reopening readiness evaluation of academic units in the era of COVID-19. *J. Intell. Fuzzy Syst.* **2022**, *43*, 6461–6476. [CrossRef]
44. Yager, R.R. Pythagorean membership grades in multicriteria decision making. *IEEE Trans. Fuzzy Syst.* **2013**, *22*, 958–965. [CrossRef]
45. Liang, D.; Zhang, Y.; Xu, Z.; Jamaldeen, A. Pythagorean fuzzy VIKOR approaches based on TODIM for evaluating internet banking website quality of Ghanaian banking industry. *Appl. Soft Comput.* **2019**, *78*, 583–594. [CrossRef]
46. Chen, T.Y. New Chebyshev distance measures for Pythagorean fuzzy sets with applications to multiple criteria decision analysis using an extended ELECTRE approach. *Expert Syst. Appl.* **2020**, *147*, 113164. [CrossRef]
47. Ayyildiz, E.; Taskin Gumus, A. Pythagorean fuzzy AHP based risk assessment methodology for hazardous material transportation: an application in Istanbul. *Environ. Sci. Pollut. Res.* **2021**, *28*, 35798–35810. [CrossRef]
48. Zeng, S.; Zhang, N.; Zhang, C.; Su, W.; Carlos, L.A. Social network multiple-criteria decision-making approach for evaluating unmanned ground delivery vehicles under the Pythagorean fuzzy environment. *Technol. Forecast. Soc. Chang.* **2022**, *175*, 121414. [CrossRef]

49. Liu, P.; Rani, P.; Mishra, A.R. A novel Pythagorean fuzzy combined compromise solution framework for the assessment of medical waste treatment technology. *J. Clean. Prod.* **2021**, *292*, 126047. [CrossRef]
50. Rani, P.; Mishra, A.R.; Mardani, A.; Cavallaro, F.; Štreimikienė, D.; Khan, S.A.R. Pythagorean fuzzy SWARA—VIKOR framework for performance evaluation of solar panel selection. *Sustainability* **2020**, *12*, 4278. [CrossRef]
51. Akram, M.; Luqman, A.; Alcantud, J.C.R. An integrated ELECTRE-I approach for risk evaluation with hesitant Pythagorean fuzzy information. *Expert Syst. Appl.* **2022**, *200*, 116945. [CrossRef]
52. Bulut, M.; Özcan, E. Ranking of advertising goals on social network sites by Pythagorean fuzzy hierarchical decision making: Facebook. *Eng. Appl. Artif. Intell.* **2023**, *117*, 105542. [CrossRef]
53. Mishra, A.R.; Rani, P.; Bharti, S. Assessment of agriculture crop selection using Pythagorean fuzzy CRITIC–VIKOR decision-making framework. In *Pythagorean Fuzzy Sets*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 167–191. https://doi/10.1007/978-981-16-1989-2_7.
54. Liu, C.; Rani, P.; Pachori, K. Sustainable circular supplier selection and evaluation in the manufacturing sector using Pythagorean fuzzy EDAS approach. *J. Enterp. Inf. Manag.* **2021**, *35*, 1040–1066. [CrossRef]
55. Molla, M.U.; Giri, B.C.; Biswas, P. Extended PROMETHEE method with Pythagorean fuzzy sets for medical diagnosis problems. *Soft Comput.* **2021**, *25*, 4503–4512. [CrossRef]
56. Zhao, M.; Wei, G.; Wei, C.; Wu, J. Pythagorean fuzzy TODIM method based on the cumulative prospect theory for MAGDM and its application on risk assessment of science and technology projects. *Int. J. Fuzzy Syst.* **2021**, *23*, 1027–1041. [CrossRef]
57. Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. Determining objective weights in multiple criteria problems: The critic method. *Comput. Oper. Res.* **1995**, *22*, 763–770. [CrossRef]
58. Mitrović Simić, J.; Stević, Ž.; Zavadskas, E.K.; Bogdanović, V.; Subotić, M.; Mardani, A. A novel CRITIC-Fuzzy FUCOM-DEA-Fuzzy MARCOS model for safety evaluation of road sections based on geometric parameters of road. *Symmetry* **2020**, *12*, 2006. [CrossRef]
59. Mishra, A.R.; Rani, P.; Pandey, K. Fermatean fuzzy CRITIC-EDAS approach for the selection of sustainable third-party reverse logistics providers using improved generalized score function. *J. Ambient. Intell. Humaniz. Comput.* **2022**, *13*, 295–311. [CrossRef]
60. Kamali Saraji, M.; Streimikiene, D.; Kyriakopoulos, G.L. Fermatean fuzzy CRITIC-COPRAS method for evaluating the challenges to industry 4.0 adoption for a sustainable digital transformation. *Sustainability* **2021**, *13*, 9577. [CrossRef]
61. Yang, K.; Duan, T.; Feng, J.; Mishra, A.R. Internet of things challenges of sustainable supply chain management in the manufacturing sector using an integrated q-Rung Orthopair Fuzzy-CRITIC-VIKOR method. *J. Enterp. Inf. Manag.* **2021**, *35*, 1011–1039. [CrossRef]
