INTERNET-BASED SOCIAL ENGINEERING ATTACKS, DEFENSES AND PSYCHOLOGY: A SURVEY

A PREPRINT

Theodore Longtchi1,* Rosana Montañez Rodriguez2,* Laith Al-Shawaf3 Adham Atyabi1

Shouhuai Xu1

August 2, 2022

1 Department of Computer Science, University of Colorado Colorado Springs, Colorado Springs, CO 80918
2 Department of Computer Science, University of Texas at San Antonio, San Antonio, TX 78249
3 Department of Psychology, University of Colorado Colorado Springs, Colorado Springs, CO 80918

* Shared first-author

ABSTRACT

Social engineering attacks are a major cyber threat because they often serve as a first step for an attacker to break into an otherwise well-defended network, steal victims’ credentials, and cause financial losses. The problem has received due amount of attention with many publications proposing defenses against them. Despite this, the situation has not improved. In this paper, we aim to understand and explain this phenomenon by looking into the root cause of the problem. To this end, we examine the literature on attacks and defenses through a unique lens we propose—psychological factors (PFs) and techniques (PTs). We find that there is a big discrepancy between attacks and defenses: Attacks have deliberately exploited PFs by leveraging PTs, but defenses rarely take either of these into consideration, preferring technical solutions. This explains why existing defenses have achieved limited success. This prompts us to propose a roadmap for a more systematic approach towards designing effective defenses against social engineering attacks.

Keywords: Social engineering attacks, email-based attacks, website-based attacks, online social network-based attacks, psychological factors, psychological techniques, phishing, deception

Correspondence: sxu@uccs.edu

1 Introduction

It is often said that humans are the weakest link in cybersecurity. However, the cause of this phenomenon is poorly understood, and solutions are elusive. These issues motivate us to take a deeper look into the following problems: (i) What is the root cause that enables social engineering attacks? (ii) Why have existing defenses achieved very limited success in mitigating social engineering attacks? (iii) What kinds of research need to be done in order to adequately mitigate social engineering attacks? In order to answer these questions, we need to narrow down the scope, since human factors are such a broad topic (see, e.g., [Montañez et al. (2022)]). This prompts us to focus on Internet-based social engineering attacks to which humans often fall victim. Specifically, we will focus on three classes of social engineering attacks: email-based, website-based, and online social network (OSN)-based social engineering attacks.

The importance of the aforementioned motivating problems in the context of Internet-based social engineering attacks is demonstrated by the multitude of studies on the aforementioned attacks and defenses against them, and by the many existing surveys from various perspectives of the problem (cf. [Das et al. (2019a); Khojaj et al. (2013); Zaimi et al. (2020); Dou et al. (2017); Aimomani et al. (2013); Basit et al. (2020); Ali et al. (2020); Jain and Gupta (2021); Sahu...].
Our Contributions. In this paper we systematize Internet-based social engineering attacks and defenses through the lens of psychology. We resolve the aforementioned motivating problems with a systematic characterization of attacks and defenses with respect to psychological factors and techniques that contribute to human susceptibility to social engineering attacks. Specifically, we make the following contributions.

First, we systematize the human psychological factors (PFs) that have been deliberately exploited by attackers to wage effective attacks, while noting that these factors have been scattered in the literature. The success of these attacks suggests that attackers have to give the problem due diligence in understanding PFs, especially those factors that can be exploited effectively. In order to deepen our understanding of how these PFs can be exploited to wage attacks, we further systematize what we call psychological techniques (PTs), which can be seen as the means of exploiting PFs. The PFs and PTs help understand the root cause that enable social engineering attacks from a psychological perspective. To the best of our knowledge, this is the first systematization of PFs and PTs with respect to social engineering attacks.

Second, we systematize Internet-based social engineering attacks, with emphasis on the PFs they exploit. This is made possible by the “bridge” of PTs. Moreover, we systematize defenses with an emphasis on whether a defense leverages certain PFs. We find that very few do. This means that most defenses are designed without considering the root cause of these attacks, which explains why current defenses have achieved limited success.

Third, the above finding prompts us to propose a research roadmap towards designing effective defenses. The roadmap is centered at creating a psychological framework tailored to social engineering attacks. The framework aims to tailor psychological principles to the cyber domain. The framework highlights the role and relevance of each PF, including the relationships between each. These relationships are important because they are not necessarily independent of, or orthogonal to, each other. The envisioned quantitative understanding will guide us to design effective defenses in the future.

Related Work. We focus on social engineering attacks in cyberspace, which is in contrast to social engineering attacks in the physical world. Table 1 contrasts the present survey with related previous surveys through the coverage of the following attributes: PFs are the human attributes that can be exploited by social engineering attacks (e.g., greed); PTs describe how social engineering attacks exploit PFs; Attacks waged by social engineering attackers (e.g., whaling); Defenses which have been proposed in the literature. For example, Khonji et al. [Khonji et al. (2013)] surveyed phishing definitions and detection methods. When compared with these studies, we stress two fundamentally important aspects: PFs and PTs, because we must understand them before we can design effective defenses. Indeed, this perspective has three immediate payoffs as shown in the paper: (i) we can map social engineering attacks to PFs through the “bridge” of PTs; (ii) defenders largely lag behind attackers because most defenses do not adequately take PFs into consideration, even though attacks have been regularly exploiting PFs in crafty ways, explaining the limited success of current defenses; (iii) this understanding prompts us to propose a research roadmap towards the development of effective defenses against social engineering attacks.

Paper Outline. Section 2 reviews some preliminary psychology knowledge and describes our methodology. Section 3 presents an overview of our study following the methodology. Section 4 systematizes PFs and PTs. Section 5 systematizes social engineering attacks. Section 6 systematizes defenses against social engineering attacks. Section 7 systematizes the relationships between PFs, PTs, social engineering attacks, and social engineering defenses. Section 8 presents a roadmap for future research directions. Section 9 concludes the present study.
Table 1: Comparison between existing surveys and ours, where a number in parentheses is the number of PFs or PTs discussed in a paper. Only Montañez et al. (2020) and the present paper systematize PFs even though Montañez et al. (2020) only discusses 19 PFs (which are significantly less comprehensive than the 41 discussed in the present paper); the others merely mention some PFs. Only the present paper explores the relationships between the PFs, PTs, attacks, and defenses.

| Ref.                          | PFs | PTs | Attacks | Defenses | Relationships |
|-------------------------------|-----|-----|---------|----------|---------------|
| Das et al. (2019a)            | ✓ (6)| ✓   | ✓       | ✓        |               |
| Khonji et al. (2013)          | ✓   | ✓   | ✓       |          |               |
| Zaimi et al. (2020)           | ✓   | ✓   | ✓       |          |               |
| Dou et al. (2017)             | ✓   | ✓   | ✓       |          |               |
| Almomani et al. (2015)        | ✓   | ✓   | ✓       |          |               |
| Bast et al. (2020)            | ✓   | ✓   | ✓       |          |               |
| Ali et al. (2020)             | ✓   | ✓   | ✓       |          |               |
| Jain and Gupta (2021)         | ✓   | ✓   | ✓       |          |               |
| Sahu and Dubey (2014)         | ✓   | ✓   | ✓       |          |               |
| da Silva et al. (2020)        | ✓   | ✓   | ✓       |          |               |
| Alabdan (2020)                | ✓ (19)| ✓ | ✓       |          |               |
| Vijayalakshmi et al. (2020)   | ✓   | ✓   | ✓       |          |               |
| Jampen et al. (2020)          | ✓ (18)| ✓ | ✓       |          |               |
| Chanti and Chithralekha (2020)| ✓   | ✓   | ✓       |          |               |
| Rastens et al. (2020)         | ✓   | ✓   | ✓       |          |               |
| Gupta et al. (2018)           | ✓   | ✓   | ✓       |          |               |
| Chiew et al. (2018)           | ✓   | ✓   | ✓       |          |               |
| Alroud and Zhou (2017)        | ✓   | ✓   | ✓       |          |               |
| Yasin et al. (2019)           | ✓   | ✓   | ✓       |          |               |
| Montañez et al. (2020)        | ✓ (19)| ✓ | ✓       |          |               |
| Gupta et al. (2016)           | ✓   | ✓   | ✓       |          |               |
| Heartfield and Loukas (2015)  | ✓ (2)| ✓   | ✓       |          |               |
| Alharthi et al. (2020)        | ✓   | ✓   | ✓       |          |               |
| Salahdine and Kaabouch (2019) | ✓   | ✓   | ✓       |          |               |
| The present paper             | ✓ (41)| ✓ (13)| ✓       | ✓        | ✓             |

2 Psychological Preliminaries and Study Methodology

2.1 Psychological Background Knowledge

We briefly review the psychological background knowledge that is helpful for understanding the paper. This knowledge serves as a baseline for guiding us in defining what constitute as PFs.

**Big Five Personality Traits (BFPT).** The Five Factor Model of personality traits – also known as the Big Five – refers to the five factors that constitute the basic structure of human personality [Goldberg, 1981]. These factors, discovered using factor analysis and other statistical techniques, are OPENNESS, CONSCIENTIOUSNESS, extraversion, agreeableness, and neuroticism. The evidence for the existence and robustness of the Big Five comes from numerous studies conducted in different languages and across cultures over the span of many decades [Costa Jr and McCrae, 2008; Digman, 1990; McCrae and John, 1992]. These basic personality traits are relatively stable across the lifespan, and they predict life outcomes ranging from career success to likelihood of divorce to lifespan longevity [Soto, 2019]. They even appear to be present in other species [Nettle, 2006]. Given this robustness and for the purposes of the present paper, each of the five factors constitutes a PF.

**Cialdini’s Principles of Persuasion.** Persuasion Principles are a set of strategies used to influence individuals into behaving in a desired way. These principles, derived from field studies on sales and marketing [Cialdini and James, 2009], include: (i) LIKING which denotes being easily influenced by those one likes or those with common beliefs as them; (ii) RECIPROCATION which denotes feeling obliged to return a favor; (iii) SOCIAL PROOF (conformity) which denotes imitating the behaviours of others; (iv) CONSISTENCY (commitment) which denotes consistency of behaviour or sticking to a promise; (v) AUTHORITY, which denotes submitting to experts or obeying orders from one’s superior or authoritative figures; and (vi) SCARCITY which denotes placing more value on things that are in short supply. When persuasion is undetected, it encourages the use of heuristic reasoning [Cialdini and James, 2009]; Cialdini and Trox.  

3
The use of persuasion in social engineering messages has been studied extensively by Lin et al. (2019a); Rajivan and Gonzalez (2018); Ferreira and Lenzini (2015); Stajano and Wilson (2011); Van Der Heijden and Allodi (2019). For the purposes of this paper, each of the six persuasion principles constitutes a PF.

2.2 Study Methodology

Scope. Since social engineering attacks are a broad topic, we choose to focus on Internet-based social engineering attacks, especially the ones exploiting emails, websites, and online social networks (OSNs). Therefore, the term “social engineering attacks” or simply “attacks” in this paper refers to these attacks. We will use terms “individuals” and “users” interchangeably; the term “victims” refer to the users that are successfully compromised by social engineering attacks.

Methodology. In order to understand why humans are susceptible to social engineering attacks, we aim to systematize the PFs and PTs that have been, or could be, exploited by attacks. In this paper, the term psychological factor is used to represent the psychological attributes that can be exploited by attacks (i.e., what to exploit). In order to make our definitions of PFs psychological sound, we leverage the afore-reviewed BFPT and Principles of Persuasion among others from Cognitive Psychology, to define PFs to guide us in identifying other psychological attributes that can be deemed as PFs in a psychological sense. By contrast, the term PT is used to describe how attacks exploit these factors. This distinction turns out to be useful because the PTs will be leveraged to build a “bridge” for mapping attacks to PFs. In other words, PTs build a bridge between the two disciplines of psychology and cybersecurity. Note that one PT can exploit multiple PFs and one PF can be exploited by multiple PTs.

Searching academic publication databases with social engineering related keywords
Manually filtering the papers resulting from the search according to their relevance
Systematizing psychological factors and techniques
Systematizing social engineering attacks
Systematizing social engineering defense
Systematizing relationships between psychological factors and techniques, attacks and defenses
Leveraging the understanding to draw insights into future research directions

Figure 1: Methodology of our study

Figure 1 highlights our methodology, which can be adopted or adapted by others to conduct their own studies. The methodology consists of the following five steps. First, identify the relevant literature, ideally automatically or semi-automatically because there are so many publications. Second, manually filter the papers resulting from the previous step according to their relevance to the purpose of the study. The preceding two steps correspond to preparation. Third, extracting and systematizing the PFs, PTs, attacks, and defenses that are discussed in the papers resulting from the previous step. Fourth, systematizing the relationships between the PFs, PTs, attacks, and defenses identified from the previous step. Fifth, leveraging the understanding resulting from the systematization to draw insights into future research directions.

Note that the methodology can have useful variants. For example, it can be adapted to search the literature in an iterative fashion when one does not know enough information about PFs, PTs, attacks, or defenses; in this case, it may be helpful to start the search with few well-known keywords, filtering the resulting literature, and extracting other PFs, PTs, attacks, or defenses for further search. This iteration can also be leveraged to assure whether some relevant papers are overlooked. As another example, one can incorporate the PFs, PTs, attacks, and defenses that are known to the investigator but are not found in the academic literature. As we will see, this is particularly relevant to attacks because there can be attacks that are discussed by practitioners in social media but are not investigated in the academic literature yet.
3 Systematization Overview

The overview corresponds to the five steps of the methodology. First, to identify papers for manual filtering, we consider the following digital libraries: IEEE (including IEEE Symposium on Security and Privacy and IEEE Transactions), ACM (including ACM Conference on Computer and Communications Security and ACM Transactions), Usenix (including Usenix Security Symposium), and Network and Distributed System Security Symposium (NDSS), Elsevier, Springer, PlosOne, Wiley, Frontiers in Psychology, and Information & Computer Security (ICS). These venues are selected because they are the main security venues or psychological venues that publish social engineering related papers. We start the search with the only keyword “social engineering”, which yields thousands of papers. Since it is infeasible to manually filter this many papers, we add another keyword “phishing” (i.e., a paper is relevant when containing these two keywords simultaneously). We choose phishing because it is the most common social engineering attack [Touchstone (2021); kaspersky (2022)] and may have been more widely studied from a psychological perspective.

Second, the search identifies 663 papers. We manually examine these papers based on their treatment and relevance to the motivation and scope of the present study, leading to 154 papers which include 24 survey/review papers (while noting that the other references are cited for further exploration purposes, such as those published in psychology literature). We eliminate the papers that just mention social engineering and/or phishing without presenting substantial investigation; 268 papers fall into this category. We further eliminate the ones that do not consider specific PFs or do not consider Internet-based social engineering attacks; 146 papers fall into this category. Finally, we look into the remaining 249 papers and eliminate the ones that do not appear to present a high-quality exploration (which is a judgement call), ending up with the aforementioned 154 papers for systematization.

