



ISSN: 0067-2904

Unveiling Patterns of Nomophobia Using Data Mining Techniques

Hadeel Jabar, Mustafa S. Abd, Suhad Faisal Behadili, Inas Ali *

Department of Computer Science, College of Science, University of Baghdad, Baghdad, Iraq

Received: 13/9/2023

Accepted: 4/2/2024

Published: 30/8/2024

Abstract

Nowadays, almost everyone is glued to their phones. It turns out that the fear of being without your phone has a fancy name: nomophobia. Researchers can now analyze our phone usage using data mining techniques to determine how much we rely on them. They can monitor everything from screen time and social media activity to email habits and app addiction. This information assists us in understanding the impact of technology on our daily lives and may even lead to new interventions or treatment options for those who suffer from nomophobia. Nomophobia, like addiction, progresses through multiple aspects such as initiation, affirmation, need, and dependency. It also manifests in a variety of ways, including socially, physiologically, and physically. The study goal is to look into the nomophobia patterns of the Iraqi academic population (professors, students, and employees) at the University of Baghdad. A descriptive, cross-sectional survey design was used to collect data between 17th October, 2021, and 1st October, 2022. The sample for this study consists of 305 participants. A sociodemographic data sheet, Internet usage profiles, and a nomophobia questionnaire are used to collect information. Thus, data mining techniques have been used to analyze the collected data, hence the concluded results emphasize that there are two major patterns (students group that are annoying during inability to find information on a mobile phone, inability to use it, and inability to check it, and panic when they consume out the credits or hit the monthly data limit, awkward because they couldn't check their notifications for updates from their connections and online networks, subsequently they would feel weird because they would not know what to do). They exhibit nomophobia, and all the examined individuals have acceptable impacts of nomophobia.

Keywords: Data Mining, Nomophobia, Iraqi academic population.

الكشف عن أنماط نوموفوبيا باستعمال تقنيات التنقيب في البيانات

هديل جبار جريش ، مصطفى سلمان عبد ، سهاد فيصل البهادلي ، ايناس علي عبد المنعم *

قسم علوم الحاسوب، كلية العلوم، جامعة بغداد، بغداد، العراق

الخلاصة

في الوقت الحاضر، أصبح الجميع تقريباً ملتصقين بهواتفهم. اتضح ان الخوف من البقاء بدون هاتفك له اسم غريب: نوموفوبيا. يمكن للباحثين الآن تحليل استعمالنا للهاتف باستعمال تقنيات استخراج البيانات لتحديد مدى اعتمادنا عليها. يمكنهم مراقبة كل شيء بدءاً من وقت الشاشة ونشاط الوسائط الاجتماعية وحتى عادات البريد الإلكتروني وإدمان التطبيقات. تساعدنا هذه المعلومات في فهم تأثير التكنولوجيا على حياتنا اليومية وقد تؤدي الى تدخلات جديدة أو خيارات علاجية لأولئك الذين يعانون من رهاب النوموفوبيا. يمكن اعتبار

*Email: hadeel.jriash@sc.uobaghdad.edu.iq

النوموفوبيا مثل الادمان، من خلال جوانب متعددة مثل البدء والتأكيد والحاجة والتبعية. كما يتجلى في مجموعة متنوعة من الطرق، بما في ذلك اجتماعيا وفسولوجيا وجسديا. هدف الدراسة هو النظر في أنماط النوموفوبيا لدى المجتمع الأكاديمي العراقي (الأساتذة والطلبة والموظفين) في جامعة بغداد. تم استعمال تصميم المسح الوصفي المقطعي لجمع البيانات بين 17 كانون الثاني 2021 – 1 كانون الثاني 2022. تتكون عينة هذه الدراسة من 305 مشارك. يتم استعمال ورقة البيانات الاجتماعية والديموغرافية وملفات تعريف استعمال الانترنت واستبيان نوموفوبيا لجمع المعلومات. وبالتالي تم استعمال تقنيات التنقيب في البيانات لتحليل البيانات التي تم جمعها، ومن هنا تؤكد النتائج التي تم التوصل إليها أن هناك نمطين رئيسيين. حيث ان مجموعة الطلبة التي تكون منزوعة أثناء عدم القدرة على العثور على المعلومات على الهاتف المحمول، وعدم القدرة على استعماله، وعدم القدرة على التحقق منه يشعرون بالذعر عندما يستفدون الأصدقاء أو يصلون الى حد البيانات الشهري، وهو أمر محرج لأنهم لم يتمكنوا من التحقق من اشعاراتهم للحصول على تحديثات من اتصالاتهم وشبكاتهم عبر الانترنت، وبالتالي سيشعرون بالغرابة لأنهم لن يعرفوا ما يجب فعله. إنهم يظهرون رهاب النوموفوبيا، وجميع الأشخاص الذين تم فحصهم لديهم تأثيرات مقبولة على رهاب النوموفوبيا.