62. Peng, X.; Krishankumar, R.; Ravichandran, K. A novel interval-valued fuzzy soft decision-making method based on CoCoSo and CRITIC for intelligent healthcare management evaluation. *Soft Comput.* **2021**, *25*, 4213–4241. [CrossRef]
63. Naik, M.G.; Kishore, R.; Dehmourdi, S.A.M. Modeling a multi-criteria decision support system for prequalification assessment of construction contractors using CRITIC and EDAS models. *Oper. Res. Eng. Sci. Theory Appl.* **2021**, *4*, 79–101. [CrossRef]
64. Biswas, T.; Chatterjee, P.; Choudhuri, B. Selection of commercially available alternative passenger vehicle in automotive environment. *Oper. Res. Eng. Sci. Theory Appl.* **2020**, *3*, 16–27. [CrossRef]
65. Pan, B.; Liu, S.; Xie, Z.; Shao, Y.; Li, X.; Ge, R. Evaluating operational features of three unconventional intersections under heavy traffic based on CRITIC method. *Sustainability* **2021**, *13*, 4098. [CrossRef]
66. Zadeh, L.A. Fuzzy sets. *Inf. Control.* **1965**, *8*, 338–353. [CrossRef]
67. Atanasov, K. Intuitionistic fuzzy sets Fuzzy sets and systems. *Fuzzy Sets Syst*. **1986**, *20*, 87–96. [CrossRef]
68. Yager, R.R. Pythagorean fuzzy subsets. In Proceedings of the 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), Edmonton, AB, Canada, 24–28 June 2013; IEEE: New York, NY, USA, 2013; pp. 57–61. https://doi/10.1109/ifsa-nafips.2013.6608375.
69. Zhang, X.; Xu, Z. Extension of TOPSIS to multiple criteria decision making with Pythagorean fuzzy sets. *Int. J. Intell. Syst.* **2014**, *29*, 1061–1078. [CrossRef]
70. Ejegwa, P.A. Distance and similarity measures for Pythagorean fuzzy sets. *Granul. Comput.* **2020**, *5*, 225–238. [CrossRef]
71. Lin, Y.H.; Chang, L.R.; Lee, Y.H.; Tseng, H.W.; Kuo, T.B.; Chen, S.H. Development and validation of the Smartphone Addiction Inventory (SPAI). *PLoS ONE* **2014**, *9*, e98312. [CrossRef]
72. Demirci, K.; Orhan, H.; Demirdas, A.; Akpinar, A.; Sert, H. Validity and reliability of the Turkish Version of the Smartphone Addiction Scale in a younger population. *Klin. Psikofarmakol.-BÜLteni-Bull. Clin. Psychopharmacol.* **2014**, *24*, 226–234. : 10.5455/bcp.20140710040824. [CrossRef]
73. Ching, S.M.; Yee, A.; Ramachandran, V.; Sazlly Lim, S.M.; Wan Sulaiman, W.A.; Foo, Y.L.; Hoo, F.K. Validation of a Malay version of the smartphone addiction scale among medical students in Malaysia. *PLoS ONE* **2015**, *10*, e0139337. : 10.1371/journal.pone.0139337. [CrossRef] [PubMed]
74. Burnell, K.; Kuther, T.L. Predictors of mobile phone and social networking site dependency in adulthood. *Cyberpsychol. Behav. Soc. Netw.* **2016**, *19*, 621–627. [CrossRef] [PubMed]
75. Turel, O.; Serenko, A. The benefits and dangers of enjoyment with social networking websites. *Eur. J. Inf. Syst.* **2012**, *21*, 512–528. [CrossRef]

76. Gerhart, N. Technology addiction: How social network sites impact our lives. *Informing Sci.* **2017**, *20*, 179. [CrossRef]
77. Billieux, J.; Philippot, P.; Schmid, C.; Maurage, P.; De Mol, J.; Van der Linden, M. Is dysfunctional use of the mobile phone a behavioural addiction? Confronting symptom-based versus process-based approaches. *Clin. Psychol. Psychother.* **2015**, *22*, 460–468. [CrossRef]
78. Middleton, C.A.; Cukier, W. Is mobile email functional or dysfunctional? Two perspectives on mobile email usage. *Eur. J. Inf. Syst.* **2006**, *15*, 252–260. [CrossRef]
79. D'souza, J.B.; Sharma, S.; Jaiboonma, P.; ReinThong, N. Smartphone Dependency in Relation to Cognitive Presence of Thai and International Accounting Students. Available online: http://journals.apheit.org/jounal/Inter-vol9no1/10.pdf (accessed on 6 January 2023).
80. Ilbahar, E.; Cebi, S.; Kahraman, C. Prioritization of renewable energy sources using multi-experts Pythagorean fuzzy WASPAS. *J. Intell. Fuzzy Syst.* **2020**, *39*, 6407–6417. [CrossRef]
81. Göçer, F. Limestone supplier selection for coal thermal power plant by applying integrated PF-SAW and PF-EDAS approach. *Soft Comput.* **2022**, pp. 1–22. [CrossRef]
82. Kahraman, C.; Onar, S.C.; Oztaysi, B.; Ilbahar, E. Selection Among GSM Operators Using Pythagorean Fuzzy WASPAS Method. *J. Mult. Valued Log. Soft Comput.* **2019**, *33*, 459–469.