Third, given the 154 papers (including the 24 surveys), we initially identified 63 PFs from these papers where each PF is discussed in one or multiple papers as a psychological factor that has an impact on social engineering attacks. We found that these PFs contain some redundant ones. This prompts us to eliminate the redundant ones as follows. (i) If two PFs are considered similar to each other in a psychological sense, we keep the PF that is investigated in a quantitative fashion, representing a deeper understanding. (ii) If two PFs are considered redundant in a psychological sense but none of them is investigated in a quantitative fashion, we keep the PF that is most relevant to this paper. (iii) If two PFs are considered redundant and both are investigated in a quantitative fashion, we keep the one that is more often used in the literature according to our psychological knowledge. This pre-processing leads to 41 PFs, which are PFs that are widely accepted in the psychology community, as reviewed above. One example of the preceding (i) is the pair of PFs known as "false consensus effect" and "social proof", which are considered redundant in their psychological meanings. We keep the latter because it is investigated in a quantitative fashion [Das et al. (2014)]. On example of the preceding (iii) is the pair of PFs known as "inattentiveness" and "lack of vigilance", which are redundant because they essentially represent the same psychological factor. Since they both have been investigated in a quantitative fashion [Tu et al. (2019)], we keep the former because the former is used in the literature more often (perhaps because of its succinctness). After finalizing the 41 PFs, we leverage our psychological expertise to classify them into five classes: cognitive, emotion, social psychology, personality and individual difference, and workplace PFs. These PFs help understand the root cause of social engineering attacks from a psychological perspective.

In addition, we systematize the 13 PTs that have been mentioned in the literature. At this point, it is not clear to us how to further group these 13 PTs into a smaller number of categories. We hope future studies can resolve this issue. We systematize attacks with respect to those PFs, including the PF(s) exploited by an attack and the extent to which a PF’s impact on human susceptibility has been quantified. We systematize defenses with respect to the attacks, leading to defenses against email-based, website-based, and OSN-based attacks, respectively.

Fourth, we systematize the relationships between the PFs, PTs, attacks and defenses by proposing mappings between them. This is made possible because the PTs serve as a “bridge” between the attacks and the PFs. It is ironic to observe that only one PF has been leveraged by defenses. Nevertheless, the mapping gives a succinct representation of the state-of-the-art knowledge in this domain, and also allows us to understand the motivating problem of the cause of the limited success of existing defenses.

Fifth, we propose a roadmap for future research to pursue the motivating problem of finding the solution to internet-based social engineering attacks. The roadmap is prompted by the observation that very few empirical studies have been carried out to quantify the impact of PFs on the susceptibility of humans to social engineering attacks. The few studies that attempted quantitative studies have some drawbacks, such as involving a small number of participants (e.g., 53 participants [Welk et al. (2015)] or participants being undergraduate students [Welk et al. (2015); Hong et al. (2013); Tu et al. (2019)] (rather than average users). The lack of quantitative results published in the literature (e.g., the impact of PFs) prevents us from conducting any meta-analysis.
4 Systematizing Psychological Factors and Techniques

4.1 Systematizing Psychological Factors (PFs)

We categorize the PFs that may be exploited by Internet-based social engineering attacks into five groups, with 42 factors in total: (i) **cognitive PFs**, which describe how individuals process information; (ii) **emotion PFs**, which describe individuals’ feelings, motivational state, and approaches or avoidance behaviors; (iii) **social psychology PFs**, which describe individuals’ interpersonal attributes in various groups; (iv) **personality and individual difference PFs**, which are individuals’ relatively stable attributes; and (v) **workplace PFs**, which describe cultural and organizational interactions within a workplace. Note that there is more than one way to divide these factors. We have adopted this framework because it is in line with the traditional branches and subdivisions in psychology, and because it may help readers decide where to direct their efforts in training victims to become less vulnerable – but it is not a conclusive categorization.

It is worth mentioning that the categorization is somewhat subjective because several PFs can fall into more than one category. For example, we have listed **overconfidence** as a **cognitive PF**, but it could reasonably be considered an **personality and individual difference PF** because there are stable individual differences in this factor.

**Cognitive PFs.** These PFs describe how an individual processes information, including heuristics they may use, the knowledge they may possess, the confidence they may exhibit, and the attention they may give.

1. **Cognitive Miser.** This PF describes one’s use of decision-making heuristics, namely the use of mental shortcuts in a decision-making process [McAlaney and Benson (2020)]. Generally speaking, people tend to be cognitive misers and rely more on heuristic-based processing to make decisions [Kim and Lee (2021)]. McAlaney and Hills [McAlaney and Hills (2020)] argued that people are motivated tacticians and will apply a cognitive miser (or naïve scientist) approach based on the urgency, perceived importance and complexity of the situation.

2. **Expertise.** This PF describes one’s knowledge about a particular domain. Albladi and Weir [Albladi and Weir (2020)] showed that expertise plays a role in raising an individual’s perception of risk associated with online social networks, but the perceived risk does not significantly increase individuals’ competence in coping with these threats. Qualitatively speaking, expertise does not necessarily make one less vulnerable to social engineering attacks [Chafir et al. (2016), Das et al. (2019b)]; quantitatively speaking, expertise, when effectiveness, does make one more capable in coping with social engineering attacks (i.e., incurring lower false-positive and false-negative rates [Henshel et al. (2015)]. Redmiles et al. [Redmiles et al. (2020)] show that the expertise associated with a given social-demographic background may affect the prioritization of advice in coping with online threats.

3. **Overconfidence.** This PF describes individuals’ tendency in having too much confidence in themselves [Williams et al. (2017)], especially their ability to detect phishing [Chen et al. (2020)], which can be improved via education and training [Moody et al. (2017)]. This PF may correlate with too much self-confidence [House and Raja (2020)]. In an experiment with 53 undergraduates students (34% computer science majors, 66% psychology majors), Hong et al. [Hong et al. (2013)] found that approximately 92% of participants misclassified phishing emails even though 89% had earlier indicated that they were confident of their ability to identify phishing emails.

4. **Absentmindedness.** This PF describes the degree to which one’s attention is diverted from a particular task. Reb et al. [Reb et al. (2015)] found that employees’ absentmindedness is positively related to emotional exhaustion, which negatively affects job performance. Absentminded people can easily click phishing links because they do not pay attention to what they are doing [Zafar et al. (2019)]. Collier and Collier (2020).

It is intuitive that **cognitive PFs** play important roles in influencing individuals’ susceptibility to social engineering attacks. However, our understanding is superficial.

**Emotion PFs.** These PFs describe human feelings, motivational states, and approaches or avoidance behaviors. They include so-called **visceral triggers**, which are strong internal drivers to satisfy a basic need.

1. **Greed.** This PF is well recognized [Mondal et al. (2019), Kano and Nakajima (2021), Alyahya and Weir (2021), Wang et al. (2017), Alabdan (2020), Chiew et al. (2018), Yasin et al. (2019)] and describes one’s intense and selfish desire for something, especially wealth, power, or food. **Greed** is one of the persuasion tools used in phishing attacks [Siadati et al. (2017)] and is often paired with need (i.e., the attacker knows what a victim needs and present what the victim needs as a bait) [Ferreira (2018)]. Greed is recognized by some researchers as a human limitation when comparing human-based security versus technology-based security [Safalbine and...
The preceding discussion suggests that emotion first are derived from Cialdini's principles of persuasion. Demand/request interactions between the individual and one or more others. There are 8 such PFs, among which the Social Psychology PFs or quantitative understanding of their impact on individuals' susceptibility to attacks. Worth mentioning that attackers often exploit Authority (described below) Schaab et al. (2017). Bullée et al. (2018) found that reciprocation is the third most used principle of persuasion exploited by social engineering attacks. This PF is often exploited in online scams Williams et al. (2017); Bullée et al. (2018) and phishing emails. For example, social engineer attacks. Williams et al. (2017). Authority is a vulnerability trigger which social engineering attackers use Authority to lure their victims to divulge confidential information, especially through spear phishing Zheng et al. (2019). Bullée et al Bulée et al. (2018) found that, out of the six principles of persuasion, the effect of authority alone exceeds that of the other five principles together. It is worth mentioning that attackers often exploit Authority and Scarcity (which is described below) together Zheng et al. (2019). An empirical study with 612 participants Workman (2007) showed that individuals who are more obedient to authority succumb more frequently to social engineering attacks.

Social Psychology PFs. These PFs describe one’s interpersonal behaviors and often involve connection, influence, and demand/request interactions between the individual and one or more others. There are 8 such PFs, among which the first 6 are derived from Cialdini’s principles of persuasion.

1. Authority. This PF describes power or dominance over someone Aldawood and Skinner (2019b). Social engineering attackers use Authority to lure their victims to divulge confidential information, especially through spear phishing Zheng et al. (2019). Bullée et al. (2018) found that, out of the six principles of persuasion, the effect of authority alone exceeds that of the other five principles together. It is worth mentioning that attackers often exploit Authority and Scarcity (which is described below) together Zheng et al. (2019). An empirical study with 612 participants Workman (2007) showed that individuals who are more obedient to authority succumb more frequently to social engineering attacks.

2. Reciprocation. This PF describes the tendency to pay back a favor done for them in the past Lea et al. (2009). Lin et al. (2019b). Ghair et al. (2016). It is sometimes tied to people’s urge to consistency (described below) Schaab et al. (2017). Bullée et al. (2018) found that reciprocation is the third most used principle of persuasion exploited by social engineering attacks.

3. Liking (similarity). This PF describes individuals’ tendency to react positively to those with whom they hold some kind of relationship Schaab et al. (2017). It reflects that people may be persuaded to obey others if they display certain favourable or familiar characteristics Frauenstein and Flowerday (2020). This PF has been exploited to create profiles that portray trusted traits or appear friendly to lure victims Williams et al. (2017). Bullée et al. (2018) found that Liking is widely exploited by social engineering attacks. Hatfield Hatfield (2018) found that Liking is an individual variable that explains a person’s tendency to fall victim to social engineer attacks.

4. Scarcity. This PF describes the lack of goods/services and is used to lure their victims. It has been widely exploited in online scams Williams et al. (2017); Bullée et al. (2018) and phishing emails. For example, Heijden et al. Van Der Heijden and Allden (2019) found that Scarcity is a vulnerability trigger which social engineering attackers often craft in their phishing emails to push users to respond. This PF is often exploited together with the Authority PF to lure victims into submitting to their demands Zheng et al. (2019); Kearney and Kruger (2016).
5. **Social Proof.** This PF describes one’s tendency to imitate others regardless of the importance or correctness of the behavior [Algarni et al. (2017); Frauenstein and Flowerday (2020); Van Der Heijden and Allodi (2019); Moody et al. (2017); Wang et al. (2021)]. It can put people at risk because they tend to let down their suspicion when everyone else appears to share the same or a similar behavior [Schaab et al. (2017)]. In an experiment with 50,000 Facebook users, Das et al. [Das et al. (2014)] found that users with ten or more Facebook friends tend to update their security settings after being informed that their friends have updated their own security settings.

6. **Consistency (aka Commitment).** This PF describes the degree to which one is dedicated to a person, object, task, or idea [Wang et al. (2021)]. Social engineering attacks use commitment to persuade their victims [Ghafir et al. (2016); Algarni et al. (Algarni et al. (2017))]. found that dogmatic adherence to past decisions may influence the decisions a person will make in the future. Social engineering attacks can exploit this consistency to exploit victims without their knowledge [Van Der Heijden and Allodi (2019); Kano and Nakajima (2021)].

7. **Disobedience.** This PF describes one’s dogmatic refusal to obey authority or rules set forth by authority, which can make one susceptible to social engineering attacks [Collier and Collier (2020)]. While it is well known that people who are more trusting and obedient to authority are more susceptible to social engineering attacks [Jampen et al. (2020)], it is less known that willful disobedience of employees can also be exploited by social engineering attacks [Kirlappos et al. (2014)].

8. **Respect.** This PF describes an individual’s esteem for another, which is the degree to which they are perceived as valuable or worthwhile to the individual in question [Algarni et al. (2017)]. For example, an individual may not question a suspicious request from a friend (e.g., an unsolicited email that contains a link) out of respect for their relationship [Redmiles et al. (2018)]. This PF may be exploited together with the aforementioned **Authority** [Abe and Soltys (2019); Ghafir et al. (2016)].

The preceding discussion suggests the following PFs have been widely exploited by social engineering attacks: **Authority, Scarcity, Liking (Similarity),** and **Reciprocity.** Deep understanding of these PFs might shed light on the design of effective defense. For example, an effective defense may first identify whether an incoming email falls into the **Authority** category and if so tailored defenses may be used to decide whether the email is indeed from an authority; this would be more effective than using the same detector which treats all incoming emails equally without leveraging the PFs behind them.

**Personality and Individual Difference PFs.** These PFs are relatively stable and dispositional and differentiate one individual from another. For example, some people are habitually more meticulous and attentive to detail than others, while some people are habitually more trusting.

1. **Disorganization.** This PF describes the tendency of an individual to act without prior planning or to allow their environment to become or remain unstructured or messy. These conditions may blind them to anomalies or cues of social engineering attacks, resulting in higher susceptibility [Collier and Collier (2020)].

2. **Freewheeling.** This PF describes the degree of one’s disregard for rules or conventions and of their unconstraint or disinhibition. This PF contributes to ones’ susceptibility to social engineering attacks [Collier and Collier (2020)].

3. **Individual Indifference.** This PF describes the degree to which one shows disinterest toward an assigned or necessary task. A sustained indifference towards security can cultivate a culture of risky human behaviors, which can be exploited by social engineering attacks [Chowdhury et al. (2019)].

4. **Negligence.** This PF describes an individuals’ failure to take proper care during a particular task. It is an important reason of security breaches [Safa et al. (2015); Adil et al. (2020); Li et al. (2019); Ndibwile et al. (2019)]. Li et al. [Li et al. (2019)] reported that 27% of data breaches are due to negligent employees or contractors, who usually have remote access to organizations’ internal networks.

5. **Trust.** This PF describes the tendency of one to trust or believe in someone else (i.e., not doubting the honesty of others). People who are more trusting are more susceptible to social engineering attacks [Jampen et al. (2020)], which is not surprising because developing trust is a key element of social engineering attacks [Zheng et al. (2015a); Aldawood and Skinner (2019b)]. Moreover, people are predisposed to trust others they view as likable and phishers make use of this PF to scam victims [Hattfield (2018)]. In a study with 612 participants, Workman [Workman (2007)] found that people who are more trusting succumb more frequently to social engineering attacks.

6. **Self Control.** This PF describes one’s ability to regulate their decision-making processes in the face of strong emotions and desires. A lack of self control allows individuals to fall victim to online scammers [Williams et al. (2017)]. Individuals with low self-control tend to exhibit a higher willingness to take risks in situations that violate cybersecurity principles [Chowdhury et al. (2019); Van de Weijer and Leukfeldt (2017); Hoit et al. (2020)].
7. **Vigilance.** This PF describes the degree to which one is watchful for possible dangers or anomalies. A high vigilance makes one less vulnerable to social engineering attacks. In a phishing experiment with 3000 university students, it was found that vigilance reduced susceptibility to scams. However, even though an individual with a high vigilance, who usually does not want to open a suspicious email, may actually end up opening it due to spontaneous curiosity. This highlights the possible interactions between PFs, namely that one PF may dominate another under certain circumstances, which explains the difficulty in coping with social engineering attacks.

8. **Impatience.** This PF describes one’s frustration while waiting for a particular event to occur or at the length of time needed to accomplish a task. Impatience makes people unwilling to do the necessary work or apply the effort to mitigate risk, and thus makes them more susceptible to social engineering attacks.

9. **Impulsivity.** This PF describes the tendency of one acting without much thought. Online scammers exploit victims’ impulsivity to encourage errors in judgement and decision-making or serve as a persuasion technique to lure their victims. It has been found that impulsivity better managed phishing emails.