1. Introduction

The emergence of new information and communication technologies (ICTs) in the digital epoch provided facilities for quick communication, data retrieval, and Internet access efficiently via the network of the largest global communication network [1]. This epoch is defined by the widespread and prevalent use of mobile devices and smartphones. They are primarily used to access the internet, contact family and friends, and search for anything due to their smaller dimensions, which boost portability. An obsession with the most recent mobile apps can undoubtedly create an environment in which people spend more time with technology than with each other [2, 3]. Notwithstanding, mobile phones are currently an indispensable medium of modern life. The use of smartphones has led to significant problems and community consequences [4, 5]. Therefore, nomophobia, or non-mobile dread, is a modern illness caused by mobile technology that has a detrimental effect on the community and the reliance that its use has created among residents [6, 7]. The inability to contact or get in touch with other people, plus losing rapid access to their networks and information, would all lead to the phobia egressing. Actually, nomophobia is distinguished by discomfort, feelings of nervousness, anxiety, or distress if not using a mobile phone, and it may additionally provoke suicidal thoughts and assaults [8, 9].

Nomophobia has a relationship with the fear of becoming incapable of interacting, losing their connection, feeling alone, and losing their convenience. In other instances, nomophobia is extensively, positively, and considerably related to challenges utilizing the Internet, concern about their social media profile, and dependence on social media [10]. Further investigations have found that individuals with nomophobia use inaccurate stress-coping strategies, and those with substantial levels of nomophobia seek memories, oneself, and close proximity. Previous studies pointed out three symptoms of this situation: nervousness, obsessive smartphone usage, and fear senses [11]. Moreover, nomophobia has been demonstrated to induce anxiety as a consequence of interpersonal threats, especially if the situation involves ambiguity or losing control [2], [12], and [13].

Interpersonal interaction in an era of modern technology can result in fewer interpersonal connections among individuals in the community and a lack of many aspects required for developing a typical individuality. As a result, technological advancement and progress are viewed as factors in psycholoneyness and periodic anxiety [14], [15], and [16]. Likewise, the proliferation of complex forms of interpersonal interaction with other people, especially via media outlets and the internet, has resulted [17]. As a consequence of this, the person in

question gains beliefs that could clash with the beliefs of the family while additionally losing the beliefs and features that distinguish them [8, 18]. Indeed, cell phone devices were established to be used to connect at first; thereby, it seems reasonable to associate loneliness with the possession of mobile phones [19]. Loneliness is a powerful indicator of cellular phone usage [20]. Actually, [21] realized a significant correlation between loneliness and nomophobia, with loneliness estimating nomophobia. Individuals likewise utilize cell phones as substitutes for loneliness and social anxiety [8, 22, 23]. However, the data mining techniques are used to identify customer behavior, market trends, and social media interactions [24]. The aim of mining is to identify the common traits and features in the data set that will help to understand the underlying processes and make better decisions [6, 25]. This process involves clustering [26], classification [27], and association analysis [28] to identify trends and patterns [29]. Consequently, the results can vary from simple descriptive graphs to complex predictive models [30]. The process uses machine learning and statistical techniques to identify patterns and trends that can lead to valuable insights [31, 32]. The results can be used to develop marketing strategies, customer segmentation, and product recommendations. Accordingly, data mining has several advantages [33], including improved decision-making, better customer service, and increased revenue [34, 35].

2. Related Work

Earlier research has found that alone people are more likely to overuse Internet technology, and if they have been incapable of utilizing a mobile phone, they have been almost certain to suffer from being embarrassed [36–37]. Furthermore, loneliness may lead to the disproportionate use of mobile phones due to the mediator effect of escape motivation [38–39]. This has become an unfamiliar challenge to the internet era that is being exacerbated by people's growing utilization of cell phones in the course of their daily activities [8]. As a result, it seems that it is necessary to investigate whether nomophobia and loneliness have a correlation in a dataset of the Saudi Arabian population. This research looked into the association between the sensation of loneliness and nomophobia and found a significant and positive relationship between them [3].

