Modelling Perceptions of Netizens towards New Age AI Based Crimes Using Non-Parametric Correlation and Regression Metrics

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Abstract

The recent rise of artificial intelligence has enabled new age cybercrimes, which include different AI-based crimes like automated phishing, deep fakes, voice swapping, and others. So, it is very important to understand how netizens recognize and respond to these crimes in recent time. In this cross-sectional study a survey was conducted by using a structured, literature-based questionnaire consisting 5 sections, circulated among netizens by means of google forms. A total of 204 responses has been collected from netizens. Perception scores were calculated by summing awareness, cyber security practice, and confidence scores. Data were coded and statistically analyzed by using Microsoft Excel, 2019. Descriptive statistical analysis, t-tests, Pearson and Spearman correlation, and simple linear regression models have been utilized for the statistical analysis process in Microsoft Excel, 2019. Result has shown no significant gender-based differences, and demographic factors have shown extremely weak and statistically non-significant relationships with perception score, including age, education level, professional hierarchy, and place of residence. But, daily duration of online activities has been highlighted as the only significant predictor, by explaining 3.50% of variance within perception scores (R^2 = 0.035; p = 0.007). This key finding has indicated that netizens spending more time online possess higher awareness, which helps in better cybersecurity practice, and show greater confidence in identifying AI-generated scams. Additionally, combined awareness and cyber security practice scores have significantly predicted confidence level in identifying these advanced cybercrimes, accounting for 4.34% of variance (R^2 = 0.0434; p = 0.003). It can be concluded from the study that, behavioral digital engagement- rather than demographic background- plays most significant role in shaping preparedness against advanced AI driven and dark-web based cybercrimes.

Keywords: artificial intelligence, new age cybercrimes, awareness, cybersecurity practices, confidence.

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1. Introduction

AI technologies have transformed digital environment by improving efficiency, automation, and data-based decision making. However, with advancements and innovations, the cyber threat landscape is also increasing due to AI-generated phishing, misinformation, deepfakes, and autonomous malware. Misuse of generative AI models, for example, ChatGPT derivatives like FraudGPT has enabled low skilled attackers to perform successful cyberattacks, and social engineering campaigns, while handling traditional cybersecurity barriers (Falade, 2023). In parallel, the dark web works as a platform for illicit trade, ransomware-as-a-service (RaaS), and anonymous data exchanges (Temara, 2024).

Therefore, the integration of AI tools and dark web makes the identification and mitigation of these threats more complex, posing challenges for digital users and law enforcement. This highlights the growing importance of human factor in cybersecurity in terms of awareness, perception, and behavioural preparedness (Mukherjee et al., 2025).

The recent studies show that individual awareness and digital literacy help to create resilience against cyberattacks, often more than technical defences alone. For example, users with more digital citizenship skills, knowledge of digital rights, ethical use, and cybersecurity practices show reduced susceptibility to cyber threats (Buchan et al., 2024).

The empirical findings are related to demographic and behavioural factors of cybersecurity preparedness. A study found significant age differences across cybersecurity behaviours like password generation, proactive checking, and securing device. Elder users are found less likely to protect their devices as compared to young generation users. In young adults, the online security behaviour is found to be strongly predicted by cyber risk awareness (Althibyani & Al-Zahrani, 2023). It is supported by a research among Saudi secondary school students, where it is found that duration of internet use strengthens the link between awareness and data protection practices. Therefore, it is suggested that threat simulation practices should be included to increase the perception of cybersecurity threats in students(Alqarni, 2025). Gender has not been found as a significant predictor of cybersecurity behaviour. A study found that teachers from developed areas had more cybersecurity knowledge than the underdeveloped areas like districts, particularly due to more digital exposure, ICT resources, and institutional support (Sawale, 2025).

These findings align with the growing research suggesting that the behavioural exposure, for example, daily online activity help more in creating awareness and preparedness as compared to demographic traits.

In India there is a rapid digitization and exposure of AI technologies, therefore this present study systematically evaluates the demographic (gender, age, education, profession, and place of residence) and behavioural (online duration) predictors of perception, awareness, and confidence regarding AI and dark web threats. This research combines research evidence to improve understanding of the human readiness and resilience against AI-based cybersecurity threats.

2. Objectives

This study aims to identify and evaluate relationship between demographic and behavioural factors influencing awareness, cybersecurity practices, and confidence towards AI-enabled and dark web related crimes by answering following questions:

1. To determine whether gender influences the perception and preparedness related to AI and dark web based cyber threats.