10. **Submissiveness.** This PF describes the degree of one’s readiness to conform to authority or will of others. In a study with approximately 200 participants, it is found that high submissiveness implies a high susceptibility to phishing emails.

11. **Curiosity.** This PF describes the degree at which one desires to know something. Online scammers exploit victims’ curiosity to encourage errors in judgement and decision-making or serve as a persuasion technique to lure their victims. A study found that those who are sensation-seeking, which is a form of impulsivity, were more likely to become scammed.

12. **Laziness.** This PF describes the degree of one’s voluntary inactivity to carry out the work required to accomplish it. Laziness makes people unwilling to do the necessary work or apply the effort to mitigate risk, and thus makes them more susceptible to social engineering attacks.

13. **Vigilance.** This PF describes the degree to which one is watchful for possible dangers or anomalies. A high vigilance makes one less vulnerable to social engineering attacks.

14. **Openness.** This PF describes one’s active imagination and insight. Individuals with high openness are often curious about the world and other people, eager to learn new things, enjoy new experiences, and are more adventurous and creative. High openness has been found to increase susceptibility to phishing attacks.

15. **Conscientiousness.** This PF describes one’s thoughtfulness, impulse control, and goal-directed behaviors. People with high conscientiousness tend to be organized, mindful of details, self-disciplined, goal-oriented, proficient planners, and considerate about how their behaviors might affect others. It is found that people with a high conscientiousness are less susceptible to spear phishing attacks.

16. **Extraversion.** This PF, also known as extroversion, describes the degree to which one is sociable, assertive, talkative, and emotionally expressive. People with a high extraversion are outgoing and tend to gain energy in social situations. A study found that extraversion (and openness and agreeableness) increase one’s susceptibility to phishing attacks.

17. **Agreeableness.** This PF describes one’s attributes related to trust, altruism, kindness, affection, and other prosocial behaviors. A study found that people with a high agreeableness (and neuroticism, which is described below) are more susceptible to phishing attacks.

18. **Neuroticism.** This PF describes one’s moodiness and emotional instability. People with high neuroticism often exhibit mood swings, anxiety, irritability, and sadness. Individuals with high neuroticism are more susceptible to phishing attacks.

We observe that enhancing some PFs (e.g., vigilance) and reducing others (e.g., openness) can reduce one’s susceptibility to social engineering attacks. These should be leveraged to design future defenses. Moreover, the PFs are not independent of, or orthogonal to, each other. This suggests the importance of characterizing the relationships between them (e.g., “openness increases curiosity”) because it would help identify the root cause of susceptibility to social engineering attacks.
Workplace PFs. These PFs have to do with the culture and organizational structure of workplace. This is relevant because various workplace environments may result in various levels of stress, employee engagement, or employee loyalty.

1. **Workload.** This PF describes the amount of work that one has to do. A survey of 488 employees at three hospitals showed that the level of employee workload is positively correlated with the likelihood of employees clicking on phishing links [Jalali et al. (2020)]. Another study found that subjective mental workload creates memory deficit that leads to an inability to distinguish between real and fake messages, increasing susceptibility to attacks [Aldawood and Skinner (2019a)].

2. **Stress.** This PF describes the physical, emotional, or psychological strain on a person incurred by their environment. It has been found that when people are stressed, their ability to notice suspicious communications (e.g., distinguishing real from fake messages) is reduced, making them more susceptible to social engineering attacks [Williams et al. (2017); Aldawood and Skinner (2019a)].

3. **Busyness.** This PF describes the degree to which one has too much to do, which may or may not be associated with workload. People with a high busyness are more susceptible to phishing emails as they do not pay much attention to details [Chowdhury et al. (2019)] or have reduced cognitive processing [Conway et al. (2017)].

4. **Hurry.** This PF describes the degree one is rushing to complete a task. Hurried people may not adhere to secure practices because they reduce the amount of time available for the individual’s active task [Chowdhury et al. (2019)]; these people are susceptible to social engineering attacks under these circumstances [Rastenis et al. (2020)].

5. **Affective Commitment.** This PF describes one’s emotional attachment to an organization. A study with 612 participants found that people with a high affective commitment more likely fall victim to social engineering attacks [Workman (2007)].

6. **Habitation.** This PF describes one’s tendency to perform a particular task repeatedly. A study on how users perceive and respond to security messages using eye-tracking with 62 participants found that people gazed less at warnings over successive viewings (i.e., they were more habituated to the warnings) and thus were less attentive to security warnings [Brinton Anderson et al. (2016)]. In other words, increased habituation increases susceptibility to attacks.

The preceding discussion suggests that workplace PFs have a significant impact on individuals’ susceptibility to social engineering attacks and should be taken into consideration when designing future defenses.

### 4.2 Systematizing Psychological Techniques (PTs)

Our analysis of the literature prompts us to consider the following 13 PTs.

1. **Urgency.** Urgency has an impact on cybersecurity when a victim is confronted with a situation which requires immediate action or is ostensibly under time pressure [Chowdhury et al. (2019)], such as decreasing the chance of detecting deceptive elements in a message [Vishwanath et al. (2011)]. It leverages the cognitive miser, fear and negligence PFs. It is often used in scareware attacks to urge users to install software to avoid threats (e.g., viruses) or missing a plug-in which prevents them from viewing some desired contents [Nelms et al. (2016)].

2. **Attention Grabbing.** This technique uses visual and auditory elements to prompt a victim to focus attention on deceptive attack elements to increase compliance. It leverages the absentmindedness and curiosity PFs. The malvertising, scareware, and click-baiting attacks use attention grabbing along with visceral triggers and incentives (below) to encourage compliance [Nelms et al. (2016)].

3. **Visual Deception.** This technique repurposes benign visual elements to induce trust [Vishwanath et al. (2011)]. It leverages the overconfidence, trust, and habituation PFs. The typosquatting and clone-phishing attacks exploit this technique by creating URLs that are visually similar to benign URLs.

4. **Incentive and Motivator.** This technique encourages a desired behavior or compliance with a request. Incentive provides external rewards for action, while motivator provides internal rewards (i.e., gratification) for an individual. In social engineering attacks, incentive often leverages visceral triggers, which are commonly used in malvertising and click-baiting attacks as well as in the Nigerian scam [Herley (2012)]. Motivator exploits sympathy, empathy, loneliness, and disobedient. Wire transfer scams exploit victims’ sympathy for the attacker as a motivator to encourage someone to transfer money to an attacker who claims to have made an erroneous money transfer.
5. **Persuasion.** This technique encourages a particular behavior by exploiting the LIKING, RECIPROCATION, SOCIAL PROOF, CONSISTENCY, and AUTHORITY PFs. The effectiveness of each persuasion technique depends on other things like age [Lin et al. (2019b)] and request type [Goel and Jain (2018); Alohal et al. (2018)]. The use of persuasion is prevalent in email-based attacks such as phishing [Goel and Jain (2018); Ferreira and Lenzini (2015); Wright et al. (2014)].

6. **Quid-Pro-Quo.** Quid-Pro-Quo in Latin means "something for something". This technique attempts to make a victim willing to take risk on exchange for a high payoff (e.g., money, free services or avoiding embarrassment). It leverages the RECIPROCATION, GREED, and DISHONESTY PFs [Stajano and Wilson (2011)]. For example, an attacker can impersonate a police officer to make a victim pay for illegal content (e.g., pornography) on the victim’s computer [Heartfield and Loukas (2015)]; otherwise, the attacker threatens with arresting the victim for the possession of illegal content. In the Nigerian Prince Scam (419) [Herley (2012)], the Quid-Pro-Quo is the expectation that the victim give a small amount of money to receive a larger amount of money later.

7. **Foot-in-the-Door.** This technique attains compliance for a large request by making small requests over time [Freedman and Fraser (1966)]. It exploits the CONSISTENCY PF. It is commonly used in honey trap and catfishing.

8. **Trusted Relationship.** This technique exploits an existing trust relationship by taking advantage of the AUTHORITY, RESPECT, and TRUST PFs. For example, through LinkedIn (a trusted service provider), an attacker posing as a recruiter can connect to employment-seeking victims [Alodi et al. (2019)]; spambexing (SEO) exploits a user’s trust in a search engine provider’s (e.g., Google) results; Business Email Compromise exploits the trusted relationship between an executive staff officer and a subordinate employee.

9. **Impersonation.** This technique assumes a false identity to increase a victim’s compliance. It exploits the AUTHORITY, RESPECT and TRUST PFs. In OSN-based attacks like Honey Trap, an attacker uses fake profiles to lure victims into interacting with them [Algarni et al. (2017)]; an attacker using Business Email Compromise assumes the persona of a senior executive to exploit their authority by prompting a victim to transfer money to an account [Junger et al. (2020)].

10. **Contextualization.** This technique projects an attacker as a member of the victim’s group in order to establish commonality with potential victims and increase the success of attacks [Goel et al. (2017); Rajivan and Gonzalez (2018)]. It is often used in attacks like whaling, catfishing, and drive-by downloads [Goel and Jain (2018)].

11. **Pretexting.** This technique increases the engagement of victim with the attacker. It leverages the TRUST PF. For example, phishing emails can use this technique to increase responsiveness by adding elements that refer to current events like holiday festivities or news [Al-Hamar et al. (2010); Goel et al. (2017)].

12. **Personalization.** This technique uses personal information to tailor messages or express similar interest to the victim to engender trust [Hirsh et al. (2012); Jagatic et al. (2007)]. It exploits the PERSONALITY and INDIVIDUAL DIFFERENCES PFs.

13. **Affection trust.** This technique establishes an affectionate relationship with a victim. It exploits the AFFECTIVE COMMITMENT PF. Affection does not lower risk perceptions or increase trust, but makes an individual more willing to take risks and thus increases compliance [McAllister (1995)]. It is commonly used in catfishing and honey traps.

As we will see, these PTs help build bridges to map social engineering attacks and the PFs they exploit.

## 5 Systematizing Social Engineering Attacks

This section presents the objectives of social engineering attacks and a taxonomy of them. This would help us understand how attackers may choose specific attacks based on their objectives, which could help us design effective defenses against threats of given objectives. It is worth mentioning that in order to see if we overlooked some literature investigating these attack names, we conducted another round of search by using the attack names as keyword in the digital libraries mentioned above. This leads to 6 papers which were not identified in the previous search. In addition, we were aware of two social engineering attacks which are discussed in online materials but not academic literature, namely Honey Trap [Copado (2021)] and Angler Phishing [Fraudwatch (2017); Velasquez (2017)], which we included as well.

### 5.1 Attack Objectives

We categorize social engineering attacks according to the following four main types of attack objectives.
1. **Getting access to systems.** Social engineering attacks are often used as a first step of full-fledged attacks against networked systems (e.g., advanced persistent threats).

2. **Stealing money.** Social engineering attacks such as phishing are often used to steal victims' money.

3. **Stealing sensitive information.** Social engineering attacks such as phishing are often used to steal sensitive information such as passwords.

4. **Revinging.** Social engineering attacks can be used to take revenge against enterprises, organizations, or individuals by releasing damaging information about them [Chitrey et al. (2012)].

### 5.2 Attacks

Figure 2 highlights the taxonomy of Internet-based social engineering attacks based on the medium they leverage: email vs. website vs. online social network (OSN). It is worth mentioning that these attacks relate to each other; for example, the below-mentioned drive-by download attack may leverage various kinds of phishing emails to deceive a victim to visit malicious websites. These attacks are elaborated below.

![Internet-Based Social Engineering Attacks Diagram](image-url)

**Figure 2:** Taxonomy of social engineering attacks exploiting emails, websites, and online social networks (OSN), where BEC stands for Business Email Compromise.

**Email-based Attacks.** This category includes six attack techniques, which are varying flavors of phishing. These attacks are largely complementary to each other.

1. **Traditional Phishing.** In this attack, a phishing email is sent without a particular target in mind, but with the hope that someone will fall victim to it (i.e., no personalization in such phishing emails) [Ho et al. (2019); Dou et al. (2017); Steves et al. (2019)]. This attack is often motivated to steal money. This attack exploits the GREED factor because it attempts to entice victims for rewards such as in the 419 scam that promises a large amount of money if a victim pays a small amount of money.

2. **Spear Phishing.** A spear phishing email contains information personalized for a specific target, usually addressing the target by name and title. This attack is often motivated to steal money, get access to systems, steal sensitive information, or for revenge. This attack exploits the AUTHORITY factor because it attempts to deceive a victim into believing that the phisher/attacker is a person of authority and a victim must act promptly [Ho et al. (2017); Heartfield and Loukas (2015); Goel and Jain (2018)].

3. **Clone Phishing.** Such an email is cloned from a previously sent/received email, replaces its links and/or attachments with malicious ones, and spoofs the legitimate sender’s email address so that the target would not suspect the clone email [Bhavsar et al. (2018); Alam et al. (2020); Prem and Reddy (2019)]. This attack is often motivated to steal money and sensitive information. This attack exploits the TRUST factor because it attempts to make a victim think that the cloned email is a continuation of a previous communication and in order to help comply with the attacker’s request.

4. **Whaling.** A whaling email is similar to a spear phishing email by targeting specific individuals. Unlike spear phishing which can target arbitrary individuals, whaling emails target management, such as CEOs [Goel and Jain (2018); Heartfield and Loukas (2015); Salahdine and Kaabouch (2019)]. This attack is often motivated to steal money, get access to systems, steal sensitive information, or for revenge. This attack exploits the TRUST factor.
factor because it attempts to deceive, for example, a CEO into believing in the content an email and then following the instructions described in it, often by impersonating someone that the victim knows.

5. **Wire Transfer Scam.** In this attack, an email is sent to targeted individuals in order to deceive the individual into sending money (via, for example, Western Union) to pay for services or goods [Burch et al. (2015)]. The attacker often impersonates a service company, such as a utility, that threatens that the victim’s services will be cut off immediately unless a wire transfer is made, ans sometimes impersonate reputable individuals [Chaganti et al. (2021)]. It is motivated to steal money and exploits the FEAR factor because it threatens to cut services to victims.

6. **Business Email Compromise (BEC).** This attack uses email frauds against private, government and non-profit organizations, by targeting specific employees with spoofed emails impersonating a senior colleague, such as the CEO or a trusted customer [Cidon et al. (2019); Venkatesha et al. (2021)]. This attack is motivated by the objective of stealing money [Cidon et al. (2019)]. It exploits the TRUST factor because it attempts to deceive victims into thinking that they are paying a legitimate bill for goods/services received from a trusted party.

### Website-based Attacks.
This category includes 11 attacks. These attacks are not necessarily complementary or orthogonal to each other because one attack may leverage another as a supporting technique (e.g., *Ad Fraud* may use *malvertizing* as a support technique).

1. **Scareware.** This attack is to pop up a window with warning content which tells the user that the computer has been infected by malware and that the user should click a link or call a number shown on the pop-up window to get help. The attacker’s intent is to scare the user to click the link or to call the number shown on the pop-up window, which will give the attacker the opportunity to access the user’s sensitive information or ask the user to send a gift card number to have the problem fixed remotely. Most scareware do not harm the computer, but are instead used to scare victims to provide information or money to the attacker [Or-Meir et al. (2019)]. This attack exploits the FEAR factor because it scares victims into thinking that their computer is compromised and needs immediate attention.