Actually, [40] examined mobile phone activities that are correlated with mobile phone addictive disorders in male and female users. In this study, an internet-based questionnaire was filled out by university students. This survey took ten to fifteen minutes to respond to and included a mobile phone addictive behavior scale as well as queries regarding the amount of time users spend every day on 24 mobile phone activities. The results thereof confirmed that mobile phone use has a strong correlation with mobile phone addictive disorders such as Instagram and Pinterest. These activities contribute to cell phone addictive disorders (CPA), which have been found to differ significantly between male and female mobile phone users.

Whereas, in [41], it addressed mobile phone user impressions and analyzed them regarding their dependent behaviors over a 6-hour interaction shutdown in South Korea in 2014. This research listed two categories of reliance determined by conversations with 70 mobile phone owners: functional reliance, which emphasizes the mobile phone's critical helpfulness, in addition to existential reliance, which is based on obsessive, usually unconsciously, adherence to the mobile phone. Even though the two categories of reliance could overlap, individuals who consider fundamental reliance have been less inclined to discuss the negative effects of using mobile phones compared to those who think of functional reliance. Furthermore, functionally reliant users seemed more inclined than existentially reliant individuals to alter their reliance behavior. Mobile phone users, irrespective of their form of addiction, rejected the claim of being addicted to the mobile phone. Moreover, the [42] research focuses on the influence of nomophobia on young individual behavior and

habits. It acquired features and offered alternatives for those suffering from nomophobia. Also, it has some limitations because most of the participants were 1st grade undergraduates. The constraint was that there was an unbalance in the age distribution between the individuals polled. It is recognized that outcomes could be limited due to the socioeconomic status of those who were polled and could vary for different individuals and cultures. However, in [43], the contextual, usage-related, and personality-related indicators affecting the impressions of 72 fictional situations of mobile absence have been examined employing an internet-based factorial questionnaire of 146 German mobile phone owners. By employing a multifaceted technique, the study discovered how the location, motive, and probable time period of absence, in addition to the anticipated number of communication attempts, affect contextual mobile absence. Individual influences, including the importance of mobile availability, attainable anticipations of others, a feeling of FOMO (fear of missing out), and a high degree of commitment, affect the impression of lacking situations. There are also cross-level consequences among contextual and personal variables.

3. Methodology

3.1 Investigated Data

Indeed, the examined dataset has been collected according to the nomophobia questionnaire (NMP-Q) created by [4], and the questionnaire version has been translated into Arabic, and it was applied in the present investigation with no changes. It contains twenty questions that have ratings on a Likert rating system from 1 to 7, with 1 confirming completely disagree and 7 confirming completely agree (or totally agree). The four main categories stated in this study have been organized into questions about data lack (items 1-4): frustration due to lacking the ability to properly utilize a mobile phone to search for information on the Internet or access information at any time as well; offering up comfort (items 5–9): the comfort and ease that cell phones provide, especially in regards to batteries, coverage, and credits; a failure of communicating (items 10-15): sensations about not being able to communicate instantly and becoming incapable of utilizing immediate communication services; failure to communicate (items 10-15): sensations regarding being incapable of utilizing immediate messaging services; sensations regarding lacking connection (items 16–20) [3] [4]. The target population in the Iraqi academic domain (University of Baghdad) during October 17, 2021–October 1, 2022 was 305 participants.

3.2 Data Set Characterization

The characterization action is the process of manipulating and converting the data set features into symbols to simplify them, especially some algorithms that could work on nominal values, numeric data, binary values, and unary attributes, so they can benefit from this process to make the features understood more smoothly. The data sets are usually large and contain millions of data points, so it requires advanced algorithms and systems to analyze them effectively. Indeed, in this paper, the characterization results, as shown in Table1, of converting the questionnaire answers will be easily analyzed in the next phase below, where X is the general literal of all questionnaire questions from A to T.