2. To examine the predictive value of demographic variables like age, education, profession, and place of residence on the perception and confidence levels,

3. To evaluate how behavioural exposure measured through daily duration of online activities affects awareness and cybersecurity practices.

4. To assess the correlation between combined awareness and cybersecurity practice scores and the users' confidence in mitigating AI-based and dark web related threats.

3. Materials and Method

3.1 Study design

This study has employed a quantitative, cross-sectional survey design for assessing the perceptions of netizens regarding advanced AI-based crimes and dark web threats. The data has been collected from a well-structured questionnaire via google forms. The questionnaire was made based on current literatures present within this domain. The structured questionnaire was consisted of 5 sections. Section 1 has contained the description about the form and the title of the google form.

Section 2 has contained prior consents; those have been taken from the participants before filling the questionnaire. Along with it in this section age (in years), gender (male, female or others), educational level (high school, bachelor's degree, master's degree, or PhD/professional degree), professional hierarchy (unemployed, retired, student, non-tech professional, or tech professional), place of residence (rural, semi-urban, or urban) and the certain amount of time a netizen spends being online in hours has been asked to the participants. These variables were later analyzed to identify their correlation with perception scores.

Section 3 (named as awareness) was based on awareness questions related to different advanced AI based crimes like deepfakes, synthetically generated voice for mimicking real persons, AI automated phishing, utilization of dark web for illegal trading and hacking services, utilization of AI tools for creating fake identities or forged documents, AI generated malwares for avoiding detection, and face-swap deepfakes. Along with it, 3 additional questions were there related to checking participants idea about knowing atleast one method to differentiate between deepfake video, audio, and real ones, idea about that dark web is utilized for buying or accessing illegal services like stolen data, malware, and their idea about law enforcement can use forensic tools including AI to investigate these crimes, but these tools are not infallible. In this section, the participants have been asked to provide their responses based on trichotomous scale: yes, no, and not sure.

Section 4 (names as cybersecurity practices) was based cyber security practices done by the netizens in their daily life to protect themselves from these advanced crimes, or atleast they have idea about these practices or not. The questions were related to their response on, whether they use two factor or multiple factor authentication on at least one account or they regularly update their device operating system and antivirus or if they use password manager to manage important passwords, whether they verify unknown links or emails before clicking or use VPN, when they are on public Wi-Fi network. The responses collected in this section based on dichotomous scale: yes and no.

Section 5 (named as confidence), this final section was based on only question with was based on assessing the confidence of netizens in identifying and, mitigating advanced AI generated scams. The responses were recorded in this section based on 1 (not confident at all)-5 (highly confident) Likert scale.

The source of the questionnaire: https://forms.gle/FbgUWNpSRy4mxq6C7

3.2 Scoring Framework

The overall perception score was calculated by aggregating 3 factors- awareness score (data collected from section 3), section 4- cybersecurity practice score, (data collected from section 4) and confidence score (data collected from section 5).

Responses have been quantitatively coded for further statistical analysis.

- In the awareness section (section 3), responses were coded as yes= 1, no= 0, and not sure=0.
- In the cybersecurity practices section (section 4), responses were coded as yes= 1 and no= 0.
- In the confidence section (section 5), responses were already coded in 1 to 5 Likert scale.

Now, demographic data were also coded for further statistical analysis except age, daily duration of online activity, and gender.

- Education levels were coded as: high school= 1, bachelor's degree= 2, master's degree= 3, and PhD degree= 4. So, here education level was treated as ordinal variable. Because the categories highlight an order of progression of academic attainment. Previous academic works have also identified educational level as a canonical instance of an ordinal variable (Arvidsson, 2019; Miot, 2020; Shukla, 2023).
- Professional hierarchy were coded as: unemployed= 1, retired= 2, student= 3, non-tech professional= 4, and tech-professional= 5. This ordering reflects increasing levels of professional activity and technological exposure, both of which are theoretically related with awareness and confidence regarding AI based new age crimes. Previous literatures have also treated professional scale as ordinal, so this framework completely aligns with it (Avvisati, 2020; Pramanik et al., 2023; Saleem & Jan, 2021).
- Similarly, place of residence was also, coded as: rural= 1, semi-urban = 2, and urban = 3. This ordering has also reflected place of residence in ordinal scale because it is representing a progressive gradient of digital exposure and access to online digital ecosystem. Previous studies have highlighted that netizens in urban areas generally show higher digital literacy (Chaudhuri, 2024; Jagathkar & Jain, 2020). So, that completely supports the decision of assigning place of residence in ordinal scale.