2. **Typosquatting** (or **URL Spoofing**). This attack takes a user to a malicious website when the user mistypes a character in a URL, such as mistyping www.bankofamerica.com for www.bankofamerica.com, where the former mimics the latter in terms of website content while incorporating a malicious payload [Heartfield and Loukas (2015)]. This attack exploits the NEGLIGENCE factor because it anticipates individuals mistyping.

3. **Spamdexing** (or **Search Engine Poisoning**). This attack tricks a search engine to list a malicious website on the top of the list returned by a search [Heartfield and Loukas (2015)]. It is effective because many users trust the search results listed on the top and treat them as most relevant, causing them to most likely visit them. It exploits the TRUST factor because it anticipates that users treat the websites on the top of search results as most relevant.

4. **Drive-by Download.** This attack is used to compromise a vulnerable browser when it visits a malicious or compromised website, possibly prompted by phishing emails containing the malicious URL [Provos et al. (2007)]. It exploits the TRUST factor because a victim may trust the website in question, or the VULNERABILITY factor when a victim is not aware of this attack, or the NEGLIGENCE factor when a user does not update/patch a browser or does not pay careful attention to recognize malicious websites.

5. **Click-baiting.** This attack is to place an enticing text/image on a web page to draw the attention of visitors so that they click on a link to a malicious or compromised website [Meinert et al. (2018)]. An example is a message on a website reading "Betty reveals how she gets to 100 years of age without ever doing sports". It exploits the CURIOSITY factor because it entices victims to click on the link to figure out more information.

6. **Malvertising.** This attack abuses advertisement such that when a user clicks on the advertisement, the user may be redirected to a malicious website [Chiew et al. (2018)]. It exploits the TRUST factor because victims think they are getting legitimate ads. It also takes advantage of the NEGLIGENCE factor when victims do not perform due diligence.

7. **Reverse Social Engineering.** This attack creates a situation causing a victim to contact the attacker [Irani et al. (2011)]. It exploits the TRUST factor because it puts a victim in a situation of need, thereby contacting the attacker.

8. **Pharming.** This attack builds malicious websites to steal money or sensitive information from victims when visiting them [Adil et al. (2020)]. It exploits the TRUST factor because victims do not think these websites are malicious and the NEGLIGENCE factor because victims do not perform due diligence.

9. **Water Holing.** This attack exploits vulnerabilities of third party websites to attack victims when visiting them [Wang et al. (2021)]. This attack if often waged to steal money or sensitive information. It exploits the TRUST factor because victims think that the websites that they are visiting to be secure.
10. **Tabnabbing.** This attack attempts to deceive a victim into visiting a malicious website which mimics a legitimate website and asks the victim to login into the malicious website, while making the victim think that the malicious website is the legitimate website and forwarding the victim’s login credential to the legitimate website [Salahdine and Kaabouch 2019](#). It often leverages the same origin policy of browsers, where a second page on a browser can access scripts from another page as long as both pages have the same origin [Steffens et al. 2019](#). It attempts to steal sensitive information (e.g., login credentials). It exploits the **ABSENTMINDEDNESS** factor because a victim thinks that a previously visited website is asking for login credentials again.

11. **Ad Fraud.** This attack exploits ads to defraud advertisements, where the fraudster deceives the victims that are using a platform to advertise their goods and services by generating fake traffic (possibly via malvertising, scareware, click-baiting, and likejacking) [Kanei et al. 2020](#). It often attempts to steal money in the sense that the ads do not incur real traffic from real users, but forged traffic instead. It exploits the **TRUST** factor because victims believe that they are getting legitimate traffic to their advertisements.

**Online Social Network-based (OSN-based) Attacks.** This category includes five attack techniques.

1. **Honey Trap.** This attack targets a particular victim with a love-related relationship and may be seen as the counterpart of spear phishing. For example, John knows that Philip likes blonds and thus creates a fake profile of a blond on Instagram to like and comment on Philip’s posts; Philip sees a blond liking his posts and thinks it is an opportunity for him to meet a blond; once a relationship is established, John can deceive Philip in many ways, including financial extortion [Copado 2021](#). Our evaluation shows that this attack exploits the **LONELINESS** factor because lonely people turn to the platform to seek attention.

2. **Catfishing.** This attack creates a fake persona to seek online dating to lure victims interested in the persona, similar to the traditional phishing because the attack does not target a specific victim [Simmons and Lee 2020](#). For example, the attacker posts as women to lure men to send them money for made-up reasons, for example, “My Internet service will be suspended for accumulated bills, please help me pay or I’ll not be able to chat with you if my Internet is suspended”. This attack exploits the **LIKING (SIMILARITY)** factor because victims have the tendency to react positively to someone that they have some relationship with [Schaab et al. 2017](#).

3. **Angler Phishing.** This attack is used to lurk among the comments posted by users on social forums, like yelp, and then takes advantage of any comment that may need a resolution to defraud advertisements [Fraudwatch 2017](#). For example, an attacker may see a comment of a customer complaining about a bank transaction or a purchase. The attacker then poses as a customer satisfaction specialist of that company and asks the customer for detailed information in order to address the customer’s problem [Velasquez 2017](#). An unsuspecting customer may give away personal information with the hopes that the problem will be resolved, not knowing that they have been phished. This attack exploits the **VULNERABILITY** factor because frustrated victims desperately need solutions and the **TRUST** factor that victims put in the service companies.

4. **App Spoofing.** This attack uses bogus apps to spoof legitimate ones on platforms which are less regulated than (for example) iPhone App stores or Google Play Store. When a user uses the same credential for multiple platforms, the attacker can steal a user’s credentials to get access to the user’s account on other platforms [Malisa et al. 2017](#). It exploits the **OPENNESS and CURIOSITY** factors because users who are open and curious will often try new things.

5. **Likejacking.** This is the social media version of click-jacking attack. This attack places a transparent layer (e.g., transparent iframe) on a legitimate webpage so that when a user clicks anywhere on the webpage, the user is actually clicking on the transparent layer which directs the user to the attacker’s website [Alabdan 2020](#); [Calzavara et al. 2020](#). In Likejacking, when a user sees the “like” button on a Facebook post, on top of which there is a transparent layer not visible to the user, the user may click on the page and then be directed to a malicious website. This attack exploits the **LIKING AND SIMILARITY** factor because the attacker sets the trap knowing that people tend to like comments of people they follow on OSN.

### 5.3 Discussion

Attackers have been exploiting PFs to wage website-based social engineering attacks. For example, a phishing email can be crafted to exploit PFs like **FEAR**, **AUTHORITY**, and **CURIOSITY**, causing victims to react in a manner desired by the attacker. In principle, exploiting PFs increases the likelihood that a victim will overlook important cues of attacks.

**Insight 1** Social engineering attackers have made due effort at identifying and exploiting the relevant human PFs for waging attacks.
6 Systematizing Social Engineering Defenses

Similar to the systematization of attacks, we naturally divide defenses into three categories: email-based, website-based, and online social network-based attacks. Although it is intuitive to present defenses with respect to each attack mentioned above, this is less constructive because one defense may be able to defend against multiple attacks. Since our systematization is centered on PFs, we further divide defenses into two sub-categories: those that do not leverage PFs and those that leverage PFs. This makes it easy to recognize which PFs have been leveraged for defense purposes.

6.1 Defenses against Email-based Attacks

Defenses Not Leveraging PFs. Most studies on defenses against email-based social engineering attacks fall into this category. Defenses against various kinds of phishing have been extensively investigated, for which we refer to previous surveys for a large body of literature Khonji et al. (2013); Ali et al. (2020); Jain and Gupta (2021); Sahu and Dubey (2014); Alabdan (2020). Ho et al. Ho et al. (2017) proposed using anomaly detection to identify real-time credential spear phishing attacks in enterprise settings. Ho et al. Ho et al. (2019) proposed a classifier for detecting lateral phishing emails, which are spear phishing emails that are sent by an attacker after compromising some computers in a network and are seemingly coming from colleagues. Cidon et al. Cidon et al. (2019) proposed a defense against Business Email Compromise attacks by leveraging supervised learning and statistics about email histories. All these defenses, including those which are surveyed in the previous literature, leverage technological aspects (e.g., statistical data).

Defenses Leveraging PFs. There are few studies falling into this category. These primarily focus on eye tracking, which is related to the VIGILANCE PF. One study Pfeffel et al. (2019) leverages eye tracking to investigate gaze patterns when individuals are reading phishing emails. However, it showed: (i) even in the best-case scenario, when individuals are expecting phishing emails and are motivated to discover them, many cannot distinguish a legitimate email from a phishing email; and (ii) well-crafted phishing emails can still fool 40% of the participants. This means that leveraging eye tracking is not effective. Nevertheless, another study Heartfield and Loukas (2018) shows that incorporating a human in the defense loop can substantially reduce the success rate of some spear phishing attacks from 81% to below 10%. This highlights the importance of incorporating humans into the defense, but it is not clear how the participants exactly achieved this and whether this can be generally applied to other settings.

6.2 Defenses against Website-based Attacks

There are many studies on detecting malicious websites, including website-based social engineering attacks. The simplest method would be to use blacklists to filter malicious websites. However, the trustworthiness of blacklists is questionable because they may be outdated and/or be provided in a black-box fashion without justification Xu et al. (2013).

Defenses Not Leveraging PFs. There are many studies in this sub-category, primarily leveraging Artificial Intelligence/Machine Learning (AI/ML). For example, VisualPhishNet Abdelnabi et al. (2020) leverages visual similarities between websites to detect phishing websites; Phishpedia Lin et al. (2021) leverages deep learning to detect phishing websites via identity logos; Mnemosyne Allen et al. (2020) is a postmortem forensic analysis engine for accurately reconstructing, investigating, and assessing the ramifications of watering hole attacks; Mao et al. Mao et al. (2018) presents a method to detect phishing websites by leveraging learning-based aggregation analysis to decide page layout similarity; Nakamura and Dabashi Nakamura and Dobashit (2019) propose to detect new phishing sites by leveraging domain name generation and other attributes.

Another approach is to leverage hardware features. For example, Fidelius Eskandarian et al. (2019) is an architecture which uses trusted hardware enclaves to protect sensitive user information from potentially compromised browsers and operating systems; FIDO (First IDentity Online) is a web-authentication mechanism for mitigating phishing attacks in real time, by leveraging one-time-password as a second factor for authentication Ulqinaku et al. (2020).

Defenses Leveraging PFs. There are few studies falling into this sub-category. One of them is Aladawy et al. (2018), which presents a game-based training against social engineering attacks by leveraging social psychology PFs with the help of cards. The game is designed to provide knowledge and train people through social psychology theories on resistance to persuasion. This game is further enhanced to contain more content and to accommodate contexts Goeke et al. (2019).
6.3 Defenses against Online Social Network-based Attacks

There are many studies on detecting OSN-based social engineering attacks. Since defenses against website-based social engineering attacks can be leveraged to defend against some OSN-based social engineering attacks, we will focus on the defenses that are unique to OSN-based attacks.

**Defenses Not Leveraging PFs.** These defenses primarily leverage AI/ML techniques. For example, Yuan et al. [Yuan et al. (2019)] present a method to Sybil accounts; Xu et al. [Xu et al. (2021)] present a method to detect abusive accounts in OSNs; Wang et al. [Wang et al. (2020)] present a chatbot to actively collect intelligence to help detect e-commerce frauds.

**Defenses Leveraging PFs.** The only study we are aware of that falls into this sub-category is Junger et al. (2017), which investigates the effectiveness of two defense interventions: one is to prime the user with cues to raise awareness about the dangers of social engineering attacks and the other is to warn against the disclosure of personal information. They find that warnings do help improve the user’s behavior but most users do not adjust their behaviors when monetary rewards are at stake. This does suggest the importance of incorporating PFs into defenses.

6.4 Discussion

The preceding section suggests that current defenses primarily leverage technological solutions, especially AI/ML, but rarely incorporates PFs; when a defense does incorporate a human in the loop, a much higher effectiveness can be expected [Heartfield and Loukas (2018)]. Since social engineering attacks primarily exploit weaknesses in human information processing, we argue that effective defenses would have to incorporate the “right” PFs because they are the “root cause” of the problem in a sense, where the “right” factors need to be precisely pinned down in future studies.

*Insight 2* Current defenses against social engineering attacks have achieved limited success because they do not adequately take into account human PFs.

7 Systematizing the Relationships between Attacks, PTs, PFs, and Defenses

Figure 3 systematizes the aforementioned relationships.

**Relationships between Defenses and Attacks.** First, *email-based defenses not leveraging PFs* have been proposed to defend against the following attacks: Traditional Phishing, Spear phishing, Clone Phishing, Whaling, Wire Transfer, and BEC (Business Email Compromise). Whereas, *email-based defenses leveraging PFs* have been proposed to defend against Traditional Phishing, Spear Phishing, and Clone Phishing. Second, *website-based defenses not leveraging PFs* have been proposed to defend against Traditional Phishing, Scareware, Drive-by Download, and Watering Holes. Whereas, *website-based defenses leveraging PFs* have been proposed to defend against Traditional Phishing, Click-baiting, Reverse Social Engineering, Honey Trap, and Catfishing. Third, *OSN-based defenses not leveraging PFs* have been proposed to defend against OSN-based Honey Trap, Catfishing, and Angler phishing. Whereas, we are not aware of any *OSN-based defenses leveraging PFs*.

**Relationships between Attacks and PTs.** Social engineering attacks leverage PTs to take effect on PFs. In what follows we systematize the PTs leveraged by email-based, website-based, and OSN-based attacks, respectively.

First, PTs leveraged by email-based social engineering attacks are summarized as follows. (1) Traditional Phishing leverages Urgency, Visual Deception, Incentive and Motivator, and Quid-Pro-Quo. (2) Spear Phishing leverages Urgency, Visual Deception, Incentive and Motivator, Quid-Pro-Quo, Contextualization, Pretexting, and Personalization. (3) Clone Phishing leverages Urgency, Attention Grabbing, Visual Deception, Incentive and Motivator, Persuasion, Trusted Relationship, Impersonation, Pretexting, and Personalization. (4) Whaling leverages the Contextualization technique. (5) Wire Transfer Scam leverages Incentive and Motivator as well as Impersonation. (6) BEC (Business Email Compromise) leverages Trusted Relationships and Impersonation.

Second, PTs leveraged by website-based attacks are summarized as follows. (1) Scareware leverages Quid-Pro-Quo, Incentive and Motivator, and Attention Grabbing. (2) Typosquatting leverages Visual Deception. (3) Spamdexing leverages Trusted Relationship, Incentive and Motivator, and Attention Grabbing. (4) Drive-by Download leverages Visual Deception. (5) Click-Baiting leverages Persuasion and Visual Deception. (6) Malvertising leverages Incentive and Motivator, and Attention Grabbing. (7) Reverse Social Engineering leverages Incentive and Motivator as well as Impersonation. (8) Pharming leverages Trusted Relationship. (9) Water Hosing leverages Trusted Relationship. (10) Tabnabbing leverages Visual Deception and Impersonation. (11) Ad Fraud leverages Persuasion, Incentive and Motivator, Attention Grabbing, and Visual Deception.
Third, PTs leveraged by OSN-based attacks are summarized as follows. (1) Honey Trap leverages Impersonation and Affection Trust. (2) Catfishing leverages Impersonation and Affection Trust. (3) Angler Phishing leverages Impersonation and Trusting. (4) App Spoofing leverages Impersonation and Visual Deception. (5) Likejacking leverages Persuasion and Visual Deception.