Table 1: Questionnaire Characterization Stage

Attributes	Features of Attributes
Gender	(G _{n0} = Female, G _{n1} = male)
Age	(18<=Ag ₀ <=28), (29<=Ag ₁ <=39), (40<=Ag ₂ <=50), (51<=Ag ₃ <=61)
O _{cc}	(O _{ccs} = Students, O _{ccT} =Teachers, O _{ccE} =Employee)
Answers Features	X ₀ =neutral, X ₁ = I somewhat disagree, X ₂ =I somewhat agree, X ₃ =Strongly Disagree, X ₄ =Strongly agree, X ₅ = disagree, X ₆ = Agree

3.2 Feature Selection

It is a crucial step in data mining that entails choosing relevant features or attributes from a large pool of potential variables. This procedure is critical for reducing redundancy, improving model accuracy and interpretability, and avoiding overfitting [44, 45, 46]. Filter methods, wrapper methods, and embedded methods are among the feature selection techniques available. Before deciding on the best technique for a specific data mining task, it is critical to carefully evaluate and compare various approaches. Accordingly, feature selection is an important step in data mining that can have a significant impact on the performance and interpretability of predictive models. However, only the most relevant attributes of a dataset have been chosen for analysis. Thus, feature selection has been used to identify the key factors that contribute to nomophobia in the context of this phenomenon. These variables may include age, gender, occupation, social media use, and mobile phone reliance. Researchers can gain a better understanding of the causes and effects of nomophobia by focusing on these specific characteristics, leading to better diagnosis, treatment, and prevention strategies.

In this phase, the classifier attribute evaluator estimates the worth attribute using a user-specified classifier (Simple CART Tree) [47] [48] with the evaluation measure Area Under ROC Curve (AUC) regarding the search based on the ranker search method. However, classification and regression trees (CART) are a more modern term for decision trees. To assess a piece of data, they build a tree and begin at the base, working their way up to the leaves (roots) until they can make a forecast. In order to create a decision tree, first choose the best split point repeatedly in order to generate predictions. The procedure is then repeated until the tree reaches a fixed depth. Thus, to increase the model's capacity to generalize to new data, the tree is trimmed once it is built.

This process produced the results that determined the nine extracted attributes from the 23 attributes of the main class, which were age attributes. Hence, they are considered the pivotal steps to start the execution of the apriori and association rule algorithms as presented in Table 2.

Table 2: Selected attributes

O_{cc}	F_q	T_q	B_q	R_q	E_q	I_q	K_q	D_q	Class (A_g)
----------	-------	-------	-------	-------	-------	-------	-------	-------	-----------------

3.4 Apriori and Association Approach

Actually, the effective patterns could be obtained from utilization of apriori and association rule mining approach. One such machine learning system that determines likely associations and establishes association rules [49] is the Apriori algorithm . Thus the used platform of this study (WEKA) offers the Apriori algorithm implementation. When calculating these rules, you can choose the acceptable confidence level and the minimal support.

This is performed according to the parameters of Table 3, which explores the most effective super item set (Occ, Bq, Dq, Iq) in the case of occupation (Occ) is the main class, which is composed of an apriori algorithm that represents the most regular patterns in the Nomophobia phenomenon of the investigated dataset, which are equivalent to accepting options in the investigation. Thereafter, confidence has to be determined in order to estimate association rules that represent the relationship strengths among the super-item set. The accepted rule is 86% as presented in Rule 1, which exceeded the metric confidence of 80%. So, it would be possible to classify the individual's tendency to use their mobile devices, thus deducing the strength of nomophobia in the investigated data set.

Table 3: Apriori and association parameters

Lower bound	Delta	Upper bound	Metric confidence	Number of rules
0.06	0.05	1	0.8	10

$$D_{q6}, I_{q6}, O_{cc6} \Rightarrow B_{q6} \tag{1}$$

Nevertheless, the repetition has been estimated based on (upper, lower) bound and delta in decreasing steps from the upper till reaching the lower bound or sufficient number of rules, as in formula 2:

$$I_{acc} = I_{all} * L_b \tag{2}$$

Where, I_{acc} is the number of accepted instances that satisfy the threshold values. Whereas, I_{all} is the total instances that are 305 in this experiment, and L_b is the minimum support. However, the number of performed cycles that are utilized for superset extraction from the main dataset could be obtained using formula 3:

$$N_c = \frac{(Max_b - Min_b)}{\Delta(Max_b, Min_b)} \tag{3}$$

Where, N_c is the number of cycles and Max_b and Min_b are the maximum and minimum supports, respectively. In addition, $\Delta (Max_b, Min_b)$ is the iterative reduction of the supporting factor that reduced the maximum support until it reached the minimum support or produced a predetermined number of rules. The detected superitem sets were entered into the association algorithm to produce the dominant associated rules [50].