3.3 Ethical Considerations

All respondants have provided informed consent in the time of participation in the google form. The study was conducted in compliance with research ethical guidelines by ensuring voluntary participation, confidentiality, and anonymity.

3.4 Data sorting and Statistical Analysis

The calculated perception scores of 204 respondants (n= 204) were assessed in relation to various demographic variables in *Microsoft Excel 2019*. Gender based variation of perception score has been examined using descriptive statistical analysis, followed by an independent samples *t*-test (assuming equal variances) because, *standard deviations (SD)* were nearly equal.

Now, the correlation of perception score and age were assessed using *Pearson's correlation test* because both variables were continuous and the relationship has been assumed linear. *Linear regression analysis* was later applied to model and quantify the direction and magnitude of the relation between them.

The correlation between educational level, professional hierarchy, place of residence with perception were assessed using *Spearman's rank correlation test* and *linear regression*, because of their ordinal nature.

Next, correlation between daily duration of online activity and perception score was also analyzed using *Pearson's correlation test* and *linear regression analysis.*

Lastly, the association between combined (awareness+ cybersecurity practice) score and confidence score was assessed using *Spearman's rank correlation* and *linear regression analysis*.

Scatterplot visualizations were used to illustrate correlational trends in this study.

3.5 Limitations:

It is cross sectional study, it could not prove the cause-and-effect relation, but only association between the variables. The research was conducted using an online Google form that may have introduced bias by excluding the individuals with low digital literacy. Data were collected through self-reported online questionnaire, which may bring response bias.

4. Result

Firstly, a descriptive statistical analysis has been performed to compare the average perception scores of both gender (male and female) towards AI-based crimes and dark web threats. Male respondants (n= 105, *M*= 15.246, SD= 3.42) and female respondants (n = 99, *M = 15.208,* SD= 3.36) has shown nearly identical mean perception score, as shown in table 1. The difference was very minimal, highlighting gender does not substantially affect overall perception of netizens in relation to awareness, cybersecurity practices and confidence toward advanced AI and dark web-based crimes and threats.

Table 1: Representation of descriptive statistical analysis of perception score of male and female responses.

Gender	**No. of Respondants (n)**	**Mean perception score (*M*)**	**Standard Deviation (SD)**
Male	105	15.24630542	3.429576
Female	99	15.20812183	3.364843

To confirm the finding, an independent sample *t*-test for equal variances was performed, because standard shown in the table 1 for both genders are nearly equal. The findings revealed that the mean perception for male respondants (15.13 ± 3.97) and female respondants (15.37 ± 2.76) have not differed significantly (t (202) = -0.50, p value > 0.05). The result confirms that gender has no significant impact on perception of the respondants.

x	Regression Equation	R	R^2	Percentage R^2	F (1,202)	p-value	β (Slope)
Age	y = -0.0302x + 16.094	0.102	0.011	1.06	2.16	0.143	-0.0302
Educational Level	y = 0.131x + 89.077	0.119	0.0142	1.42	2.91	0.090	0.131
Profession	y = 0.0551x + 96.852	0.051	0.0026	0.26	0.52	0.470	0.0551
Place of Residence	y = 0.1615x + 85.949	0.129	0.0167	1.67	3.44	0.065	0.1615
Daily Duration of Online Activities	y = 0.2786x + 13.987	0.187	0.0350	3.50	7.32	0.007	0.2786

Table 2: Representation of the findings of the statistical analysis for assessment of correlation between different demographic factors (x) and perception score (y)

Table 2 has presented the findings of correlational and regression analysis performed to assess the extent to which selected demographic and behavioural factors (x), such as: age, educational levels, profession, place of residence and daily duration online activities can predict perception score, which is again calculated by aggregating awareness score, cyber security practice score, and confidence in identifying AI- generated scams.

Person correlation was utilized for assessing the correlation between perception score and age, and daily duration of online activities respectively. Spearman correlation was utilized for educational level, profession, and place of residence because these variables ordinals and rank based, which has made non-parametric correlation more appropriate. Lastly, linear regression analysis was applied for all variables to examine predictive effects using a consistent modelling frame work.