**Relationships between PTs and PFs.** Although a PT can exploit multiple PFs, we observe that a given PT often exploits PFs within a single psychological category. This prompts us to systematize their relationships according to the five categories of PFs as follows. First, PTs exploiting cognition PFs are summarized as follows. (1) Attention Grabbing exploits the ABSENTMINDNESS and CURiosITY factors. (2) Visual Deception exploits OVERCONFIDENCE, TRUST, and HABITUATION. Second, PTs exploiting emotion PFs are summarized as follows. (1) Urgency leverages COGNITIVE MISER, FEAR and NEGLIGENCE. (2) Incentive and Motivator leverages GREED, FEAR, SYMPATHY, EMPATHY, LONELINESS, and DISOBEDIENT. Third, PTs exploiting social PFs are summarized as follows. (1) Persuasion leverages the LIKING, RECIPROCATION, SOCIAL PROOF, CONSISTENCY, and AUTHORITY factors. (2) Quid-Pro-Quo leverages RECIPROCATION, and GREED. (3) Foot-in-the-Door leverages CONSISTENCY. (4) Trusted Relationship leverages AUTHORITY, RESPECT, and TRUST. (5) Impersonation leverages AUTHORITY, RESPECT (i.e., close relationship) and TRUST. (6) Contextualization leverages LIKING (SIMILARITY). Fourth, PTs exploiting individual differences and personality PFs are summarized as follows. (1) Pretexting leverages the TRUST factor. (2) Personalization leverages DISORGANIZED, FREEWHEELING, INDIVIDUAL INDIFFERENCE, NEGLIGENCE, TRUST, SELF CONTROL, VULNERABILITY, IMPATIENCE, IMPULSIVITY, SUBMISSIVENESS, CURiosity, LAZINESS, VIGILANCE, OPENNESS, CONSCIENTIOUSNESS, EXTRAVERSION, AGREABLENESS and NEUROTICISM. Fifth, PTs exploiting workplace PFs are summarized as follows. The Affection Trust leverages AFFECTIVE COMMITMENT.
Relationships between Defenses and PFs. To our knowledge, vigilance is the only PF that has been considered in defenses against email-based, website-based and OSN-based attacks [Tu et al. (2019); Aldawood and Skinner (2019b); Alsharnouby et al. (2015); Jung et al. (2020)]. This means that much research is needed before leveraging PFs to design effective defenses. This also prompts us to explore future research directions in the next section.

Summary. Figure 3 leads to the following. First, PTs are widely exploited for attacks but are rarely incorporated into defenses. This discrepancy gives attackers a big advantage. Second, some PTs are leveraged by attacks more often than others. For example, impersonation, attention grabbing and visual deception are widely used across email-based, website-based, and OSN-based social engineering attacks. This means that future defenses should target such PTs. Third, there is a good potential to leverage workplace PFs to design effective defenses because they cannot be manipulated by attackers.

Insight 3 Current defenses have achieved a limited success as they rarely incorporate human PFs.

8 Future Research Directions

The preceding systematization suggests that effective defenses should be guided by psychological principles. This prompts us to seek psychological principles that can guide the design of effective defenses.

Guiding Principle: The Theory of System 1 vs. System 2 in Human Information Processing. The human mind processes information from the environment likely through a variety of cognitive mechanisms. A popular theory is centered at the distinction of System 1 (heuristic) vs. System 2 (analytic) [Kahneman (2011)]. System 1 is fast, effortless, based on heuristics, and often thought of as error-prone; whereas, System 2 is slow, effortful, and involves deep analytical thinking [Kahneman (2011)]. Putting another way, the theory suggests that deliberate reasoning, which is typically logical or mathematical, falls into the scope of System 2 [Ney and Pennycook (2019)]. While common in psychology, the theory does not come without criticism, especially the fact that despite the characteristics of the two processes is often clear, but the factors that determine when an individual will think analytically or rely on their intuition is unclear [Pennycook et al. (2015)]. This has inspired research in cognitive psychology [Lin et al. (2022)] using electroencephalography (EEG) to decipher their respective underlying neural mechanisms [Williams et al. (2019)], and in improving Artificial Intelligence learning from human decision making capabilities [Booch et al. (2020)]. There have also been attempts to improve this dual-thinking process to a three-stage dual process model of analytic engagement [Pennycook et al. (2015)]. Moreover, a recent development is that humans can actually process deliberate reasoning involving logical principles in an intuitive fashion (i.e., without deliberation) [Ney and Pennycook (2019)]. This sheds light on leveraging the theory to guide us in understanding social engineering attacks through the psychological lens and in designing new defenses without forcing humans to trap into System 2 when dealing with social engineering attacks.

The preceding systematization and guiding principle prompt us to propose the following research directions: (i) use psychological principles to guide the design of a qualitative framework to describe social engineering attacks; (ii) conduct empirical studies to quantify the effect of PFs on human susceptibility to social engineering attacks; and (iii) leverage these quantitative findings to guide the design of effective defenses.

8.1 Creating a Qualitative Psychological Framework Tailored to Social Engineering Attacks

Our premise is that in the context of social engineering attacks, both heuristics and analytic processing can help prevent victimization under different conditions, and it may not be accurate to regard heuristics as uniquely error-prone. We thus use this framework as a starting point towards a more robust framework later in the paper.

In order to design effective defenses, we need to understand how the human information processing procedure interprets information associated with these attacks. This prompts us to propose a framework for describing human information processing of materials associated with social engineering attacks.

Figure 4 highlights the framework we propose. It is inspired by the state-of-the-art System 1 vs. System 2 framework. The new framework has two internal components, information processing and risk attitude, which collectively determine one’s behavior (e.g., clicking a link in a phishing email or not) based on: (i) individual baseline, namely the PFs that may be influenced by an attack to benefit the attacker; (ii) the external attacker effort at earning one’s trust (e.g., how real a phishing email looks); and (iii) defense alerts (e.g., one’s competence in raising suspicions against phishing emails). The framework is elaborated below.

Risk Attitude. We propose incorporating risk attitude because studies show that it affects the likelihood of social engineering victimization and it may be independent of human information processing [Conway et al. (2017); Lea et al. (2009)]. This is not surprising because risk attitude affects motivators which drive humans to act [Maslow (1943)].
There are three well-known risk attitudes: \textit{risk seeking}, \textit{risk aversion} and \textit{risk-neutral}. For example, even when information processing triggers suspicions, a risk-seeking user may still comply with a malicious request because the prospect of reward exceeds the perceived risk, explaining why some people make risky decisions in cyberspace especially when they feel they have less to lose \cite{Conway2017, Howe2012} and why some people still fall victim even if they recognize the risk \cite{Lea2009}.

\textbf{Heuristic vs. Analytic Processing}. This is inspired by the System 1 vs. System 2 framework. However, our goal is to identify the conditions that would push one into \textit{heuristic processing} or \textit{analytic processing}, respectively.

- \textbf{Heuristic processing}. This uses patterns and rules, or a trial-and-error approach, to reach a decision. Heuristics are often used in situations of uncertainty where information or time is limited. In social engineering attacks, non-experts are more likely to rely on heuristics to determine the credibility of the message. In addition to rules and patterns, non-expert users also rely on previous experiences (often acquired through trial and error) to detect social engineering messages \cite{Abbasi2016, Redmiles2018}. Heuristics are useful, but can cause errors when the rules used to determine credibility are based on elements that can be manipulated by attackers, or when they are unable to discriminate between benign and social engineering messages.

- \textbf{Analytic processing}. This involves evaluating multiple factors to reach a decision. It requires that an individual is knowledgeable on factors relevant to the outcome and have the information required to support the decision. In social engineering attacks, individuals with cybersecurity \textit{EXPERTISE} are more likely to use analytic processing to detect social engineering messages. For example, experts would consider multiple factors to determine the credibility of emails and attend to suspicious elements in them \cite{Kumaraguru2006}.

The preceding categorization is important because attackers often attempt to deceive victims into heuristic processing but not analytic processing to increase their chance of success. It remains to be investigated how heuristic processing and analytic processing would work together.

\textbf{Individual Baseline}. These are the PFs that affect information and risk attitude. As discussed above, the following PFs encourage the use of heuristic processing: \textit{HABITUATION}, \textit{STRESS} and \textit{WORKLOAD}. \textit{HABITUATION} because they reduce suspicions. Moreover, a combination of \textit{STRESS} and \textit{WORKLOAD} increases the reliance on heuristic processing and decreases \textit{VIGILANCE}.

\textbf{Attacker Effort}. This is an attacker’s effort at exploiting human PFs to earn victims’ trust and encourage their compliance. For example, an attacker can earn trust from a victim by creating emails of high quality and appealing to the victim. This is because many users judge credibility based on superficial attributes, like the professional appearance of a website, absence of grammatical errors, or recognizable logos in emails \cite{Dhamija2006, Kim2005}. To generate an appealing message, an attacker can exploit a combination of PTs (e.g., persuasion, personalization, contextualization). Having identified the PTs exploited by attacks, it is an important open problem to investigate how attacks influence PFs, which in turn influences the heuristic vs. analytic processing as mentioned above.

\textbf{Defense Alerts}. These include the mechanisms that are employed to warn users of potential threats to trigger their \textit{VIGILANCE}. Intuitively, an effective alert would cause users to switch their attention to the warning information and maintain their attention long enough to process it. An effective warning would trigger suspicion \cite{Montanez2020}, such as cue salience triggering attention switching \cite{Wogalter2018}. It is an important open problem to investigate how defenses can influence PFs to offset the influence of attackers.
Future research needs to confirm, dispute, or refine the qualitative framework.

### 8.2 Creating a Quantitative Psychological Framework Tailored to Social Engineering Attacks

The preceding qualitative framework, or its refined version, paves the way for quantifying the effectiveness of social engineering attacks and defenses. Specifically, we propose a hierarchical quantitative framework to describe individuals’ susceptibility to social engineering attacks as

\[
\text{susceptibility} = f(\text{processing\_route}, \text{risk\_attitude}),
\]

where \( f \) is a family of mathematical functions that are to be identified by future studies, \( \text{processing\_route} \) means the use of heuristic or analytic processing, and \( \text{risk\_attitude} \) indicates how the individual trades risk for reward. Moreover, the \( \text{processing\_route} \) would be determined by

\[
\text{processing\_route} = g(\text{individual\_baseline}, \text{attacker\_effort}, \text{defense\_alerts}).
\]

where \( g \) is another family of mathematical functions that are to be determined by future studies, and \( \text{individual\_baseline}, \text{attacker\_effort} \) and \( \text{defense\_alerts} \) are defined above.

Future research needs to enrich the quantitative framework, or its refinement, with characteristics of the impact of the variables, including the relevant PFs and PTs. We envision that the resulting quantitative framework will be seamlessly incorporated into broader frameworks for investigating cybersecurity from a holistic perspective, such as Cybersecurity Dynamics Xu (2014, 2019, 2020); Pendleton et al. (2016); Cho et al. (2019). Indeed, human susceptibility to social engineering attacks has been explicitly described in the mathematical models of preventive and reactive cybersecurity dynamics Li et al. (2011); Xu et al. (2012a,b); Zheng et al. (2018); Lin et al. (2019c); Han et al. (2021). Moreover, human susceptibility to social engineering attacks needs to be adequately incorporated into other kinds of models, such as adaptive, proactive, and active cyber defense dynamics Xu et al. (2014); Da et al. (2014); Han et al. (2014); Xu et al. (2015b); Zheng et al. (2015b). Since human susceptibility to social engineering attacks would not be independent from individual to individual as shown above (e.g., people exhibiting similar PFs would be susceptible to social engineering attacks to a similar extent), this kind of dependence needs to be explicitly considered in holistic cybersecurity models, as highlighted in Xu and Xu (2012); Da et al. (2014); Xu et al. (2015a); Lu et al. (2013); Chen et al. (2018, 2021).

### 8.3 Using Psychological Principles and Quantitative Findings to Guide Design of Effective Defenses

The qualitative framework discussed above suggests approaches to designing effective defenses as follows. First, under the premise that the standard theory of System 1 vs. System 2 is perfectly suitable for describing the phenomena resulting from social engineering attacks, effective defense should strive to train users in enhancing their System 1 decision-making when coping with potential social engineering attacks. Moreover, if the aforementioned recent development — humans can actually process deliberate reasoning involving logical principles in an intuitive fashion (i.e., without deliberation) Neys and Pennycook (2019) — is true, then this insight can be leveraged to build effective defense. These psychological principles play a fundamental role because it is not feasible to force humans to use System 2 when dealing with social engineering attacks simply because of (for example) the large amount of emails they will process on a daily basis.

The quantitative understanding resulting from the quantitative framework mentioned above would offer insights into designing effective defenses. The basic idea is to identify the important factors, namely the most relevant PFs and PTs, such that defenses can be tailored to influence them to minimize individuals’ susceptibility to social engineering attacks. For example, if TRUST turns out to be an important factor, then defenses can be tailored to minimize individuals’ TRUST (e.g., making everyone practice zero-trust on everything coming from Internet may be an effective defense against social engineering attacks). As another example, if warnings can reduce individuals’ susceptibility, then it is important to investigate how to make warnings effective (e.g., using dynamic warnings instead of static warnings in order to reduce HABITUATION Brinton Anderson et al. (2016)).

### 8.4 Summary

The discussion presented above reflects our firm belief that effective defenses cannot be achieved without the guidance of sound psychological principles that are tailored to the domain or social engineering attacks.

**Insight 4** A quantitative psychological theory tailored to the social engineering domain is needed to guide the design of effective defenses.
9 Conclusion

In order to understand why current defenses against social engineering attacks have achieved limited success, we have systematized human PFs and PTs (psychological factors and techniques) which have been exploited by attackers in particularly crafty ways. Our systematization of these attacks and current defenses against them highlights a key discrepancy which can explain the limited success of current defenses: defenses do not consider human PFs to the same degree that attacks do. This prompts us to propose a systematic roadmap for future research towards effective defenses.

Acknowledgement. We thank Eric Ficke and Shawn Emery for feedback and proofreading the paper.

References

Ahmed Abbasi, F Mariam Zahedi, and Yan Chen. 2016. Phishing susceptibility: The good, the bad, and the ugly. In 2016 IEEE Conference on Intelligence and Security Informatics (ISI). IEEE, Tucson, AZ, 169–174.

Sahar Abdelnabi, Katharina Krombholz, and Mario Fritz. 2020. VisualPhishNet: Zero-Day Phishing Website Detection by Visual Similarity. In Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security. Association for Computing Machinery, New York, NY, USA, 1681-1692. https://doi.org/10.1145/3372297.3417233

Noelle Abe and Michael Soltys. 2019. Deploying Health Campaign Strategies to Defend Against Social Engineering Threats. Procedia Computer Science 159 (2019), 824–831.

Muhammad Adil, Rahim Khan, and M Ahmad Nawaz Ul Ghani. 2020. Preventive techniques of phishing attacks in networks. In 2020 3rd International Conference on Advancements in Computational Sciences (ICACS). IEEE, Lahore, Pakistan, 1–8.

David Airehrour, Nisha Vasudevan Nair, and Samaneh Madanian. 2018. Social engineering attacks and countermeasures in the new zealand banking system: Advancing a user-reflective mitigation model. Information 9, 5 (2018), 110.

Mariam Al-Hamar, Ray Dawson, and Lin Guan. 2010. A culture of trust threatens security and privacy in Qatar. In 2010 10th IEEE International Conference on Computer and Information Technology. IEEE, Bradford, 991–995.