4. Results Discussion

Turning now to the experimental evidence on the feature selection method of the classifier attribute evaluator based on the simple CART Tree algorithm, in addition to the area under the ROC curve (AUC) as an evaluation measure with 5 folds. Accordingly, it has gained 9 columns (in Table 1) from a total of 23 in origin, with age (Ag) as the main class. Actually, the confidence of all patterns has been estimated at 86%, along with the superitem sets (patterns). So, the most effective rule has been extracted, which emphasizes that the superitem sets have the most effective impact on the observed phenomena of 19 execution cycles with regard to formula 3 execution. Thus, the $\{B_{q6}, D_{q6}, I_{q6}, O_{cc6}\}$ and $\{F_{q3}, T_{q3}, R_{q3}\}$ item sets are exceeding the common confidence of 85%. On the other hand, these results are based on minimum support = 0.06 and maximum support = 1, and the delta = 0.05, as shown in tables 4 and 5, respectively.

Table 4: First most effective pattern

Symbol	Option response	Feature
B_{q6}	I would be annoyed if I could not look information up on my smartphone when I wanted to do so.	6=Agree
D_{q6}	I would be annoyed if I could not use my smartphone and/or its capabilities when I wanted to do so.	6=Agree
I_{q6}	I If I could not check my smartphone for a while, I would feel a desire to check it.	6=Agree
O_{cc6}	Individual occupation student	S=Student

Additionally, the associated rules have been extracted based on a confidence = 0.85 and produced the following rule:

$$\{ D_{q6}, I_{q6}, O_{cc6} \} ===> B_{q6} = 18$$

Where, the pattern set (superitem set) is $\{B_{q6}, D_{q6}, I_{q6}, O_{cc6}\}$ represents the first most repeated answer of 18 repetitions. Whereas, other associated rules have been extracted with a confidence=0.86, the following rule is produced:

$$\{ F_{q3}, T_{q3} \} ===> R_{q3} = 18$$

Where, the pattern set and $\{F_{q3}, T_{q3}, R_{q3}\}$ represent the second most repeated answer of 18 repetitions.

Table 5: Second most effective pattern

Symbol	Option response	Feature
F_{q3}	If I were to run out of credits or hit my monthly data limit, I would panic.	3=Somewhat disagree
T_{q3}	I would feel awkward because I could not check my notifications for updates from my connections and online networks.	3=Somewhat disagree
R_{q3}	I would feel weird because I would not know what to do.	3=Somewhat disagree

These rules satisfy the threshold condition, which is 18 times of repeated items together (accepted item sets and super item sets) that are obtained from 19 cycles of execution. Then, emerging from the results reported here, is extracting the superset that reveals effective patterns of nomophobia for the investigated data set. Indeed, the O_{cc} feature indicates the students' instances from the total O_{cc} features of the investigated dataset (employees, teaching members, and students) of the University of Baghdad; they are the most influenced ones in the experimented phenomena. Therefore, a deep classification has been performed in detail to explore whether the influence gender is women or men who are the most affected; thus, the results indicate that they have equivalent influential ratios for both of them.

5. Conclusions

According to the nonparametric investigation, the total pattern set (superitem set) $\{B_{q6}, D_{q6}, I_{q6}, O_{ccs}\}$ has a significant and dominant role with regards to nomophobia. Whereas, the responses that are associated with student groups that are annoying are the inability to find information on a mobile phone, the inability to use it, and the inability to check it. Furthermore, the pattern set (item set) $\{F_{q3}, T_{q3}, R_{q3}\}$ has also a second significant role within regards to nomophobia. The responses that are associated with the total investigated individuals in the questionnaire that panic when they consume out the credits or hit the monthly data limit are awkward because they couldn't check their notifications for updates from their connections and online networks; subsequently, they would feel weird because they would not know what to do. This work proposes that a variety of academic fields require psychoeducation to raise awareness about the psychological ramifications of nomophobia. So, approaches could help to minimize the time spent online for random causes and to uncover innovative and informative means for communicating among people. This study found that nearly all of the investigated population possesses an acceptable amount of nomophobia, owing to the inability to socially interact and the sacrifice of comfort. Subsequently, the education degree and the daily regularity of mobile Internet usage are decisive indicators of nomophobia degrees in the investigated dataset. According to the findings, more research will be required to increase consciousness concerning the psychological effects of nomophobia through psychological counseling. Sessions with counseling, which supervise individuals in regards to procedures offered, aim to assist them in decreasing the time that they consume online for irrelevant motives, excluding time spent online for studying and assessments. In addition to motivating them in the direction of imaginative and stimulating techniques for connecting among them, this may additionally be good for them.