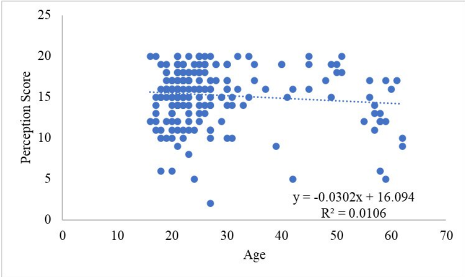

Figure 1: Scatterplot representation of correlation between age and perception (Source: Author)

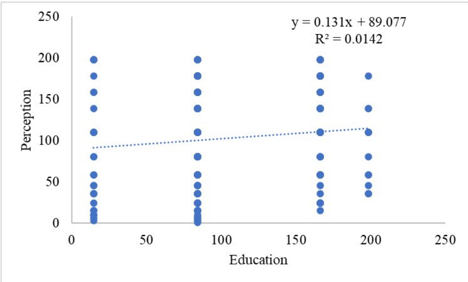

Figure 2: Scatterplot representation of correlation between education level and perception (Source: Author)

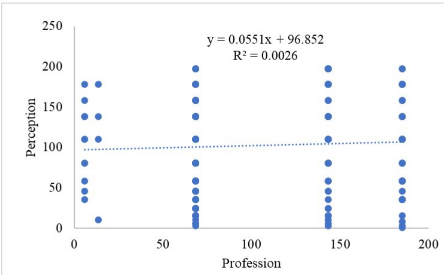

Figure 3: Scatterplot representation of correlation between profession hierarchy and perception (Source: Author)

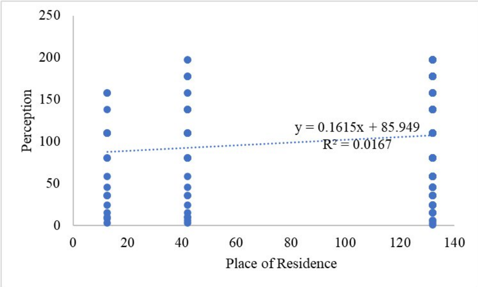

Figure 4: Scatterplot representation of correlation between place of residence and perception (Source: Author)

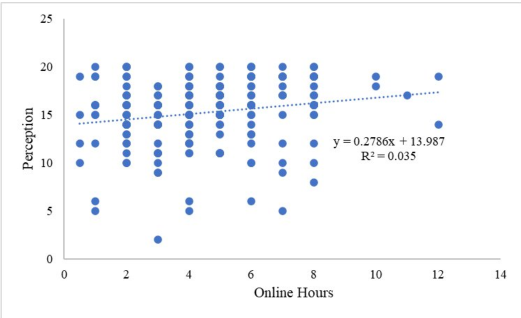

Figure 5: Scatterplot representation of correlation between daily duration of online activities and perception (Source: Author)

According to Table 2, The first analysis between age and perception score has indicated a weak and statistically non-significant influence of age on perception (F (1,202) = 2.16, p = 0.143), accounting for only 1.06% of the variance, based on R^2= 0.0106, as shown in figure 1. Similarly, educational level has shown a marginal positive trend (F (1,202) = 2.91, p = 0.090), but the effect has remained statistically in significant, with an explanatory power of just 1.42% (R^2= 0.0142), as shown in figure 2. The effect of profession was also notably negligible, contributing only 0.26% of the variance (R^2= 0.0026) and again failing to reach statistical significance (p= 0.470), as shown in figure 3. These findings have suggested that individuals across different academic and occupational strata illustrate comparable levels of awareness and cyber security preparedness.

Next, place of residence has presented a borderline trend (F (1,202) = 3.44, p = 0.065), yet has not contributed to the model, by accounting for only 1.67% of the variance (R^2=0.0167), as shown in figure 4.

But, in contrast, daily duration of online activities has only emerged as the only statistically significant predictor of perception of scores. This model for this variable has yielded a significant effect (*F* (1,202) = 7.32, p = 0.007) and explained 3.50% (R^2= 0.0350) of the variance, as shown in figure 5. The positive regression coefficient (β= 0.2786) has indicated that individuals with longer daily exposure has higher level of awareness, more systematic cyber-security practices, greater confidence in identifying and mitigating advanced AI and Darkweb based crimes and threats.