Rana Alabdan. 2020. Phishing Attacks Survey: Types, Vectors, and Technical Approaches. Future Internet 12, 10 (2020), 168.

Dina Aladawy, Kristian Beckers, and Sebastian Pape. 2018. PERSUADED: fighting social engineering attacks with a serious game. In International Conference on Trust and Privacy in Digital Business. Springer, Bratislava, Slovakia, 103–118.

Mohammad Nazmul Alam, Dhiman Sarma, Farzana Firoz Lima, Ishita Saha, Sohrab Hossain, et al. 2020. Phishing attacks detection using machine learning approach. In 2020 third international conference on smart systems and inventive technology (ICSSIT). IEEE, Tirunelveli, India, 1173–1179.

Samar Muslah Albladi and George RS Weir. 2020. Predicting individualsâ€™ vulnerability to social engineering in social networks. Cybersecurity 3, 1 (2020), 1–19.

Hussain Aldawood and Geoffrey Skinner. 2019a. Reviewing Cyber Security Social Engineering Training and Awareness Programsâ€™ Pitfalls and Ongoing Issues. Future Internet 11, 3 (2019), 73.

Hussain Aldawood and Geoffrey Skinner. 2019b. A Taxonomy for Social Engineering Attacks via Personal Devices. International Journal of Computer Applications 975 (2019), 8887.

Ahmed Aleroud and Lina Zhou. 2017. Phishing environments, techniques, and countermeasures: A survey. Computers & Security 68 (2017), 160–196.

Abdullah Algarni, Yue Xu, and Taizan Chan. 2017. An empirical study on the susceptibility to social engineering in social networking sites: the case of Facebook. European Journal of Information Systems 26, 6 (2017), 661–687.

Dalal N Alharthi, Mahmoud M Hammad, and Amelia C Regan. 2020. A taxonomy of social engineering defense mechanisms. In Future of Information and Communication Conference. Springer, Vancouver, BC, Canada, 27–41.

Mohammed Mahmood Ali, Mohd S Qaseem, and Md Ateeq Ur Rahman. 2020. A Survey on Deceptive Phishing Attacks in Social Networking Environments. In Proceedings of the Third International Conference on Computational Intelligence and Informatics. Springer, Delhi, India, 443–452.

Joey Allen, Zheng Yang, Matthew Landen, Raghav Bhat, Harsh Grover, Andrew Chang, Yang Ji, Roberto Perdisci, and Wenke Lee. 2020. Mnemosyne: An Effective and Efficient Postmortem Watering Hole Attack Investigation System. In Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security. ACM, USA, 787–802.
Luca Allodi, Tzouliano Chotza, Ekaterina Panina, and Nicola Zannone. 2019. The need for new antiphishing measures against spear-phishing attacks. *IEEE Security & Privacy* 18, 2 (2019), 23–34.

Ammar Almomani, Brij B Gupta, Samer Atawneh, Andrew Meulenberg, and Eman Almomani. 2013. A survey of phishing email filtering techniques. *IEEE communications surveys & tutorials* 15, 4 (2013), 2070–2090.

Manal Alohali, Nathan Clarke, Fudong Li, and Steven Furnell. 2018. Identifying and predicting the factors affecting end-users’ risk-taking behavior. *Information & Computer Security* 26, 3 (2018), 306–326.

Ibrahim Alseadoon, Taizan Chan, Ernest Foo, and Juan Gonzalez Nieto. 2012. Who is more susceptible to phishing emails?: a Saudi Arabian study. In *23rd Australasian Conference on Information Systems*. Association for Information Systems, Australia, –.

Ibrahim Alseadoon, MFI Othman, and Taizan Chan. 2015. What is the influence of users’ characteristics on their ability to detect phishing emails? In *Advanced computer and communication engineering technology*. Springer, USA, 949–962.

Mohamed Alsharnouby, Furkan Alaca, and Sonia Chiasson. 2015. Why phishing still works: User strategies for combating phishing attacks. *International Journal of Human-Computer Studies* 82 (2015), 69–82.

Ahmed Alyahya and George RS Weir. 2021. Understanding Responses to Phishing in Saudi Arabia via the Theory of Planned Behaviour. In *2021 National Computing Colleges Conference (NCCC)*. IEEE, Taif, Saudi Arabia, 1–6.

Maha Rita Arabia-Obedoza, Gloria Rodriguez, Amber Johnston, Fatima Salahdine, and Naima Kaabouch. 2020. Social Engineering Attacks A Reconnaissance Synthesis Analysis. In *2020 11th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*. IEEE, USA, 0843–0848.

Abdul Basit, Maham Zafar, Xuan Liu, Abdul Rehman Javed, Zunera Jalil, and Kashif Kifayat. 2020. A comprehensive survey of AI-enabled phishing attacks detection techniques. *Telecommunication Systems* 76 (2020), 1–16.

Nikos Benias and Angelos P Markopoulos. 2018. Hacking the human: Exploiting primordial instincts. In *2018 South-Eastern European Design Automation, Computer Engineering, Computer Networks and Society Media Conference (SEEDA_CECNSM)*. IEEE, Kastoria, Greece, 1–6.

Vaishnavi Bhavsar, Aditya Kadlak, and Shabnam Sharma. 2018. Study on phishing attacks. *Int. J. Comput. Appl* 178 (2018), 27–29.

Grady Booch, Francesco Fabiano, Lior Horesh, Kiran Kate, Jonathan Lenchner, Nick Linck, Andrea Loreggia, Keerthiram Murugesan, Nicholas Mattei, Francesca Rossi, et al. 2020. Thinking fast and slow in AI. (2020).

Bonnie Brinton Anderson, Anthony Vance, C Brock Kirwan, David Eargle, and Jeffrey L Jenkins. 2016. How users perceive and respond to security messages: a NeuroIS research agenda and empirical study. *European Journal of Information Systems* 25, 4 (2016), 364–390.

Susanne Buecker, Marlies Maes, Jaap JA Denissen, and Maike Luhmann. 2020. Loneliness and the Big Five personality traits: A meta–analysis. *European Journal of Personality* 34, 1 (2020), 8–28.

Jan-Willem Bullee, Lorena Montoya, Marianne Junger, and Pieter Hartel. 2017. Spear phishing in organisations explained. *Information & Computer Security* 25, 5 (2017), 593–613.

Jan-Willem Hendrik Bullée, Lorena Montoya, Wolter Pieters, Marianne Junger, and Pieter Hartel. 2018. On the anatomy of social engineering attacks: A literature-based dissection of successful attacks. *Journal of investigative psychology and offender profiling* 15, 1 (2018), 20–45.

Greg Burch, Adrian Taylor, and Christie Yeung. 2015. Wire Transfer Email Fraud and What to Do About It. *Intellectual Property & Technology Law Journal* 27, 1 (2015), 13.

Stefano Calzavara, Sebastian Roth, Alvise Rabitti, Michael Backes, and Ben Stock. 2020. A tale of two headers: A formal analysis of inconsistent click-jacking protection on the web. In *29th {USENIX} Security Symposium ({USENIX} Security 20)*. USENIX, USA, 683–697.

Rajasekhar Chaganti, Bharat Bhushan, Anand Nayyar, and Azroul Mourad. 2021. Recent trends in Social Engineering Scams and Case study of Gift Card Scam. (2021).

S Chanti and T Chithralekha. 2020. Classification of anti-phishing solutions. *SN Computer Science* 1, 1 (2020), 1–18.

Huashan Chen, Hasan Cam, and Shouhuai Xu. 2021. Quantifying Cybersecurity Effectiveness of Dynamic Network Diversity. *IEEE Transactions on Dependable and Secure Computing* –, – (2021), 1–1. https://doi.org/10.1109/TDSC.2021.3107514

H. Chen, J. Cho, and S. Xu. 2018. Quantifying the security effectiveness of firewalls and DMZs. In *Proc. HoTSoS’2018*. ACM, USA, 9:1–9:11.
Rui Chen, Joana Gaia, and H Raghav Rao. 2020. An examination of the effect of recent phishing encounters on phishing susceptibility. Decision Support Systems 133 (2020), 113287.

Kendra Cherry. 2012. The big five personality dimensions: 5 major factors of personality. (2012).

Kang Leng Chiew, Kelvin Sheng Chek Yong, and Choon Lin Tan. 2018. A survey of phishing attacks: Their types, vectors and technical approaches. Expert Systems with Applications 106 (2018), 1–20.

Anubhav Chitrey, Dharmendra Singh, and Vrijendra Singh. 2012. A comprehensive study of social engineering based attacks in india to develop a conceptual model. International Journal of Information and Network Security 1, 2 (2012), 45.

J. Cho, S. Xu, P. Hurley, M. Mackay, T. Benjamin, and M. Beaumont. 2019. STRAM: Measuring the Trustworthiness of Computer-Based Systems. ACM Comput. Surv. 51, 6 (2019), 128:1–128:47.

Noman H Chowdhury, Marc TP Adam, and Geoffrey Skinner. 2019. The impact of time pressure on cybersecurity behaviour: a systematic literature review. Behaviour & Information Technology 38, 12 (2019), 1290–1308.

Robert B Cialdini and Lloyd James. 2009. Influence: Science and practice. Vol. 4. Pearson education, Boston, MA.

Robert B Cialdini and Melanie R Trost. 1998. Social influence: Social norms, conformity and compliance. In The handbook of social psychology. McGraw-Hill, USA, 151–162.

Asaf Cidon, Lior Gavish, Itay Bleier, Nadia Korshun, Marco Schweighauser, and Alexey Tsitkin. 2019. High precision detection of business email compromise. In 28th USENIX Security Symposium (USENIX Security 19). USENIX, USA, 1291–1307.

Henry Collier and Alexandra Collier. 2020. The Port Z3R0 Effect! Human Behaviors Related to Susceptibility. nature 2, 3 (2020), 5.

Dan Conway, Ronnie Taib, Mitch Harris, Kun Yu, Shlomo Berkovsky, and Fang Chen. 2017. A qualitative investigation of bank employee experiences of information security and phishing. In Thirteenth Symposium on Usable Privacy and Security (SOUPS 2017). USENIX, USA, 115–129.

T Copado. 2021. 12 Types of Social Engineering Attacks to Look Out For. https://www.copado.com/devops-hub/blog/12-types-of-social-engineering-attacks-to-look-out-for

Paul T Costa Jr and Robert R McCrae. 2008. The Revised Neo Personality Inventory (neo-pi-r). In The SAGE handbook of personality theory and assessment. Sage Publications, Inc, USA.

G. Da, M. Xu, and S. Xu. 2014. A New Approach to Modeling and Analyzing Security of Networked Systems. In Proc. HotSoS’14. ACM, USA, 6:1–6:12.

Carlo Marcelo Revoredo da Silva, Eduardo Luzeiro Feitosa, and Vinicius Cardoso Garcia. 2020. Heuristic-based strategy for Phishing prediction: A survey of URL-based approach. Computers & Security 88 (2020), 101613.

Avisha Das, Shahryar Baki, Ayman El Aassal, Rakesh Verma, and Arthur Dunbar. 2019a. SoK: a comprehensive reexamination of phishing research from the security perspective. IEEE Communications Surveys & Tutorials 22, 1 (2019), 671–708.

Sanchari Das, Andrew Kim, Zachary Tingle, and Christena Nippert-Eng. 2019b. All about phishing: Exploring user research through a systematic literature review. (2019).

Sauvik Das, Adam DI Kramer, Laura A Dabbish, and Jason I Hong. 2014. Increasing security sensitivity with social proof: A large-scale experimental confirmation. In Proceedings of the 2014 ACM SIGSAC conference on computer and communications security. ACM, USA, 739–749.

Jensen Deutrom, Vasilis Katos, and Raian Ali. 2021. Loneliness, life satisfaction, problematic internet use and security behaviours: re-examining the relationships when working from home during COVID-19. Behaviour & Information Technology 1, 1 (2021), 1–15.

Rachna Dhamija, J Doug Tygar, and Marti Hearst. 2006. Why phishing works. In Proceedings of the SIGCHI conference on Human Factors in computing systems. ACM, Montreal, Canada, 581–590.

John M Digman. 1990. Personality structure: Emergence of the five-factor model. Annual review of psychology 41, 1 (1990), 417–440.

Zuochoao Dou, Issa Khalil, Abdalllah Khreishah, Ala Al-Fuqaha, and Mohsen Guizani. 2017. Systematization of knowledge (sok): A systematic review of software-based web phishing detection. IEEE Communications Surveys & Tutorials 19, 4 (2017), 2797–2819.

Saba Eskandarian, Jonathan Cogan, Sawyer Binbaum, Peh Chang Wei Brandon, Dillon Franke, Forest Fraser, Gaspar Garcia, Eric Gong, Hung T Nguyen, Taresh K Sethi, et al. 2019. Fidelius: Protecting user secrets from compromised browsers. In 2019 IEEE Symposium on Security and Privacy (SP). IEEE, USA, 264–280.
Ana Ferreira. 2018. Why ransomware needs a human touch. In 2018 International Carnahan Conference on Security Technology (ICCST). IEEE, Quebec, Canada, 1–5.

Ana Ferreira and Gabriele Lenzini. 2015. An analysis of social engineering principles in effective phishing. In 2015 Workshop on Socio-Technical Aspects in Security and Trust. IEEE, USA, 9–16.

A Fraudwatch. 2017. Angler Phishing: The Risks and Dangers of Fake Social Media Brand Profiles â–‡A¸ S Part 1. https://fraudwatch.com/angler-phishing-the-risks-and-dangers-of-fake-social-media-brand-profiles-part-1/

Edwin Donald Frauenstein and Stephen Flowerday. 2020. Susceptibility to phishing on social network sites: A personality information processing model. Computers & Security 94 (2020), 101862.

Jonathan L Freedman and Scott C Fraser. 1966. Compliance without pressure: the foot-in-the-door technique. Journal of personality and social psychology 4, 2 (1966), 195.

Pablo L Gallegos-Segovia, Jack F Bravo-Torres, Víctor M Larios-Rosillo, Iván F Yuquilima-Albarado, and Juan D Jara-Saltos. 2017. Social engineering as an attack vector for ransomware. In 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON). IEEE, Chile, 1–6.

Ibrahim Ghafir, Vaclav Prenosil, Ahmad Alhejailan, and Mohammad Hammoudeh. 2016. Social engineering attack strategies and defence approaches. In 2016 IEEE 4th international conference on future internet of things and cloud (FiCloud). IEEE, Vienna, Austria, 145–149.

Edwin Donald Frauenstein and Stephen Flowerday. 2020. Susceptibility to phishing on social network sites: A personality information processing model. Computers & Security 94 (2020), 101862.

Jonathan L Freedman and Scott C Fraser. 1966. Compliance without pressure: the foot-in-the-door technique. Journal of personality and social psychology 4, 2 (1966), 195.

Pablo L Gallegos-Segovia, Jack F Bravo-Torres, Víctor M Larios-Rosillo, Iván F Yuquilima-Albarado, and Juan D Jara-Saltos. 2017. Social engineering as an attack vector for ransomware. In 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON). IEEE, Chile, 1–6.

Ibrahim Ghafir, Vaclav Prenosil, Ahmad Alhejailan, and Mohammad Hammoudeh. 2016. Social engineering attack strategies and defence approaches. In 2016 IEEE 4th international conference on future internet of things and cloud (FiCloud). IEEE, Vienna, Austria, 145–149.