References

[1] C. Z.-W. Qiang and A. Pitt, *Contribution of Information and Communication Technologies to Growth*. The World Bank, 2003.
 [2] N. L. Bragazzi, G. Dini, A. Toletone, F. Brigo, and P. Durando, "Leveraging Big Data for

- Exploring Occupational Diseases-Related Interest at the Level of Scientific Community, Media Coverage and Novel Data Streams: The Example of Silicosis as a Pilot Study,” *PLoS One*, vol. 11, no. 11, p. e0166051, Nov. 2016.
- [3] S. A. Facts and P. U. Statistics, “The definitive guide (2019 update),” pp. 1–30, 2019.
- [4] A. R. Kayis, B. Satici, M. E. Deniz, S. A. Satici, and M. D. Griffiths, “Fear of COVID-19, loneliness, smartphone addiction, and mental wellbeing among the Turkish general population: a serial mediation model,” *Behav. Inf. Technol.*, vol. 41, no. 11, pp. 2484–2496, Aug. 2022.
- [5] A.-J. Moreno-Guerrero, J. López-Belmonte, J.-M. Romero-Rodríguez, and A.-M. Rodríguez-García, “Nomophobia: impact of cell phone use and time to rest among teacher students,” *Heliyon*, vol. 6, no. 5, p. e04084, May 2020.
- [6] R. A. Lateef and A. R. Abbas, “Human Activity Recognition using Smartwatch and Smartphone: A Review on Methods, Applications, and Challenges,” *Iraqi Journal of Science*, vol. 63, no. 1, pp. 363–379, Jan. 2022.
- [7] Bano, Nusrat et al. “Effects of nomophobia on anxiety, stress and depression among Saudi medical students in Jeddah, Saudi Arabia,” *JPMA The Journal of the Pakistan Medical Association*, vol. 71, no. 3, pp. 854-858, 2021. doi:10.47391/JPMA.983
- [8] R. M. Hussien, “The association between nomophobia and loneliness among the general population in the Kingdom of Saudi Arabia,” *Middle East Curr. Psychiatry*, vol. 29, p. 68, 2022.
- [9] C. Yildirim and A.-P. Correia, “Exploring the dimensions of nomophobia: Development and validation of a self-reported questionnaire,” *Comput. Human Behav.*, vol. 49, pp. 130–137, Aug. 2015.
- [10] A.-M. Rodríguez-García, A.-J. Moreno-Guerrero, and J. López Belmonte, “Nomophobia: An Individual’s Growing Fear of Being without a Smartphone—A Systematic Literature Review,” *Int. J. Environ. Res. Public Health*, vol. 17, no. 2, p. 580, Jan. 2020.
- [11] R. Musa, J. Saidon, and S. A. Rahman, “Who’s at Risk for Smartphone Nomophobia and Pathology; The Young or Matured Urban Millennials?,” *Adv. Sci. Lett.*, vol. 23, no. 8, pp. 7486–7489, Aug. 2017.
- [12] W. H. Hung, L. M. Chang, and C. H. Lin, “Managing the risk of overusing mobile phones in the working environment: A study of ubiquitous technostress,” *PACIS 2011 - 15th Pacific Asia Conf. Inf. Syst. Qual. Res. Pacific*, 2011.
- [13] M. A. Olivencia-Carrión, R. Ferri-García, M. del M. Rueda, M. G. Jiménez-Torres, and F. López-Torrecillas, “Temperament and characteristics related to nomophobia,” *Psychiatry Res.*, vol. 266, no. May, pp. 5–10, 2018.
- [14] S. Behadili, H. Jabar, W. Tahlok, and S. Abdulsahib, “No Mobile Phobia Phenomenon _ A Review,” *Iraqi J. Electr. Electron. Eng.*, vol. 17, no. 1, pp. 1–11, Jun. 2021.
- [15] N. Davies, “Nomophobia : The Modern-Day Pathology,” *Psychiatry Advisor*, pp. 1–10, 2019.
- [16] T. Elmore, “Nomophobia: A Rising Trend in Students,” *Psychol. Today Heal. Help. Happiness Find a Ther.*, pp. 1–4, 2014.
- [17] F. Kaviani, B. Robards, K. L. Young, and S. Koppel, “Nomophobia: Is the Fear of Being without a Smartphone Associated with Problematic Use?,” *Int. J. Environ. Res. Public Health*, vol. 17, no. 17, p. 6024, Aug. 2020.
- [18] J. Bartwal and B. Nath, “Evaluation of nomophobia among medical students using smartphone in north India,” *Med. J. Armed Forces India*, vol. 76, no. 4, pp. 451–455, Oct. 2020.
- [19] S. Heng, Q. Gao, and M. Wang, “The Effect of Loneliness on Nomophobia: A Moderated Mediation Model,” *Behav. Sci. (Basel)*, vol. 13, no. 7, p. 595, Jul. 2023.
- [20] S. Bhattacharya, M. Bashar, A. Srivastava, and A. Singh, “NOMOPHOBIA: NO MOBILE PHONE PHOBIA,” *J. Fam. Med. Prim. Care*, vol. 8, no. 4, p. 1297, 2019.
- [21] H. Yıldız Durak, “What Would You Do Without Your Smartphone? Adolescents’ Social Media Usage, Locus of Control, and Loneliness as a Predictor of Nomophobia,” *Addicta Turkish J. Addict.*, vol. 5, no. 3, Sep. 2018.
- [22] A.-J. Moreno-Guerrero, G. Gómez-García, J. López-Belmonte, and C. Rodríguez-Jiménez, “Internet Addiction in the Web of Science Database: A Review of the Literature with Scientific Mapping,” *Int. J. Environ. Res. Public Health*, vol. 17, no. 8, p. 2753, Apr. 2020.
- [23] H. Alheneidi, L. AlSumait, D. AlSumait, and A. P. Smith, “Loneliness and Problematic Internet Use during COVID-19 Lock-Down,” *Behav. Sci. (Basel)*, vol. 11, no. 1, p. 5, Jan. 2021.
- [24] I. A. Abdulmunem, “Brain MR Images Classification for Alzheimer’s Disease,” *Iraqi Journal of*