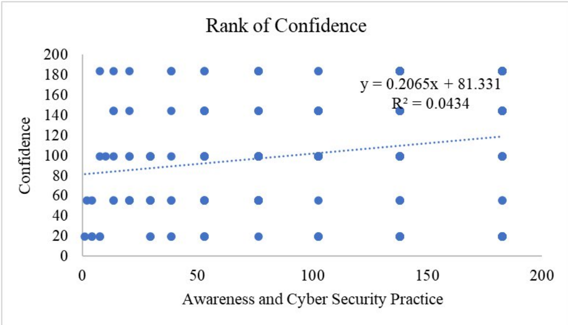

Figure 6: Scatterplot representation of correlation between combined awareness score and security practices with confidence of the respondants in identifying and mitigating new age AI based and Dark web-based crimes and threats. (Source: Author)

Lastly, another spearman correlation and simple linear regression analysis were performed to assess the association between combined awareness and cyber security scores of respondants and their confidence in identifying and mitigating new-age-AI-based and dark-web-related cyber-crimes and threats. The regression model was statistically significant (*F* (1,202) = 9.17, p = 0.003), and explained approximately 4.3% of the variance in confidence score (R^2= 0.0434), as shown in figure 6. These findings highlight that, the individuals with higher cyber-awareness and better proactive practices tend to show significantly higher confidence in identifying and mitigating emerging AI-driven and dark web enabled crimes and threats.

5. Discussion

The result in table 1 has shown that, gender did not appear to affect the overall perception of netizens related to advanced AI and dark web-based crimes. This finding clearly aligns with prior research. For instance, within a study of 579 adult participants examining different proactive netiquettes for cyber security practices, gender was not the significant predictor of security behaviour, even though males had scored high (Branley-Bell et al., 2022). At the same time, another previous literature emphasizes that, gendered norms, roles, and expectations may nevertheless impact how netizens engage with security related tasks and how training is designed and delivered. For another instance, a gender informed framework of cybersecurity design, defense, and response showcases that, woman may face different threat perceptions, different support networks, or additional burdens in the security practices (Millar et al., 2021).

The correlational and regression analyses represented in table 2 have showcased that age, education level, professional hierarchy, and place of resident (rural, semi-urban, or urban) have explained very small amount of variance in perception scores and none of them has reached the statistical significance of $p < 0.05$ except for daily duration of online activities. In simple words, netizens, who spend more time on internet have more idea about these types of crimes and threats. These findings align with researches in digital literacies and cyber-awareness, which highlight that exposure to digital ecosystem increase the opportunities both for encountering threats and learning protective behaviours (Hijji & Alam, 2022; Prümmer et al., 2024).

Similarly, research on digital literacy has demonstrated that while different demographic factors such as gender or education may set a background, but actual usage and engagement matter more for competence and awareness in the digital world (Deschênes, 2024; Musaddag Elrayah & Saima Jamil, 2023).

Future researches can pair perceptual measures with behavioural logs or simulated threat tasks to validate the relation between perception and actual security behaviour. More nuanced sub-fields like confidence vs actual cyber security practices, or awareness of niche dark-web threats vs general cyber security can reveal gender-based differences. Also, may be cultural or regional factors may interact with gender in such ways, those are not captured here and should be assessed. Future work should also integrate personality traits like risk taking and technology self-efficacy, peer networks and prior victimization experiences and training exposure.

6. Conclusion

This study examined how demographic and behavioural factors influence the volunteers' perceptions of advanced AI-based crimes and dark web threats. It evaluated this by integrating measures of awareness, cybersecurity practices, and confidence. The findings show that gender does not significantly influence overall perception, leading to comparable levels of awareness, practices, and confidence among male and female participants. This supports the existing evidence that gender alone is not a predictor of cybersecurity awareness, and preparedness related to AI-driven and dark web related crimes are uniform across traditional demographic categories.

In contrast, the daily duration of online activity is found as the only statistically significant predictor of perception. The individuals who spend longer time online exhibit higher awareness of cyber threats, more cybersecurity practices, and greater confidence in identifying AI generated scams. This finding supports the previous literatures that active engagement with digital ecosystem or simulated threat environments has an important role in creating cyber awareness and readiness.

Additionally, the positive association between combined awareness and cybersecurity practice scores and confidence proves that knowledge and proactive behaviour jointly improve the participants' self-efficiency in dealing with advanced cyber threats. The study shows the importance of digital engagement with experience, the awareness initiatives among the population, designing cybersecurity education, training programs, and policies in the era of AI-enabled cybercrimes.

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