Edwin Donald Frauenstein and Stephen Flowerday. 2020. Susceptibility to phishing on social network sites: A personality information processing model. Computers & Security 94 (2020), 101862.

Jonathan L Freedman and Scott C Fraser. 1966. Compliance without pressure: the foot-in-the-door technique. Journal of personality and social psychology 4, 2 (1966), 195.

Pablo L Gallegos-Segovia, Jack F Bravo-Torres, Víctor M Larios-Rosillo, Iván F Yuquilima-Albarado, and Juan D Jara-Saltos. 2017. Social engineering as an attack vector for ransomware. In 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON). IEEE, Chile, 1–6.

Ibrahim Ghafir, Vaclav Prenosil, Ahmad Alhejailan, and Mohammad Hammoudeh. 2016. Social engineering attack strategies and defence approaches. In 2016 IEEE 4th international conference on future internet of things and cloud (FiCloud). IEEE, Vienna, Austria, 145–149.

Edwin Donald Frauenstein and Stephen Flowerday. 2020. Susceptibility to phishing on social network sites: A personality information processing model. Computers & Security 94 (2020), 101862.

Jonathan L Freedman and Scott C Fraser. 1966. Compliance without pressure: the foot-in-the-door technique. Journal of personality and social psychology 4, 2 (1966), 195.

Pablo L Gallegos-Segovia, Jack F Bravo-Torres, Víctor M Larios-Rosillo, Iván F Yuquilima-Albarado, and Juan D Jara-Saltos. 2017. Social engineering as an attack vector for ransomware. In 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON). IEEE, Chile, 1–6.

Ibrahim Ghafir, Vaclav Prenosil, Ahmad Alhejailan, and Mohammad Hammoudeh. 2016. Social engineering attack strategies and defence approaches. In 2016 IEEE 4th international conference on future internet of things and cloud (FiCloud). IEEE, Vienna, Austria, 145–149.

Edwin Donald Frauenstein and Stephen Flowerday. 2020. Susceptibility to phishing on social network sites: A personality information processing model. Computers & Security 94 (2020), 101862.

Jonathan L Freedman and Scott C Fraser. 1966. Compliance without pressure: the foot-in-the-door technique. Journal of personality and social psychology 4, 2 (1966), 195.

Pablo L Gallegos-Segovia, Jack F Bravo-Torres, Víctor M Larios-Rosillo, Iván F Yuquilima-Albarado, and Juan D Jara-Saltos. 2017. Social engineering as an attack vector for ransomware. In 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON). IEEE, Chile, 1–6.

Ibrahim Ghafir, Vaclav Prenosil, Ahmad Alhejailan, and Mohammad Hammoudeh. 2016. Social engineering attack strategies and defence approaches. In 2016 IEEE 4th international conference on future internet of things and cloud (FiCloud). IEEE, Vienna, Austria, 145–149.

Edwin Donald Frauenstein and Stephen Flowerday. 2020. Susceptibility to phishing on social network sites: A personality information processing model. Computers & Security 94 (2020), 101862.

Jonathan L Freedman and Scott C Fraser. 1966. Compliance without pressure: the foot-in-the-door technique. Journal of personality and social psychology 4, 2 (1966), 195.

Pablo L Gallegos-Segovia, Jack F Bravo-Torres, Víctor M Larios-Rosillo, Iván F Yuquilima-Albarado, and Juan D Jara-Saltos. 2017. Social engineering as an attack vector for ransomware. In 2017 CHILEAN Conference on Electrical, Electronics Engineering, Information and Communication Technologies (CHILECON). IEEE, Chile, 1–6.
Cormac Herley. 2012. Why do nigerian scammers say they are from nigeria?. In Workshop on the Economics of Information Security. WEIS, Berlin, Germany. –.

Jacob B. Hirsh, Sonia K. Kang, and Galen V. Bodenhausen. 2012. Personalized Persuasion: Tailoring Persuasive Appeals to Recipients’ Personality Traits. Psychological Science 23, 6 (2012), 578–581. https://doi.org/10.1177/0956797611436349

Grant Ho, Asaf Cidon, Lior Gavish, Marco Schweighauser, Vern Paxson, Stefan Savage, Geoffrey M Voelker, and David Wagner. 2019. Detecting and characterizing lateral phishing at scale. In 28th USENIX Security Symposium (USENIX Security 19). USENIX, USA, 1273–1290.

Grant Ho, Aashish Sharma, Mobin Javed, Vern Paxson, and David Wagner. 2017. Detecting credential spearphishing in enterprise settings. In 26th USENIX Security Symposium (USENIX Security 17). USENIX, USA, 469–485.

Thomas J Holt, Johan van Wilsem, Steve van de Weijer, and Rutger Leukfeldt. 2020. Testing an integrated self-control and routine activities framework to examine malware infection victimization. Social Science Computer Review 38, 2 (2020), 187–206.

Kyung Wha Hong, Christopher M Kelley, Rucha Tembe, Emerson Murphy-Hill, and Christopher B Mayhorn. 2013. Keeping up with the Joneses: Assessing phishing susceptibility in an email task. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol. 57. SAGE Publications Sage, Los Angeles, CA, 1012–1016.

Deanna House and MK Raja. 2020. Phishing: message appraisal and the exploration of fear and self-confidence. Behaviour & Information Technology 39, 11 (2020), 1204–1224.

Adele E. Howe, Indrajit Ray, Mark Roberts, Malgorzata Urbanska, and Zinta Byrne. 2012. The Psychology of Security for the Home Computer User. In Proceedings of the 2012 IEEE Symposium on Security and Privacy (SP ’12). IEEE Computer Society, Washington, DC, USA, 209–223. https://doi.org/10.1109/SP.2012.23

Danesh Irani, Marco Balduzzi, Davide Balzarotti, Engin Kirda, and Calton Pu. 2011. Reverse social engineering attacks in online social networks. In International conference on detection of intrusions and malware, and vulnerability assessment. Springer, USA, 55–74.

Tom N Jagatic, Nathaniel A Johnson, Markus Jakobsson, and Filippo Menczer. 2007. Social phishing. Commun. ACM 50, 10 (2007), 94–100.

Ankit Kumar Jain and BB Gupta. 2021. A survey of phishing attack techniques, defence mechanisms and open research challenges. Enterprise Information Systems 16, 4 (2021), 1–39.

Mohammad S Jalali, Maike Bruckes, Daniel Westmattelmann, and Gerhard Schewe. 2020. Why employees (still) click on phishing links: investigation in hospitals. Journal of medical Internet research 22, 1 (2020), e16775.

Daniel Jampen, Gürkan Gür, Thomas Sutter, and Bernhard Tellenbach. 2020. Don’Äžt click: towards an effective anti-phishing training. A comparative literature review. Human-centric Computing and Information Sciences 10, 1 (2020), 1–41.

Uwe Jensen. 2002. Probabilistic Risk Analysis: Foundations and Methods. J. Amer. Statist. Assoc. 97, 459 (2002), 925–925.

Marianne Junger, Lorena Montoya, and F-J Overink. 2017. Priming and warnings are not effective to prevent social engineering attacks. Computers in human behavior 66 (2017), 75–87.

Marianne Junger, Victoria Wang, and Marleen Schlömer. 2020. Fraud against businesses both online and offline: crime scripts, business characteristics, efforts, and benefits. Crime Science 9, 1 (2020), 1–15.

Daniel Kahneman. 2011. Thinking, fast and slow. Macmillan, USA.

Fumihiro Kanei, Daiki Chiba, Kunio Hato, Katsunari Yoshioka, Tsutomu Matsumoto, and Mitsuaki Akiyama. 2020. Detecting and Understanding Online Advertising Fraud in the Wild. IEICE Transactions on Information and Systems 103, 7 (2020), 1512–1523.

Yuki Kano and Tatsuo Nakajima. 2021. Trust Factors of Social Engineering Attacks on Social Networking Services. In 2021 IEEE 3rd Global Conference on Life Sciences and Technologies (LifeTech). IEEE, Osaka, Japan, 25–28.

Security kaspersky. 2022. What is Social Engineering? https://usa.kaspersky.com/resource-center/definitions/what-is-social-engineering

Wayne D Kearney and Hennie A Kruger. 2016. Can perceptual differences account for enigmatic information security behaviour in an organisation? Computers & Security 61 (2016), 46–58.

Mahmoud Khonji, Youssef Iraqi, and Andrew Jones. 2013. Phishing detection: a literature survey. IEEE Communications Surveys & Tutorials 15, 4 (2013), 2091–2121.
Yunju Kim and Heejun Lee. 2021. Towards a Sustainable News Business: Understanding Readers’ Perceptions of Algorithm-Generated News Based on Cultural Conditioning. *Sustainability* 13, 7 (2021), 3728.

Yong Jin Kim, Rajiv Kishore, and G Lawrence Sanders. 2005. From DQ to EQ: understanding data quality in the context of e-business systems. *Commun. ACM* 48, 10 (2005), 75–81.

Iacovos Kirlappos, Simon Parkin, and M Angela Sasse. 2014. Learning from Shadow Security: Why understanding non-compliance provides the basis for effective security. In *Workshop on Usable Security*. –, USA, –.

Anna Kirmani and Rui Zhu. 2007. Vigilant against manipulation: The effect of regulatory focus on the use of persuasion knowledge. *Journal of Marketing Research* 44, 4 (2007), 688–701.

Ponnurangam Kumaraguru, Alessandro Acquisti, and Lorrie Faith Cranor. 2006. Trust modelling for online transactions: a phishing scenario. In *Proceedings of the 2006 International Conference on Privacy, Security and Trust: Bridge the Gap Between PST Technologies and Business Services*. ACM, Markham, Canada, 11.

Stephen EG Lea, Peter Fischer, and Kath M Evans. 2009. *The psychology of scams: Provoking and committing errors of judgement*. Technical Report. Office of Fair Trading.

Christina Lekati. 2018. Complexities in Investigating Cases of Social Engineering: How Reverse Engineering and Profiling can Assist in the Collection of Evidence. In *2018 11th International Conference on IT Security Incident Management & IT Forensics (IMF)*. IEEE, Hamburg, Germany, 107–109.

Tong Li, Kaiyuan Wang, and Jennifer Horkoff. 2019. Towards Effective Assessment for Social Engineering Attacks. In *2019 IEEE 27th International Requirements Engineering Conference (RE)*. IEEE, Jeju Island, Korea (South), 392–397.

X. Li, P. Parker, and S. Xu. 2011. A Stochastic Model for Quantitative Security Analyses of Networked Systems. *IEEE TDSIC* 8, 1 (2011), 28–43.

Hause Lin, Gordon Pennycook, and David Rand. 2022. Thinking more or thinking differently? Using drift-diffusion modeling to illuminate why accuracy prompts decrease misinformation sharing. (2022).

Tian Lin, Daniel E Capecci, Donovan M Ellis, Harold A Rocha, Sandeep Dommaraju, Daniela S Oliveira, and Natalie C Ebner. 2019a. Susceptibility to spear-phishing emails: Effects of Internet user demographics and email content. *ACM Transactions on Computer-Human Interaction (TOCHI)* 26, 5 (2019), 32.

Tian Lin, Daniel E Capecci, Donovan M Ellis, Harold A Rocha, Sandeep Dommaraju, Daniela S Oliveira, and Natalie C Ebner. 2019b. Susceptibility to spear-phishing emails: Effects of internet user demographics and email content. *ACM Transactions on Computer-Human Interaction (TOCHI)* 26, 5 (2019), 1–28.

Yun Lin, Ruofan Liu, Dinil Mon Divakaran, Jun Yang Ng, Qing Zhou Chan, Yiwen Lu, Yuxuan Si, Fan Zhang, and Jin Song Dong. 2021. Phishpedia: A Hybrid Deep Learning Based Approach to Visually Identify Phishing Webpages. In *30th Usenix Security Symposium*. Usenix, USA, –.

Z. Lin, W. Lu, and S. Xu. 2019c. Unified Preventive and Reactive Cyber Defense Dynamics Is Still Globally Convergent. *IEEE/ACM ToN* 27, 3 (2019), 1098–1111.

W. Lu, S. Xu, and X. Yi. 2013. Optimizing Active Cyber Defense Dynamics. In *Proc. GameSec’13*. Springer, USA, 206–225.

Luka Malisa, Kari Kostiainen, and Srdjan Capkun. 2017. Detecting mobile application spoofing attacks by leveraging user visual similarity perception. In *Proceedings of the Seventh ACM on Conference on Data and Application Security and Privacy*. ACM, USA, 289–300.

Jian Mao, Jingdong Bian, Wenqian Tian, Shishi Zhu, Tao Wei, Aili Li, and Zhenkai Liang. 2018. Detecting phishing websites via aggregation analysis of page layouts. *Procedia Computer Science* 129 (2018), 224–230.

Abraham Harold Maslow. 1943. A theory of human motivation. *Psychological review* 50, 4 (1943), 370.

John McAlaney and Vladlena Benson. 2020. Cybersecurity as a social phenomenon. In *Cyber Influence and Cognitive Threats*. Elsevier, USA, 1–8.

John McAlaney and Peter J Hills. 2020. Understanding phishing email processing and perceived trustworthiness through eye tracking. *Frontiers in Psychology* 11 (2020), 1756.

Daniel J McAllister. 1995. Affect-and cognition-based trust as foundations for interpersonal cooperation in organizations. *Academy of management journal* 38, 1 (1995), 24–59.

Robert R McCrae and Oliver P John. 1992. An introduction to the five-factor model and its applications. *Journal of personality* 60, 2 (1992), 175–215.
Judith Meinert, Milad Mirbabaie, Sebastian Dungs, and Ahmet Aker. 2018. Is it really fake?–Towards an understanding of fake news in social media communication. In International Conference on Social Computing and Social Media. Springer, USA, 484–497.

Shaheen Mondal, Diksha Maheshwari, Nilima Pai, and Ameyaa Biwalkar. 2019. A Review on Detecting Phishing URLs using Clustering Algorithms. In 2019 International Conference on Advances in Computing, Communication and Control (ICAC3). IEEE, Mumbai, India, 1–6.

Rosana Montañez, Edward Golob, and Shouhuai Xu. 2020. Human cognition through the lens of social engineering cyberattacks. Frontiers in Psychology 11 (2020), 1–.

Rosana Montañez, Adham Atyabi, and Shouhuai Xu. 2022. Cybersecurity and Cognitive Science. Elsevier, USA, Chapter Social Engineering Attacks and Defenses in the Physical World vs. Cyberspace: A Contrast Study, 3–41.

Gregory D Moody, Dennis F Galletta, and Brian Kimball Dunn. 2017. Which phish get caught? An exploratory study of individuals susceptibility to phishing. European Journal of Information Systems 26, 6 (2017), 564–584.

Akihito Nakamura and Fuma Dobashit. 2019. Proactive Phishing Sites Detection. In 2019 IEEE/WIC/ACM International Conference on Web Intelligence (WI). IEEE, Thessaloniki, Greece, 443–448.

Jema David Ndibwile, Edith Talina Luhanga, Doudou Fall, Daisuke Miyamoto, Gregory Blanc, and Youki Kadobayashi. 2019. An empirical approach to phishing countermeasures through smart glasses and validation agents. IEEE Access 7 (2019), 130758–130771.