- Science*, vol. 63, no. 6, pp. 2725–2740, Jun. 2022.
- [25] F. H. Fadel and S. F. Behadili, “A Comparative Study for Supervised Learning Algorithms to Analyze Sentiment Tweets,” *Iraqi Journal of Science*, vol. 63, no. 6, pp. 2712–2724, Jun. 2022.
- [26] S. Chakraborty, S. H. Islam, and D. Samanta, *Data Classification and Incremental Clustering in Data Mining and Machine Learning*. Cham: Springer International Publishing, 2022.
- [27] J. Han, M. Kamber, and J. Pei, “Classification,” in *Data Mining*, Elsevier, 2012, pp. 327–391.
- [28] V. Kotu and B. Deshpande, “Association Analysis,” in *Data Science*, Elsevier, 2019, pp. 199–220.
- [29] S. Alabdulwahab and B. Moon, “Feature Selection Methods Simultaneously Improve the Detection Accuracy and Model Building Time of Machine Learning Classifiers,” *Symmetry (Basel)*, vol. 12, no. 9, p. 1424, Aug. 2020.
- [30] J. Cervantes, F. Garcia-Lamont, L. Rodríguez-Mazahua, and A. Lopez, “A comprehensive survey on support vector machine classification: Applications, challenges and trends,” *Neurocomputing*, vol. 408, pp. 189–215, Sep. 2020.
- [31] S. Hassan Hashim and I. Ali Abdulmunem, “A Proposal to Detect Computer Worms (Malicious Codes) Using Data Mining Classification Algorithms,” *Eng. Technol. J.*, vol. 31, no. 2 B, pp. 142–155, Feb. 2013.
- [32] S. S. Rasheed, Suhad Faisal, I. Kamil Mohammed, and M. S. Abd, “A review of Medical Diagnostics Via Data Mining Techniques,” *Iraqi Journal of Science*, vol. 62, no. 7, pp. 2401–2424, Jul. 2021.
- [33] A. Bilal Zorić, “Benefits of Educational Data Mining,” *J. Int. Bus. Res. Mark.*, vol. 6, no. 1, pp. 12–16, 2020.
- [34] F. K. Nasser and S. F. Behadili, “A Review of Data Mining and Knowledge Discovery Approaches for Bioinformatics,” *Iraqi Journal of Science*, vol. 63, no. 7, pp. 3169–3188, Jul. 2022.
- [35] F. Hassan and S. F. Behadili, “Modeling Social Networks using Data Mining Approaches-Review,” *Iraqi J. Sci.*, vol. 63, no. 3, pp. 1313–1338, Mar. 2022.
- [36] A. Enez Darcin, S. Kose, C. O. Noyan, S. Nurmedov, O. Yılmaz, and N. Dilbaz, “Smartphone addiction and its relationship with social anxiety and loneliness,” *Behav. Inf. Technol.*, vol. 35, no. 7, pp. 520–525, Jul. 2016.
- [37] S. Parasuraman, A. Sam, S. K. Yee, B. C. Chuon, and L. Ren, “Smartphone usage and increased risk of mobile phone addiction: A concurrent study,” *Int. J. Pharm. Investig.*, vol. 7, no. 3, p. 125, 2017.
- [38] X. Shen and J.-L. Wang, “Loneliness and excessive smartphone use among Chinese college students: Moderated mediation effect of perceived stressed and motivation,” *Comput. Human Behav.*, vol. 95, pp. 31–36, Jun. 2019.
- [39] J. Li, D. Zhan, Y. Zhou, and X. Gao, “Loneliness and problematic mobile phone use among adolescents during the COVID-19 pandemic: The roles of escape motivation and self-control,” *Addict. Behav.*, vol. 118, p. 106857, Jul. 2021.
- [40] J. Roberts, L. Yaya, and C. Manolis, “The invisible addiction: Cell-phone activities and addiction among male and female college students,” *J. Behav. Addict.*, vol. 3, no. 4, pp. 254–265, Dec. 2014.
- [41] C. S. Park, “Examination of smartphone dependence: Functionally and existentially dependent behavior on the smartphone,” *Comput. Human Behav.*, vol. 93, pp. 123–128, Apr. 2019.
- [42] M. Anshari, Y. Alas, and E. Sulaiman, “Smartphone addictions and nomophobia among youth,” *Vulnerable Child. Youth Stud.*, vol. 14, no. 3, pp. 242–247, Jul. 2019.
- [43] B. Kneidinger-Müller, “When the smartphone goes offline: A factorial survey of smartphone users’ experiences of mobile unavailability,” *Comput. Human Behav.*, vol. 98, pp. 1–10, Sep. 2019.
- [44] R. A. R. Mahmood, A. Abdi, and M. Hussin, “Performance Evaluation of Intrusion Detection System using Selected Features and Machine Learning Classifiers,” *Baghdad Sci. J.*, vol. 18, no. 2(Suppl.), p. 0884, Jun. 2021.
- [45] J. Cai, J. Luo, S. Wang, and S. Yang, “Feature selection in machine learning: A new perspective,” *Neurocomputing*, vol. 300, pp. 70–79, Jul. 2018.
- [46] J. Krawczuk and T. Łukaszuk, “The feature selection bias problem in relation to high-dimensional gene data,” *Artif. Intell. Med.*, vol. 66, pp. 63–71, Jan. 2016.

- [47] S. Sameer, S. F. Behadili, M. S. Abd, and A. Salam, "CART_based Approach for Discovering Emerging Patterns in Iraqi Biochemical Dataset," *Iraqi Journal of Science*, vol. 63, no. 1, pp. 353–362, Jan. 2022.
- [48] F. Xing and L. Yang, "Machine learning and its application in microscopic image analysis," in *Machine Learning and Medical Imaging*, Elsevier, 2016, pp. 97–127.
- [49] D. Gutierrez-Rojas, I. T. Christou, D. Dantas, A. Narayanan, P. H. J. Nardelli, and Y. Yang, "Performance evaluation of machine learning for fault selection in power transmission lines," *Knowl. Inf. Syst.*, vol. 64, no. 3, pp. 859–883, Mar. 2022.
- [50] M. S. Abd and S. F. Behadili, "Recognizing Job Apathy Patterns of Iraqi Higher Education Employees Using Data Mining Techniques," *J. Southwest Jiaotong Univ.*, vol. 54, no. 4, 2019.