Terry Nelms, Roberto Perdisci, Manos Antonakakis, and Mustaque Ahamad. 2016. Towards Measuring and Mitigating Social Engineering Software Download Attacks. In 25th USENIX Security Symposium (USENIX Security 16). USENIX Association, Austin, TX, 773–789.

Alisha M Ness, Genevieve Johnson, Michael K Ault, William D Taylor, Jennifer A Griffith, Shane Connelly, Norah E Dunbar, and Matthew L Jensen. 2017. Reactions to ideological websites: The impact of emotional appeals, credibility, and pre-existing attitudes. Computers in Human Behavior 72 (2017), 496–511.

Daniel Nettle. 2006. The evolution of personality variation in humans and other animals. American Psychologist 61, 6 (2006), 622.

Wim De Neys and Gordon Pennycook. 2019. Logic, Fast and Slow: Advances in Dual-Process Theorizing. Current Directions in Psychological Science 28, 5 (2019), 503–509. https://doi.org/10.1177/0963721419855658

Ori Or-Meir, Nir Nissim, Yuval Elovici, and Lior Rokach. 2019. Dynamic malware analysis in the modern eraâ˘AˇTA state of the art survey. ACM Computing Surveys (CSUR) 52, 5 (2019), 1–48.

M. Pendleton, R. Garcia-Lebron, J. Cho, and S. Xu. 2016. A Survey on Systems Security Metrics. ACM Comput. Surv. 49, 4 (2016), 62:1–62:35.

Gordon Pennycook, Jonathan A Fugelsang, and Derek J Koehler. 2015. What makes us think? A three-stage dual-process model of analytic engagement. Cognitive psychology 80 (2015), 34–72.

Kevin Pfeffel, Philipp Ulsamer, and Nicholas H Müller. 2019. Where the user does look when reading phishing mails—an eye-tracking study. In International Conference on Human-Computer Interaction. Springer, USA, 277–287.

Santi Priyanka Prem and B Indira Reddy. 2019. Phishing and anti-phishing techniques. International Research Journal of Engineering and Technology 6, 7 (2019), 1446–1452.

N. Provos, D. McNamee, P. Mavrommatis, K. Wang, and N. Modadugu. 2007. The ghost in the browser analysis of web-based malware. In Proceedings of the First Workshop on Hot Topics in Understanding Botnets (HotBots 07). USENIX, USA, 1–.

Prashanth Rajivan and Cleotilde Gonzalez. 2018. Creative persuasion: a study on adversarial behaviors and strategies in phishing attacks. Frontiers in psychology 9 (2018), 135.

Justinas Rastenis, Simona Ramanauskaitė, Justinas Janulevičius, Antanas Cenys, Asta Slotkiene, and Kestutis Pakrjasuskas. 2020. E-mail-Based Phishing Attack Taxonomy. Applied Sciences 10, 7 (2020), 2363.

Jochen Reb, Jayanth Narayanan, and Zhi Wei Ho. 2015. Mindfulness at work: Antecedents and consequences of employee awareness and absent-mindedness. Mindfulness 6, 1 (2015), 111–122.

Elissa M Redmiles, Neha Chachra, and Brian Waismeyer. 2018. Examining the Demand for Spam: Who Clicks?. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. ACM, Montreal, Canada, 212.

Elissa M Redmiles, Noel Warford, Amritha Jayanti, Aravind Koneru, Sean Kross, Miraida Morales, Rock Stevens, and Michelle L Mazurek. 2020. A comprehensive quality evaluation of security and privacy advice on the web. In 29th {USENIX} Security Symposium ({USENIX} Security 20). USENIX, USA, 89–108.
Nader Sohrabi Safa, Mehdi Sookhak, Rossouw Von Solms, Steven Furnell, Norjihan Abdul Ghani, and Tutut Herawan. 2015. Information security conscious care behaviour formation in organizations. *Computers & Security* 53 (2015), 65–78.

Krutika Rani Sahu and Jigyasu Dubey. 2014. A survey on phishing attacks. *International Journal of Computer Applications* 88, 10 (2014), –.

Fatima Salahdine and Naima Kaabouch. 2019. Social engineering attacks: a survey. *Future Internet* 11, 4 (2019), 89.

Peter Schaab, Kristian Beckers, and Sebastian Pape. 2017. Social engineering defence mechanisms and counteracting training strategies. *Information & Computer Security* 25, 2 (2017), 206–222.

Carsten Schürmann, Lisa Hartmann Jensen, and Rósa Maria Siggjörnsdóttir. 2020. Effective cybersecurity awareness training for election officials. In *International Joint Conference on Electronic Voting*. Springer, Bregenz, Austria, 196–212.

Hossein Siadati, Toan Nguyen, Payas Gupta, Markus Jakobsson, and Nasir Memon. 2017. Mind your SMSes: Mitigating social engineering in second factor authentication. *Computers & Security* 65 (2017), 14–28.

Mariah Simmons and Joon Suk Lee. 2020. Catfishing: A Look into Online Dating and Impersonation. In *International Conference on Human-Computer Interaction*. Springer, Oldenburg, Germany, 349–358.

Christopher J Soto. 2019. How replicable are links between personality traits and consequential life outcomes? The life outcomes of personality replication project. *Psychological Science* 30, 5 (2019), 711–727.

Frank Stajano and Paul Wilson. 2011. Understanding scam victims: seven principles for systems security. *Commun. ACM* 54, 3 (2011), 70–75.

Marius Steffens, Christian Rossow, Martin Johns, and Ben Stock. 2019. Donâ ¯A ´Zt Trust The Locals: Investigating the Prevalence of Persistent Client-Side Cross-Site Scripting in the Wild.. In *NDSS Network and Distributed System Security Symposium*. NDSS, USA, –.

Michelle P Steves, Kristen K Greene, Mary F Theofanos, et al. 2019. A phish scale: rating human phishing message detection difficulty. In *Workshop on usable security (USEC)*. NDSS, USA, –.

Security Touchstone. 2021. Social Engineering Attacks on the Rise. [https://touchstonesecurity.com/social-engineering-attacks/](https://touchstonesecurity.com/social-engineering-attacks/)

Huahong Tu, Adam Doupé, Ziming Zhao, and Gail-Joon Ahn. 2019. Users really do answer telephone scams. In 28th *USENIX Security Symposium* (USENIX Security 19). USENIX, USA, 1327–1340.

Enis Ulqinaku, Hala Assal, AbdelRahman Abdou, Sonia Chiasson, and Srdjan Capkun. 2020. Is Real-time Phishing Eliminated with FIDO? Social Engineering Downgrade Attacks against FIDO Protocols. *IACR Cryptol. ePrint Arch.* 2020 (2020), 1298.

Steve GA Van de Weijer and E Rutger Leukfeldt. 2017. Big five personality traits of cybercrime victims. *Cyberpsychology, Behavior, and Social Networking* 20, 7 (2017), 407–412.

Amber Van Der Heijden and Luca Allodi. 2019. Cognitive triaging of phishing attacks. In 28th *USENIX Security Symposium* (USENIX Security 19). USENIX, USA, 1309–1326.

Eva Velasquez. 2017. What Is Angler Phishing and How Can You Avoid It? [https://www.experian.com/blogs/ask-experian/what-is-angler-phishing-and-how-can-you-avoid-it/](https://www.experian.com/blogs/ask-experian/what-is-angler-phishing-and-how-can-you-avoid-it/)

Sushruth Venkatesha, K Rahul Reddy, and BR Chandavarkar. 2021. Social Engineering Attacks During the COVID-19 Pandemic. *SN computer science* 2, 2 (2021), 1–9.

M Vijayalakshmi, S Mercy Shalinie, Ming Hour Yang, et al. 2020. Web phishing detection techniques: a survey on the state-of-the-art, taxonomy and future directions. *IET Networks* 9, 5 (2020), 235–246.

Arun Vishwanath, Tejaswini Herath, Rui Chen, Jingguo Wang, and H Raghav Rao. 2011. Why do people get phished? Testing individual differences in phishing vulnerability within an integrated, information processing model. *Decision Support Systems* 51, 3 (2011), 576–586.

Peng Wang Wang, Xiaojing Liao Liao, Yue Qin, and XiaoFeng Wang. 2020. Into the Deep Web: Understanding E-commerce Fraud from Autonomous Chat with Cybercriminals. In *Proceedings of the ISOC Network and Distributed System Security Symposium (NDSS)*. 2020. NDSS, USA, –.

Qinglong Wang, Wenbo Guo, Kaixuan Zhang, Alexander G Ororbia, Xinyu Xing, Xue Liu, and C Lee Giles. 2017. Adversary resistant deep neural networks with an application to malware detection. In *Proceedings of the 23rd ACM sigkdd international conference on knowledge discovery and data mining*. ACM, Halifax NS Canada, 1145–1153.

Zuoguang Wang, Hongsong Zhu, and Limin Sun. 2021. Social Engineering in Cybersecurity: Effect Mechanisms, Human Vulnerabilities and Attack Methods. *IEEE Access* 9 (2021), 11895–11910.
Allaire K Welk, Kyung Wha Hong, Olga A Zielinska, Rucha Tembe, Emerson Murphy-Hill, and Christopher B Mayhorns. 2015. Will the â“AI Phisher-Menâ“AI Reel You In?: Assessing individual differences in a phishing detection task. *International Journal of Cyber Behavior, Psychology and Learning (IJCBBP)* 5, 4 (2015), 1–17.

Monica T Whitty. 2018. Do you love me? Psychological characteristics of romance scam victims. *Cyberpsychology, behavior, and social networking* 21, 2 (2018), 105–109.

Chad C Williams, Mitchel Kappen, Cameron D Hassall, Bruce Wright, and Olave E Krigolson. 2019. Thinking theta and alpha: Mechanisms of intuitive and analytical reasoning. *NeuroImage* 189 (2019), 574–580.

Emma J Williams, Amy Beardmore, and Adam N Joinson. 2017. Individual differences in susceptibility to online influence: A theoretical review. *Computers in Human Behavior* 72 (2017), 412–421.

Michael S Wogalter. 2018. Communication-human information processing (C-HIP) model. In *Forensic Human Factors and Ergonomics*. CRC Press, USA, 33–49.

Michael Workman. 2007. Gaining access with social engineering: An empirical study of the threat. *Information Systems Security* 16, 6 (2007), 315–331.

Ryan T Wright, Matthew L Jensen, Jason Bennett Thatcher, Michael Dinger, and Kent Marett. 2014. Research noteâ“ATinfluence techniques in phishing attacks: an examination of vulnerability and resistance. *Information systems research* 25, 2 (2014), 385–400.

Liu Xiangyu, Li Qiuyang, and Sonali Chandel. 2017. Social engineering and Insider threats. In *2017 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC)*. IEEE, Nanjing, China, 25–34.

Li Xu, Zhenxin Zhan, Shouhuai Xu, and Keying Ye. 2013. Cross-layer detection of malicious websites. In *Third ACM Conference on Data and Application Security and Privacy (CODASPY’13)*. ACM, USA, 141–152.

M. Xu, G. Da, and S. Xu. 2015a. Cyber Epidemic Models with Dependences. *Internet Mathematics* 11, 1 (2015), 62–92.

M. Xu and S. Xu. 2012. An Extended Stochastic Model for Quantitative Security Analysis of Networked Systems. *Internet Mathematics* 8, 3 (2012), 288–320.

Shouhuai Xu. 2014. Cybersecurity dynamics. In *Proceedings of the 2014 Symposium and Bootcamp on the Science of Security*. ACM, USA, 1–2.

S. Xu. 2019. Cybersecurity Dynamics: A Foundation for the Science of Cybersecurity. In *Proactive and Dynamic Network Defense*. Springer, USA, 1–31.

Shouhuai Xu. 2020. The cybersecurity dynamics way of thinking and landscape (invited paper). In *Proceedings of the 7th ACM Workshop on Moving Target Defense*. ACM, USA, 69–80.

Shouhuai Xu. 2021. SARR: A Cybersecurity Metrics and Quantification Framework (Keynote). In *Science of Cyber Security - Third International Conference (SciSec’2021)* (Lecture Notes in Computer Science, Vol. 13005), Wenlian Lu, Kun Sun, Moti Yung, and Feng Liu (Eds.). Springer, China, 3–17.

Shouhuai Xu, Wenlian Lu, and Hualun Li. 2015b. A Stochastic Model of Active Cyber Defense Dynamics. *Internet Mathematics* 11, 1 (2015), 23–61.

Shouhuai Xu, Wenlian Lu, and Li Xu. 2012a. Push-and pull-based epidemic spreading in networks: Thresholds and deeper insights. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)* 7, 3 (2012), 1–26.

Shouhuai Xu, Wenlian Lu, Li Xu, and Zhenxin Zhan. 2014. Adaptive epidemic dynamics in networks: Thresholds and control. *ACM Transactions on Autonomous and Adaptive Systems (TAAS)* 8, 4 (2014), 1–19.

S. Xu, W. Lu, and Z. Zhan. 2012b. A Stochastic Model of Multivirus Dynamics. *IEEE Transactions on Dependable and Secure Computing* 9, 1 (2012), 30–45.

Teng Xu, Gerard Goossen, Huseyin Kerem Cevahir, Sara Khodeir, Yingyezhe Jin, Frank Li, Shawn Shan, Sagar Patel, David Freeman, and Paul Pearce. 2021. Deep Entity Classification: Abusive Account Detection for Online Social Networks. In *30th {USENIX} Security Symposium ({USENIX} Security 21)*. USENIX, USA, –.

Affan Yasin, Rubia Fatima, Lin Liu, Awaid Yasin, and Jianmin Wang. 2019. Contemplating social engineering studies and attack scenarios: A review study. *Security and Privacy* 2, 4 (2019), e73.

Dong Yuan, Yuanli Miao, Neil Zhenqiang Gong, Zheng Yang, Qi Li, Dawn Song, Qian Wang, and Xiao Liang. 2019. Detecting fake accounts in online social networks at the time of registrations. In *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security*. ACM, USA, 1423–1438.
Humayun Zafar, Adriane Randolph, Saurabh Gupta, and Carole Hollingsworth. 2019. Traditional SETA no more: investigating the intersection between cybersecurity and cognitive neuroscience. In Proceedings of the 52nd Hawaii International Conference on System Sciences. ScholarSpace / AIS Electronic Library (AISeL), USA, –.

Rania Zaimi, Mohamed Hafidi, and Mahnane Lamia. 2020. Survey paper: Taxonomy of website anti-phishing solutions. In 2020 Seventh International Conference on Social Networks Analysis, Management and Security (SNAMS). IEEE, France, 1–8.

Jin G Zheng, Daniel Howsmon, Boliang Zhang, Juergen Hahn, Deborah McGuinness, James Hendler, and Heng Ji. 2015a. Entity linking for biomedical literature. BMC medical informatics and decision making 15, S1 (2015), S4.

Kangfeng Zheng, Tong Wu, Xiujuan Wang, Bin Wu, and Chunhua Wu. 2019. A session and dialogue-based social engineering framework. IEEE Access 7 (2019), 67781–67794.

Ren Zheng, Wenlian Lu, and Shouhuai Xu. 2015b. Active cyber defense dynamics exhibiting rich phenomena. In Proceedings of the 2015 Symposium and Bootcamp on the Science of Security. ACM, USA, 1–12.

R. Zheng, W. Lu, and S. Xu. 2018. Preventive and Reactive Cyber Defense Dynamics Is Globally Stable. IEEE TNSE 5, 2 (2018), 156–170.